

MOVING ON Measuring Movement Remotely after Stroke

Mohamed Irfan Mohamed Refai

# MOVING ON: MEASURING MOVEMENT REMOTELY AFTER STROKE 

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Front: A turbulent brain depicts our lack of insight on recovery post stroke.
Back: With the insights on recovery, and the wearable tools presented in this thesis, our understanding of the brain could improve, becoming less turbulent.

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#### Abstract

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# MOVING ON: MEASURING MOVEMENT REMOTELY AFTER STROKE 

DISSERTATION

to obtain<br>the degree of doctor at the University of Twente on the authority of the rector magnificus, prof. dr. ir. A. Veldkamp, on account of the decision of the Doctorate Board, to be publicly defended on Wednesday the $7^{\text {th }}$ of July 2021 at 1645 hours

## by

Mohamed Irfan Mohamed Refai
born on the $12^{\text {th }}$ of May, 1991
in Chennai, India

# This dissertation has been approved by: 

## Supervisors

Prof. dr. ir. Peter H. Veltink
Prof. dr. Jaap H. Buurke

## Co-supervisor

dr. ir. Bert-Jan F. van Beijnum

Graduation committee:

Chair/Secretary<br>Prof. dr. ir. Joost Kok University of Twente<br>Supervisors<br>Prof. dr. ir. Peter H. Veltink University of Twente<br>Prof. dr. Jaap H. Buurke University of Twente<br>Co-supervisor<br>dr. ir. Bert-Jan F. van Beijnum University of Twente<br>Committee Members<br>Prof. dr. Claudia Mazzà<br>Prof. dr. ir. Heike Vallery<br>University of Sheffield<br>Delft University of Technology<br>Prof. dr. Vivian Weerdesteyn<br>Radboud University Medical Centre<br>Prof. dr. Johan S. Rietman University of Twente<br>dr. Edwin H. F. van Asseldonk University of Twente

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## Abbreviations

List of commonly used abbreviations.
1/2/3 D : 1/2/3 Dimensional
10 MWT : 10 m Walk Test
ADL : Activities of Daily life
AGBS : Ambulatory Gait and Balance System
AP : Anterio-posterior
ARAT : Action Research Arm Test
BBS : Berg Balance Scale
BoS : Base of Support
CMP : Centroidal Moment Pivot
CoM : Centre of Mass
CoM' : Centre of Mass projected on the horizontal plane (ground)
CoP : Centre of Pressure
CST : Corticospinal tract
DoF : Degrees of Freedom
EEG : Electroencephalography
EEKF : Error Extended Kalman Filter
EKF : Extended Kalman Filter
F\&M : Force and Moment
FAC : Functional Ambulatory Categories
FM : Fugl-Meyer assessment
FM-UE : Fugl-Meyer motor assessment for Upper Extremity
fMRI : functional Magnetic Resonance Imaging
FoG : Freezing of Gait
GRF: Ground Reaction Forces
KF : Kalman Filter
ICF : International Classification of Functioning, Disability, and Health
iM1 : ipsilateral Motor cortex

| IMU | : Inertial Measurement Unit |
| :--- | :--- |
| KP | : Knowledge of Performance |
| KR | : Knowledge of Results |
| MEMS | : Micro machined Electro-Mechanical systems |
| ML | : Medio-lateral |
| MoS | : Margin of Stability |
| NWO | : Netherlands Organisation for Scientific Research |
| PCA | : Principle Component Analysis |
| PGL | : Portable Gait Lab |
| PRISMA | : Preferred Reporting Items for Systematic Reviews and Meta- |
|  | Analyses |
| RMS | : Root Mean Square |
| SD | : Standard deviation |
| SNR | : Signal to Noise Ratio |
| SPARC | : Spectral Arc Length (Balasubramanian et al., 2015) |
| SRRR | : Stroke Recovery and Rehabilitation Roundtable |
| TUG | : Timed Up and Go |
| WMFT | : Wolf Motor Function Test |
| XCoM | : Extrapolated Centre of Mass |
| XCoM | : Extrapolated Centre of Mass projected on the horizontal plane |
| (ground) |  |
| ZMP | : Zero Moment Point |

## Legend



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Introduction
Fig. 1.1: Hippocrates
Inset: Stroke Recovery
Pattern

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## Figure

Inset: Humanoid walking using ZMP

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## Chapter II

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## Discussion

Inset: Compensation
strategies in the upper
extremity

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## Glossary of Terms

Base of Support (BoS): The possible range of the centre of pressure, loosely equal to the area below and between the feet (Hof et al., 2005). When only the feet are the contact points with the ground, the BoS can be defined using the boundaries of the feet.

Behavioural restitution of function: The return towards more normal patterns of motor control with the impaired effector (a body part such as a hand or foot that interacts with an object or the environment) and reflects the process toward 'true (neurological) recovery' (Bernhardt et al., 2017; Levin et al., 2009). Neural repair is required for true recovery.

Behavioural substitution/compensation of function: A patient's ability to accomplish a goal through substitution with a new approach rather than using their normal pre-stroke behavioural repertoire constitutes compensation (Bernhardt et al., 2017). This behaviour does not require neural repair, but may require learning.

Biomechanics: The study of continuum mechanics (loads, motion, stress, and strain) of biological systems and the mechanical effects on the body's movement, size, shape and structure (Lu and Chang, 2012).

Centroidal Moment Pivot (CMP) point: The contact point on the ground through which a line passing through the CoM is parallel to the ground reaction force vector (Popovic et al., 2005).

Centre of Mass (CoM): An imaginary point at which the total body mass can be assumed to be concentrated (Schepers et al., 2009).

Centre of Pressure (CoP): The origin or application point of the ground reaction force (GRF), the point on the contact surface between body and ground where the moments about the horizontal axes are zero (Hof et al., 2005; Schepers et al., 2009).
(Integration) Drift: A source of error when dealing with IMUs. Integration drift occurs when IMU data (acceleration or angular velocity) is integrated to derive kinematics of interest, and is present as the constant bias and sensor noise are both being integrated (Kok et al., 2017; Woodman, 2007).

Dynamic Stability: The ability to maintain balance during locomotion (Chang et al., 2010).
(End) effector: A body part such as a hand or foot that interacts with an object or the environment (Bernhardt et al., 2017; Levin et al., 2009).

Extrapolated Centre of Mass (XCoM): A vector quantity that tracks the movement of the CoM after accounting for its velocity during gait (Hof et al., 2005).

Human motion analysis: Systematic study of human motion by careful observation, augmented by instrumentation for measuring body movements, body mechanics and the activity of the muscles (Lu and Chang, 2012).

Inertial Measurement Units (IMUs): Sensors that contain a 3D accelerometer and a 3D gyroscope (Kok et al., 2017; Woodman, 2007). The accelerometer measures the external specific force acting on the sensor, whereas the gyroscope measures the sensor's angular velocity (rate of change of orientation).

International Classification of Functioning, disability, and health (ICF): A classification that provides a standard language and conceptual basis for the definition and measurement of health and disability (World Health Organization, 2002).

Margin of Stability (MoS): A measure of dynamic stability that measures the (directed) distance between the XCoM and the boundaries of the BoS (Hof et al., 2005).

Mathematical coupling: This occurs when part of a relationship between two variables is due to a common component, where one of the variables is
contained in the other variable or a third dependent variable is common to both (Archie, 1981).
(Biomechanical) Metrics: A kinematic or kinetic measure of a predefined movement. Kinematic metrics measure the motion of the body, whereas kinetic metrics measure the different forces acting on the body that causes motion.

Motor control: The process by which motor commands produced by the central nervous system activate and coordinate muscles to generate joint torques to move effectors in goal-directed actions (Haith and Krakauer, 2013).

Motor impairment: Problems in body function and structure such as a significant deviation or loss related to movement, (WHO, 2001).

Motor recovery: Improvement in motor performance dependent on the tasks and measures that are used (Krakauer et al., 2012).

Movement assays: Movement quality can be assessed using assays in two ways: Performance assays that isolate core motor execution capacities outside a motor task content and a standardized functional task that can help separate the contribution of behavioural restitution and compensation during the movement (Kwakkel et al., 2019).

Movement quality: A measure of patient's motor task execution in comparison with age-matched normative values of healthy individuals (Kwakkel et al., 2019). The closer one approaches these values, the higher the movement quality (Kwakkel et al., 2017).

Proportional recovery rule: After the onset of stroke, most patients are expected to recover about 70\% of their lost function (Hope et al., 2019; Vliet et al., 2020).

Reaching: The ICF defines reaching movement as 'Using the hands and arms to extend outwards and touch and grasp something, such as when reaching
across a table or desk for a book' (WHO, 2017). Reaching could be further differentiated as reach-to-point or reach-to-grasp.

Reference/Coordinate Frames: Data measured by the IMUs can be expressed in different reference/coordinate frames. This may include the sensor frame, mounting frame, anatomical frame, or the global frame. In this thesis, we introduce two body-centric frames; current step frame and initial contact frame.

Sensor fusion: The process of combining of sensory data such that the resulting information is in some sense better than would be possible when these sources are used individually (Gustafsson, 2018; Wikipedia, 2005). Bayesian fusion models such as Kalman Filters are commonly used to combine different sensory data.

Smoothness (of movement): The continuity or non-intermittency of a movement, independent of its amplitude or duration (Balasubramanian et al., 2015).

Spatiotemporal parameters: Parameters that measure an aspect of space or time, and is used within the context of measuring gait in this thesis. For example, spatial parameters include step length, step width etc., whereas temporal parameters includes step time, swing time etc.

Spontaneous neurobiological recovery: Improvements in recovery of behavior, occurring during a time-sensitive window of heightened recovery that begins early after stroke and slowly tapers off (Bernhardt et al., 2017; Krakauer et al., 2012).

Stable Gait: Gait that doesn't lead to falls in spite of perturbations (Bruijn et al., 2013). If the net moments around the CoM sum to zero, then the body is rotationally stable (Goswami and Kallem, 2004).

Strapdown inertial navigation: A commonly used method of inertial navigation where the miniature IMUs are mounted rigidly onto a system that is being measured, and therefore the quantities are measured in the
frame defined by the sensor orientation (Woodman, 2007). The rotation and movement of the system can be obtained by integrating the angular velocity and acceleration respectively measured by the IMU.

Stroke: A broad term that refers to a central nervous system infarction in the brain, spinal cord, or retinal cell death attributable to ischemia (Sacco et al., 2013).

Stroke recovery phases: Phases after stroke onset can be classified as hyperacute ( $0-24$ hours post onset), acute ( $1-7$ days post onset), early sub-acute ( 7 days -3 months post onset), late sub-acute ( $3-6$ months post onset), and chronic (> 6 months post onset) (Bernhardt et al., 2017).

Zero Moment Point (ZMP): The contact point on the ground where the resulting reaction forces acts on the body (Popovic et al., 2005). During gait on even surfaces, this point is the same as the CoP.

# General Introduction 

"All we have to decide is what to do with the time that is given us."
J. R. R. Tolkien, The Fellowship of the Ring

### 1.1. STROKE AND MOTOR RECOVERY

Around $5^{\text {th }}$ century B.C., Hippocrates (Fig. 1.1) described a state of paralysis, possibly due to acute non-traumatic brain injuries, as apoplexia (Clarke, 1963; Sacco et al., 2013). The Greek word implies being 'struck with violence’ (Clarke, 1963). Later, in 1689, the related word stroke was introduced to medicine by William Cole (Sacco et al., 2013). Today, stroke is an umbrella term that includes cases of neurological dysfunction presumed to be caused by ischemia or haemorrhage (Sacco et al., 2013). It is the second cause of death worldwide (Avan et al., 2019). Both environmental and genetic factors


Figure 1.1 Hippocrates (Unidentified Engraver, 2005). play an important role in the incidence of stroke (Donnan et al., 2008). The total annual costs for stroke treatment and care was estimated to be 27 billion euros in 27 European Union countries (Rajsic et al., 2019), and the prevalence for stroke is only expected to increase in 2035 (Stevens et al., 2017).

Impairments and long-term effect of stroke depends on the stroke site and lesion (Langhorne et al., 2011). Commonly found impairments include those of speech and language, swallowing, vision, sensation and cognition (Langhorne et al., 2011). Additionally, about $80 \%$ of persons with stroke suffer from motor impairment on one side of the body, which includes restricted functions in muscle movement or mobility (Langhorne et al., 2009a). Upper limb strength plays an important role in predicting health related quality of life (Lieshout et al., 2020). Only $20 \%$ of persons with upper limb limitations may demonstrate full recovery six months post stroke (Kwakkel et al., 2019). In case of persons with stroke that showed initial motor deficits in the lower extremity, we see that $65 \%$ tend to recover (Hendricks et al., 2002). Nonetheless, motor impairments influence the independence in Activities of Daily Living (ADL), balance, risk of falls, and thereby the quality of life for patients and care givers (Kwakkel et al., 2019; Li et al., 2018; Morris et al., 2013).

Neurological recovery is expected to take place biologically via spontaneous learning-dependent processes, including restitution and compensation (Inset: Stroke Recovery Pattern) (Langhorne et al., 2011). Behavioural restitution is the return towards more normal patterns of motor control with the impaired effector, whereas compensation is identified as accomplishing a goal through substitution with a new approach rather than use of normal pre-stroke behavioural repertoire (Bernhardt et al., 2017).

Recovery after stroke is quite tricky to measure (Duncan et al., 2000). The proportional recovery rule suggests that most patients will recover about 70\% of their lost function (Krakauer and Marshall, 2015). However, there are two camps in literature that either contest or support this rule. Studies that contest show that the association between initial impairments and amount of change arises due to mathematical coupling (Hawe et al., 2019; Hope et al., 2019). Mathematical coupling occurs when one variable is included in another directly or indirectly, and therefore the resulting association may be a degree of their non-independence (Archie, 1981). Additionally, the time course of recovery early post stroke is not explained by the rule (Hawe et al., 2019; Hope et al., 2019). Other studies claim that the recovery rule is the best model we have regarding population-level recovery of persons with sub-acute stroke (Kundert et al., 2019). In sum, recovery patterns post stroke are an ongoing subject of analysis (Vliet et al., 2020).

It is important to understand the progress of recovery and the underlying paradigms in order to direct appropriate training of persons with stroke in their recovery, and in design of meaningful interventions (Bernhardt et al., 2017). Clinical outcome measures such as Action Research Arm Test (ARAT) focus on accomplishment of specified tasks and are not sensitive enough to measure improvement in task performance (Levin et al., 2009; Sivan et al., 2011). The Fugl-Meyer assessment (FM) was designed to measure stroke recovery by assessing selective movements (Gladstone et al., 2002). However, clinical outcome measures are ordinal scales which may affect studying the differences in scores within or between patients (Hsueh et al., 2008).

Stroke Recovery pattern


Body functions and activities post stroke are hypothesized to recover in the pattern seen in the figure above (Langhorne et al., 2011). Spontaneous biological recovery begins soon after stroke onset and slowly tapers off. The duration of the recovery window varies across neural systems. For instance, arm movement recovery may take weeks to months post stroke, but the language system may take longer, maybe years (Bernhardt et al., 2017). Phases after stroke onset can be divided into acute (up to 7 days), subacute ( 7 days to 6 months), and chronic (> 6 months) phase (Bernhardt et al., 2017).

Furthermore, clinical outcomes often have ceiling effects and low resolution, and are therefore inadequate in differentiating behavioural restitution from compensatory strategies (Gladstone et al., 2002; Kwakkel et al., 2017; Levin et al., 2009). The consensual definition of movement quality is the comparison of the motor execution of a task or action with reference to healthy age-matched
population (Kwakkel et al., 2019). The closer the movement matches the reference population, the better the movement quality (Kwakkel et al., 2019). Thus, objective measures that can reflect movement quality and differentiate behavioural restitution from compensation are necessary for measuring motor recovery post stroke. This knowledge is of utmost value for stroke research, and can help us design interventions, and appropriate individually tailored therapies (Bernhardt et al., 2017).

### 1.2. MEASURING MOVEMENT QUALITY

Human motion analysis is the systematic study of human motion by careful observation using instrumentation that measures body movements, body mechanics, or muscle activity ( Lu and Chang, 2012). The field of biomechanics was born from the principles laid by Leonardo Da Vinci, and matured with the studies of Andrea Vesalius, and Galileo Galilei. Standing on their shoulders, Giovani Alfonso Borelli (Fig. 1.2), the Father of Biomechanics, published a treatise 'De Motu Animalum' that studied the muscular


Figure 1.2 Borelli (Wellcome Library). movement and body dynamics of animals (Lu and Chang, 2012). The advent of Newtonian mechanics helped quantify the relation between applied force and the resulting movement (Lu and Chang, 2012). Instrumentation allows us to obtain objective measurements of the movements made. In this thesis, we will consider the term biomechanics to include kinematics and kinetics of human movement.

Biomechanical analysis can provide objective information about movement components and strategies (Murphy et al., 2011), and might be better indicators of movement quality. Therefore, it is prudent to identify biomechanical metrics that reflect longitudinal change in movement quality, and can distinguish behavioural restitution from compensatory strategies post stroke (Kwakkel et al., 2019). As lack of a standardized approach to stroke research and reporting affects our understanding of motor recovery, the Stroke Recovery and Rehabilitation Roundtable (SRRR) task force was setup. The roundtable
aimed to reach consensus on a number of different aspects related to stroke recovery (Bernhardt et al., 2016). They also recommend the use of technology to objectively measure quality of motor performance.

### 1.3. WEARABLE SENSING OF MOVEMENT

Kinematic and kinetic measurements are usually performed using optical marker systems, and force plates built into the ground or treadmills respectively (Baker, 2006; Colyer et al., 2018). These are considered to be the gold standards for measuring the respective metrics. However, these systems are quite large, and not suitable for measuring movement of the user outside the laboratory. They usually have extensive setup and processing times, and cannot be installed in the living environment of the users. For instance, optical marker systems require marker placement and a lot of processing prior and post measurement. Therefore, systems that are wearable, of a minimal construction, and can measure movement are needed (Bergmann and McGregor, 2011).

The advantages of using minimal wearable systems are two-pronged. Firstly, it offers ease of use. Wearable systems can reduce the hassle of clinicians in setting up measurements and can drastically reduce the time needed for processing and analysing the data. Therefore, wearable systems can increase the number of biomechanical measurements post stroke. This can help monitor changes in movement quality (Kwakkel et al., 2019). Secondly, minimal wearable systems are better suited to monitor movement quality during functional activities of the person with stroke in their home environment (van Meulen et al., 2016a). Monitoring movement impairment at home helps understand the actual performance in daily life. One of the main missions of the Health and Care sector of the Knowledge and Innovation agenda highlighted by the Dutch government for the period 2020-2023 is to bring care to the living environment of each individual (Health Holland, 2020). Wearable setups can help achieve this mission.

### 1.4. THESIS SCOPE

The goals of the Perspectief programme NeuroCIMT funded by the Netherlands Organisation for Scientific Research (NWO) was in line with the mission statement of the Knowledge and Innovation agenda (Health Holland, 2020).

The programme aimed to develop novel ways of monitoring and treating neurological diseases through quantitative models of the brain. AMBITION was one of the eight projects of NeuroCIMT. The goal of the project, of which this thesis is a part of, was 'To develop and evaluate an on-body sensing and real-time biofeedback system for optimal, patient-tailored motor rehabilitation in neurological disorders, aimed at optimising adaptation and prevent maladaptation in motor performance of upper and lower extremities during daily life'.

The two aspects that this thesis addresses are identifying kinematic and kinetic metrics that measure movement quality and developing wearable systems that can measure them. However, the function and biomechanics of movements in the upper (reaching, grasping, etc.) and lower extremity (gait, balance, etc.) are quite different. As stroke affects the upper and lower extremities disproportionately, we need to identify relevant research questions within the context of movements performed by the two extremities separately. Furthermore, appropriate wearable systems that measure movement quality must be developed specifically for the upper and lower extremities. In the following sections, we explore the scope of the thesis in detail. We also identify concrete research questions that need to be addressed for movement in each extremity.

### 1.5. UPPER EXTREMITY

Movement quality of the upper extremity may be assessed by using performance assays or standardized functional tasks applied to both the affected and less affected arm (Kwakkel et al., 2019). Performance assays include planar reaching task, finger individuation, grip strength, and precision grip strength, whereas the functional task could include a standardized drinking task (Kwakkel et al., 2019). In order to study motor recovery, biomechanics of these movement must be obtained longitudinally at fixed times post stroke (Kwakkel et al., 2019). A $15 \%$ change in performance based on these metrics can be considered as a clinically important difference (Kwakkel et al., 2019). However, currently, there is no consensus on which metrics are a suitable measure of movement quality during these performance assays (Kwakkel et al., 2019). Earlier studies such as that of Schwarz and colleagues (Schwarz et al., 2019) addressed this gap by systematically reviewing all available metrics used
for kinematic assessments of movement tasks in the upper limb. Although the study considered functional tasks such as planar 2D pointing, and 3D reach-to-grasp, they did not focus on metrics that quantified a longitudinal change in movement quality post stroke. Therefore, analysis of metrics used in longitudinal studies conducted soon after stroke are necessary to understand changes in biomechanical metrics that reflect movement quality.

> Identifying kinematic and kinetic metrics that quantify recovery of movement quality longitudinally post stroke, and can potentially distinguish between behavioural restitution and compensation is an issue that needs to be addressed.

During a 2D reach-to-grasp movement, biomechanical metrics may be used to measure a particular aspect of reaching, or to quantify the complete task. Earlier studies grouped the different metrics available in literature based on body function and structure categories defined by the International Classification of Function (ICF) categories, or the physiological interpretation of the metrics (De Los Reyes-Guzmán et al., 2014; Nordin et al., 2014; Schwarz et al., 2019; Sivan et al., 2011; Tran et al., 2018; World Health Organization, 2002). Alternatively, within the AMBITION project, we attempted to classify them based on their mathematical definitions. For instance, metrics could be:

1. used to describe the overall movement, for example, movement time, trunk displacement (Palermo et al., 2018), movement distance (Prange et al., 2015), movement efficacy (Duret and Hutin, 2013), Path Error (Duret et al., 2019), active movement index (Colombo et al., 2013), trajectory length (van Dokkum et al., 2014), etc.
2. based on the velocity or acceleration of the reaching movement, for example, hand velocity (Duret and Hutin, 2013), posture speed, speed maxima count, min/max speed difference (Semrau et al., 2015), average velocity, normalized reaching speed (Mazzoleni et al., 2019), peak velocity, time to peak velocity (Palermo et al., 2018), max hand acceleration, deceleration time (Konczak et al., 2010), number of hand trajectory reversals (Duret and Hutin, 2013), velocity Index (Pila et al., 2017), sub-movements speed profile characteristic (Krebs et al., 2014) etc.
3. used to reflect smoothness of the reaching movement, for example, jerk (Mazzoleni et al., 2019), speed metric, mean arrest period ratio, peaks metric, tent metric (Rohrer et al., 2002), smoothness Index (Pila et al., 2017) etc.
4. used to measure the accuracy or efficiency in performing the reaching movement, for example, active range of motion (Duret et al., 2019), hand path ratio (Palermo et al., 2018), average squared Mahalanobis distance (Cortes et al., 2017), distance Index, Accuracy Index (Pila et al., 2017), initial direction error, initial distance ratio (Semrau et al., 2015), quality index (Mazzoleni et al., 2018), Movement Error (Mazzoleni et al., 2019) etc.
5. used to describe the grasping movement, for example, aperture speed, aperture efficiency, peak aperture (Edwards et al., 2012), Time of peak aperture (Lang et al., 2006b), normalized jerk grasp (Buma et al., 2016) etc.
6. used to measure rotation of joints, for example, trunk rotation, shoulder rotation, elbow rotation, forearm rotation, wrist rotation (van Kordelaar et al., 2013) etc.
7. unsuited for the earlier categories, for example, composite score, reaction time (Semrau et al., 2015) etc.

Of these categories, metrics that reflect smoothness have often been studied as an indicator of movement quality, and we pay attention to it in this thesis (Balasubramanian et al., 2012; Hogan and Sternad, 2009; Reinkensmeyer et al., 2016; Rohrer et al., 2002). However, the underlying neurophysiological mechanisms of smoothness deficits are poorly understood (van Kordelaar et al., 2014). Reduced smoothness is proposed to reflect unstable cocontractions between agonists and antagonists post stroke due to reduced or lack of reciprocal inhibition (Krylow and Zev Rymer, 1997; Rohrer et al., 2002). Another hypothesis suggests that pathological muscle synergies post stroke and discrepancies in muscle activation timing during reaching in the upper paretic limb could result in deviations of the end-effector from the optimal reaching profile shown by healthy individuals (Scano et al., 2017). This in turn could result in lower smoothness. Furthermore, maximising movement smoothness is hypothesized as one feasible method to reduce the control burden by the central nervous system (Schwartz, 2016). Unfortunately,
there is currently no commonly accepted metric for quantifying movement smoothness.

?Identifying a suitable smoothness metrics can help understand change in smoothness deficits, and possibly neurological recovery after stroke.

Addressing these two gaps in literature can help provide the basis for future studies and recommendations on stroke research in motor recovery of the upper paretic limb.

### 1.6. LOWER EXTREMITY

Gait impairments affect an individual's independence in mobility and performing Activities of Daily Life (ADL) (Li et al., 2018). Assessing gait quality contributes to rehabilitation of the lower extremity and assessing potential risk to falls or instability. Deviations of gait biomechanics post stroke from healthy gait offers insights about gait quality (Balasubramanian et al., 2009; Punt et al., 2017b).

### 1.6.1. Biomechanics of gait and gait quality

Changes in gait biomechanics post stroke manifest in different ways. For instance, asymmetry is pronounced, paretic swing phase is prolonged, paretic stance phase, walking speed, and foot clearance are all reduced, and stride length is shorter (Li et al., 2018; Perry, 1992). Additionally, changes in joint angles are also observed. For instance, during swing, the knee flexion and dorsiflexion are reduced which results in pelvic hiking, and circumduction (Kerrigan et al., 2000, 1999; Stanhope et al., 2014).

Within the AMBITION project, we focused on biomechanical gait metrics that reflected stability and balance. Stable gait can be defined as walking that doesn't lead to falls in spite of perturbations (Bruijn et al., 2013), and dynamic stability can be defined as the ability to maintain balance during locomotion (Chang et al., 2010), while accounting for any internal or external perturbations. Internal perturbations during gait may occur due to
neuromuscular capacity for instance, whereas external perturbations may be caused by wind, or floors with lower surface friction (Bruijn et al., 2013). Factors such as reduced vision or proprioception may also influence stability. Bruijn and colleagues summarized all available balance control measures used to reflect gait stability in the following three groups (Bruijn et al., 2013):

G1. those that reflect the ability to recover from small perturbations.
G2. those that reflect the ability to recover from larger perturbations.
G3. those that reflect the maximum perturbations that can be handled.

Small perturbations may include internal perturbations, small differences in floor height, etc., and large perturbations are those that require a significant change in behaviour without which the person would fall (Bruijn et al., 2013). As perturbations during swing phase of gait leads to a higher risk of fall than those compared to the stance phase, G3 could be used to indicate gait stability during swing phases (Haarman et al., 2017).

As we see in Table 1.1, there are a number of balance control metrics in literature (Bruijn et al., 2013; Devetak et al., 2019). Bruijn and colleagues did not address the final group G3, as these metrics were subject to the type and intensity of perturbations applied (Bruijn et al., 2013). They concluded that maximum Lyapunov exponent $\left(\lambda_{l}\right)$ shows good construct, predictive, and convergent validity with regards to probability of falling. An additional advantage is that it can be measured from any kinematic data expressed in any frame. As estimation of $\lambda_{l}$ requires long data series, it is ideal for clinical gait analysis using treadmill walking (Punt et al., 2017b).

Nonetheless, it is unsure which of the balance control metrics are best suited for monitoring gait recovery post stroke. Metrics of spatiotemporal symmetry across the affected and less affected side reflect the degree of inter-limb coordination post stroke (Kwakkel et al., 2017). Although these metrics are proposed to reflect gait quality (Kwakkel et al., 2017), their relation with motor recovery is unclear. This is mainly because the few studies that followed changes in these metrics longitudinally post stroke were inconclusive (Patterson et al., 2015; Shin et al., 2020).

Chapter 1
Table 1.1 Metrics for balance control.

| Balance Metrics | Definition | Advantage | Disadvantage | Reference |
| :---: | :---: | :---: | :---: | :---: |
| Metrics based on dynamic systems theory |  |  |  |  |
| Maximum Lyapunov exponent $\left(\lambda_{l}\right)$ * | The average logarithmic rate of divergence of a system after a small perturbation. | Any kinematic time series measured in any measurement frame can be used. | Large datasets are needed | (Dingwell et al., 2000) |
| Maximum floquent multiplier* | The rate of convergence/ divergence of continuous gait variables towards a nominal gait cycle, following a transient perturbation from one gait cycle to the next. | Any kinematic time series measured in any measurement frame can be used. | Large datasets are needed, and it can only be applied to strictly periodic systems | (Hurmuzlu and Basdogan, 1994) |
| Kinematic variability* | Amount of variability of a certain parameter (stride time/width etc.) over strides during walking. | Proven success in predicting the probability of falling. | Difficult to attribute variability to either noise or deterministic components | (Maki, 1997) |
| Long-range correlations* | Detrended fluctuation analysis of a selected data series, after it has been integrated. | May help quantify other relevant aspects of motor control, such as the control strategy used. | Long data series are needed. | (Hausdorff et al., 1996) |

Table 1.1 Continued.

| Balance Metrics | Definition | Advantage | Disadvantage | Reference |
| :---: | :---: | :---: | :---: | :---: |
| Metrics based on biomechanical concepts |  |  |  |  |
| Extrapolated centre of mass (XCoM) or Margin of stability (MoS) ${ }^{*,+}$ | Quantifies the movement of the centre of mass with respect to the base of support after accounting for its velocity. | Provides sound mechanical basis for assessing step wise stability. | Compared to other metrics, it requires considerably more (expensive) measurement equipment and time to measure. | (Hof et al., 2005) |
| Stabilizing and destabilizing forces* | Quantifies the forces needed to stop the CoP motion in the direction of the border of BoS (stabilizing force), and the force needed to bring the CoP outside the BoS (destabilizing force). | Stabilizing force can be used to understand limits of control when perturbed. | Stabilizing forces are similar to MoS. Destabilizing forces are too simplistic and ignores movement velocity. | (Duclos et al., 2009) |
| Foot placement estimator*, ${ }^{*}$ | Estimates where the foot should be placed such that the system energy is equal to its peak potential energy after the transition from one leg to the other. | If the underlying assumptions are valid, the FPE has a good construct validity. | Compared to other metrics, it requires considerably more (expensive) measurement equipment and time to measure. | (Rosenblatt and Grabiner, 2010) |

[^0]Balance control metrics based on biomechanics of gait have an advantage over those based on dynamic systems theory, in that they can be used to analyse individual steps (van Meulen et al., 2016c), and highlight mechanisms used during turns or specific instances during gait (Eng, 2010). Nevertheless, two major caveats influence the use of such metrics. The first is that these metrics rely on feet and Centre of Mass (CoM) positions, and therefore need extensive measurement setups for accurate estimations. Another caveat is that they are based on simple models of walking, such as the inverted pendulum model, which comes with its own set of assumptions (Inset: Inverted pendulum gait model).


The inverted pendulum analogy for gait states that the stance leg is kept relatively straight during single support, functioning like an inverted pendulum. The centre of mass, located near the hip, travels in a series of arcs prescribed by each single support phase. A related theory proposes that the swing leg also moves like a pendulum, swinging about the hip. The logical extension of the inverted pendulum theory is that walking can be performed with no muscle actuation, and therefore no energy cost (Kuo, 2007).

Recently, a study showed that bilateral temporal control is an efficient mechanism for maintaining dynamic stability during walking (Buurke et al., 2019). The Margin of Stability (MoS) (Fig. 1.3) is also shown to be useful for objective evaluation of gait quality (Hof et al., 2005; van Meulen et al., 2016c).


Figure 1.3 Top view of a step. The left and right foot are in contact with the ground. The light blue line is the Centre of Mass (CoM') trajectory projected on the horizontal plane. The arrow from the CoM' points to the Extrapolated CoM projected on the horizontal plane ( $\mathrm{XCoM}^{\prime}$ ). The $\mathrm{XCoM}{ }^{\prime}$ accounts for the walking speed. The dark blue lines denote the borders of the Base of Support (BoS). The (directed) distance from the XCoM ' and the BoS is called as Margin of Stability. If the XCoM' is outside the BoS, then, the gait is dynamically unstable (Hof et al., 2005).

The Extrapolated CoM (XCoM) is the movement of the CoM that accounts for walking speed (Hof et al., 2005). The base of support includes the boundaries of contact points by the body on the ground, which changes during gait. The MoS is defined in the Medio-lateral (ML), and Anterio-posterior (AP) directions by measuring the directed distance between XCoM and the ML or AP boundaries of the BoS respectively. In a study conducted using treadmill walking, Punt and colleagues showed that the relation between ML-MoS and falls in stroke survivors (Punt et al., 2017b) was unclear for steady state gait. However, the researchers found that a decrease in AP-MoS was correlated with a tendency to fall (Punt et al., 2017b). They found that the people with a tendency to fall maintained ML-MoS by walking with increased step widths and reduced step lengths as they were forced to maintain their speed by the treadmill (Punt et al., 2017a).

### 1.6.2. Metrics for gait recovery

Thus, in order to study changes in gait quality, and thereby gait recovery, it is wise to monitor spatiotemporal variability along with biomechanical measures such as AP- or ML- MoS for individual steps (Hak et al., 2015). Comparing spatiotemporal variability with values in healthy gait offers an idea of the degree of motor recovery post stroke (Balasubramanian et al., 2009). The MoS measures can additionally throw light on foot placement, and possible compensatory strategies per individual (van Meulen et al., 2016c).

However, akin to the efforts in the upper extremity, we need to study the above measures longitudinally soon after stroke onset in order to assess if they reflect motor recovery (Kwakkel et al., 2017). This would also help understand if these measures potentially distinguish between behavioural restitution and compensation.

The proposed gait quality measures such as MoS, and spatiotemporal measures (step width, and step length) require knowledge about ground reaction forces and relative foot and CoM movement. Accurate measurement of these metrics during gait requires large laboratory setups. This results in extended measurement times per participant, need for trained personnel, and causes a hindrance to the number of measurements performed post stroke and setting up measurements at the participant's home. Therefore, although there is a gap with respect to identifying metrics that reflect gait quality, here we shift tracks to focus on developing wearable systems for said measures. We envision that the portability of wearable systems can help accelerate studies (as it solves the aforementioned measurement problems) that aim to study gait recovery.

### 1.6.3. Portable systems for gait analysis

## Conventional systems for gait analysis

Conventional systems for gait analysis can be broadly classified into the following types (Perry, 1992):

T1. Dynamic electromyography measures the period and relative intensity of muscle function.
T2. Force plate recordings display the functional demands being experienced during weight bearing period. This includes sensor systems such as force plates and pressure insoles.
T3. Motion analysis systems are used to measure magnitude and timing of individual joint action. This includes electro goniometers, video cameras and motion markers.

Each of these systems measure an aspect of movement such as muscle activation (T1), generation of force or measuring reactive force (T2), and movement of body segments (T3). Optical measurement systems and force plates are usually considered to be gold standards for measuring movement
kinematics and ground reaction forces respectively (Baker, 2006; Devetak et al., 2019).

Conventional systems such as T2 and T3 are usually restricted to a laboratory setting. In order to improve ease of use, minimal wearable sensing systems must be developed for gait analysis. The system must be compact, preferably invisible and not stigmatizing, and contain miniature embedded sensors (Bergmann and McGregor, 2011). Wearable systems help clinicians measure more often post stroke, and also allow remote monitoring, if needed, of the person with stroke in their home environment (van Meulen et al., 2016a). There are several sensor systems for portable and minimal sensing of gait, a few of which we look at closely in the following sections (Shull et al., 2014).

## Inertial measurement units (IMU)

The miniature Inertial Measurement Units (IMUs) consist of accelerometers, gyroscopes, and sometimes magnetometers and are used to measure changes in kinematics and kinetics of motion of the system they are attached to. IMUs are similar in working principle to the human vestibular system (Inset: Inertial sensors and the human vestibular organ). Recent advances in Micromachined Electro-Mechanical systems (MEMS) have exploded the potential applications of IMUs (Woodman, 2007). They find commercial applications in areas including navigation, automotive industry, industrial fault analysis systems, consumer markets including gaming and activity tracking, and also sports (Collin et al., 2019; Wagner, 2018). Simultaneously, movement analysis research using IMUs have increased rapidly in the recent years (Fig. 1.4) in areas including rehabilitation (Al-Amri et al., 2018), and ADL (Bruno et al., 2015), etc. IMU based research is so ubiquitous that it has been accused of a large degree of redundant publications (Nilsson and Skog, 2016). Nevertheless, conceptually new methods using machine learning, and sensor fusion enable new applications using IMUs.

## Forceshoes ${ }^{\text {TM }}$

IMUs can measure specific dynamic forces due to movement or gravity. Interaction or reactive forces, however, cannot be measured by IMUs. Ground reaction forces during gait is useful for measuring joint moments, and also Centre of Pressure (CoP), and CoM trajectories (Koopman et al., 1995; Schepers et al., 2009). Therefore, the Biomedical Signals and Systems group of the


Figure 1.4 The number of publications per year on Scopus ${ }^{\circledR}$ using keywords related to inertial measurement units and movement show an exponential growth. The increasing miniaturization and accuracy of IMUs along with novel sensor fusion and machine learning methods enables interesting applications in different fields of movement science.

University of Twente and Xsens Technologies B.V., developed the Forceshoes ${ }^{\text {TM }}$ (Inset: Forceshoes ${ }^{\mathrm{TM}}$ : Over the ages) as a wearable system for measuring ground reaction forces (Veltink et al., 2005).

The system consists of shoes with 3D Force and Moment (F\&M) sensors that can be used to measure 3D ground reaction as well as movement of CoP for each foot (Veltink et al., 2005). After IMUs were added to the Forceshoes ${ }^{\text {TM }}$, a series of developments enabled estimation of several relevant gait parameters. This included improved estimation of CoP and ankle moments, lumbar moments, CoM, lateral foot placement, and stride length (Faber et al., 2010; Schepers et al., 2007, 2009, 2010b). Finally, addition of ultrasound sensors improved estimation of relative foot positions (Weenk et al., 2015), and thereby gait stability measures such as XCoM, AP- and ML-MoS (van Meulen et al., 2016b, 2016c). The individual studies also validated the different gait parameters against reference systems (force plates or VICON® motion capture systems).

## Inertial sensors and the human vestibular organ


a) During linear movement, the distance between miniature capacitive plates within the MEMS accelerometer varies, which is measured as linear acceleration. b) During rotational movement, the outer frames within the MEMS gyroscope oscillate in a direction opposite to the resonant vibration, which is measured as angular velocities. c) The otolith organs (Utricle and Saccule) in the inner ear measure linear accelerations (Day and Fitzpatrick, 2005), and the function of semicircular canals in the inner human ear (Blausen Staff, 2014) is similar to the gyroscope.

In spite of the advantages of the Forceshoes ${ }^{\mathrm{TM}}$ as a portable system, its dimensions and bulkiness are major limitations. Although the Forceshoes ${ }^{\mathrm{TM}}$ did not seem to significantly influence walking patterns (Liedtke et al., 2007), each shoe weighs about 1 kg and is 2.5 cm tall which can be quite cumbersome for use in daily life. Furthermore, the rigidity of the shoe hinders natural rolling of the feet during gait. These features are not ideal for a wearable sensing system (Bergmann and McGregor, 2011).

## Pressure Insoles

Pressure insole systems are more flexible, can be inconspicuously placed inside the shoe, and measure 1D forces acting at the pressure sensor (Abdul Razak et al., 2012). An array of sensors can measure the pressure profile under the foot, and can be used to model shear forces too (Savelberg and de Lange, 1999; Sim et al., 2015).

Nevertheless, the Forceshoes ${ }^{\mathrm{TM}}$ contain several sensor modalities (Weenk et al., 2015). This results in a need for additional protocols regarding synchronization of different sensor systems, and appropriate calibration methods. Developing wearable systems with minimal sensors can help improve its portability, and acceptability (Bergmann and McGregor, 2011).

Identifying whether the 1D plantar pressure are a lightweight alternative to the 3D F\&M sensors in the Forceshoes ${ }^{\mathrm{TM}}$ for estimating dynamic balance measures can help improve the portability of the measurement setup.

## Portable Gait Lab system

The balance control metrics that we identified including MoS, and spatiotemporal variability require knowledge of movement of the feet and CoM. Although the Forceshoes ${ }^{\mathrm{TM}}$ can do this, they are still conspicuous and not easy to use in daily life situations (van Meulen et al., 2016c). An IMU placed at the foot and pelvis can provide information about the change in kinematics at these locations, which can be used to derive the metrics of interest. Therefore, a three IMU system could be an ideal wearable sensing system as it measures the segments of interest, can be small, and easy to wear owing to the miniature sensors. For instance, the foot IMUs can be integrated with footwear. The movement of the CoM can be approximated with an IMU

placed near the pelvis (Floor-Westerdijk et al., 2012), which may be integrated into the belt or clothing around the hip. This three IMU system is what we envision as a Portable Gait Lab (PGL) system (Fig. 1.5), as it has potential to be a minimal wearable sensing system that can provide essential information about gait and balance.

With IMUs at these locations, a number of relevant gait parameters can be estimated such as gait events, joint angles, stride length, and spatiotemporal gait parameters (Caldas et al., 2017; Iosa et al., 2016; Okkalidis et al., 2020a; Pacini Panebianco et al., 2018; Peruzzi et al., 2011; Rebula et al., 2013). However, the system falls short when measuring relative movements of the feet or CoM. This is mainly due to two limitations related to IMUs. First, the IMUs
do not sense their relative positions as they only track the change in linear or angular movement of the system they are attached to. Second, drift due to strapdown inertial navigation results in errors in quantities derived from the IMUs. For instance, accelerations measured by the IMUs need to be integrated to estimate velocities during gait. The continuous integration of constant bias and sensor noise introduces a drift in the actual estimate of velocity (Kok et al., 2017). This issue is compounded when we wish to estimate positions from accelerations (Inset: Kinematic drift in Inertial Measurement


Figure 1.5 The Portable Gait Lab (PGL) consists of three IMUs: one on the pelvis, and one on each foot. Units). Although this was solved by including sensors such as ultrasound, or infrared, it increases the system complexity (Bertuletti et al., 2019; Weenk et al., 2015). Therefore, if we wish to avoid the use of additional sensors, we require additional assumptions regarding gait.

Some researchers overcame the issue of drift by enforcing artificial mathematical constraints regarding the distance between the feet (Niu et al., 2019; Skog et al., 2012). However, these constraints may not reflect the true foot positions during continuous tracking and does not provide information about the relative movement of the CoM. Other studies used biomechanical constraints related to the pattern of gait. For instance, Bancroft and Lachapelle used information of an average stride length, and Zhao and colleagues used a derivation of step length from information about limb sway to restrict drift (Bancroft et al., 2008; Zhao et al., 2018). In both cases, approximations have been made regarding a general pattern of gait cycle. A recent publication showed that using an extended set of biomechanical constraints regarding movement of the CoM and feet can help reduce drift (Sy et al., 2020). But the researchers estimated the movement of segments with respect to a fixed pelvis, and do not comment on the relative segment distances.


The positions of each foot and the Centre of Mass (CoM) measured by respective Inertial Measurement Units (IMUs) placed will start to drift away from each other after some time. This is because the IMUs do not measure relative distances, and also suffer from errors during strapdown integration. Using common constraints, the drift in foot positions can be corrected during foot contact. Therefore, the drift in foot positions is lesser than that of the CoM.

## Centroidal Moment Pivot point (CMP)

The ground reference point, CMP, finds its origins from the works of Borelli, the Father of Biomechanics (Popovic et al., 2005). The CMP point and Zero Moment Point (ZMP) have been used in control of legged locomotion in robots ever since its first demonstration on WL-10RD in Japan in 1984 (Computer History Museum, 1985; Takanishi et al., 1985; Vukobratović and Borovac, 2004). Even now, the Atlas robot uses these principles to control placement of its feet (Inset: Humanoid walking using ZMP).

The CMP is defined as the contact point on the ground from which a line passing through the CoM is parallel to the ground reaction force for 'stable' biped gait (Fig. 1.6) (Goswami, 1999; Goswami and Kallem, 2004; Popovic et al., 2005).


WL-10RD was one of the early humanoids to use zero moment point for trajectory planning. On the right, we see the futuristic Atlas ${ }^{\circledR}$ robot which also uses zero moment point principles. These simple biomechanical gait models could provide additional constraints regarding the relative positions of the feet and CoM.

This requires that the horizontal component of the whole-body angular momentum is constant, and net moments around the CoM is 0 . This assumption provides a relation for the relative movement of the CMP and CoM (Popovic et al., 2005). The CMP and ZMP overlap when the ground reaction force passes directly through the CoM of the body (Popovic et al., 2005). Normal human gait can be assumed to move with a constant angular momentum with no moments around the CoM (Herr and Popovic, 2008; Popovic et al., 2005). Thus, the CMP point can serve as a potential biomechanical constraint for reducing the drift between the foot and CoM positions measured using IMUs during gait (Schepers et al., 2009). Testing the feasibility of this approach within the PGL system can help develop a novel minimal and wearable sensing system for gait analysis.


Figure 1.6 Defining the ground reference points. Here, only the lagging foot is in contact with the ground. If the line (dotted light blue) connecting the virtual Centroidal Moment Pivot (CMP) point (blue circle) and the Centre of Mass (CoM) (orange circle) is parallel to the ground reaction forces (dark blue line), then the net moment around the CoM is zero. In this case, the CMP overlaps with the Zero Moment Point, which is otherwise referred to as the Centre of Pressure for flat ground surfaces (Herr and Popovic, 2008; Popovic et al., 2005). This assumption of 'stable' gait provides a relation between the relative movement of CMP and CoM.

Identifying whether the assumptions of the Centroidal Moment Pivot theory can offer potential biomechanical constraints when using only three inertial measurement units for estimating relative movement of the feet and CoM can help develop a wearable sensing system for gait analysis.

### 1.7. THESIS GOAL AND OUTLINE

The research gaps in the previous section allows us to define the goal of this thesis as 'To identify metrics that reflect movement quality of upper and lower extremities after stroke and develop wearable minimal systems for tracking the proposed metrics. We address the goal in several sub-questions identified within two sections: Section Upper Extremity and Section Lower Extremity. An overview is seen in Fig. 1.7.


Figure 1.7 Overview of chapters in this thesis.

### 1.7.1. Section Upper Extremity

As metrics that reflect movement quality of the upper limb are yet to be identified, the research questions related to the upper extremity deals with identifying relevant metrics. The research questions for each chapter are as follows:

Chapter II: 'Which kinematic or kinetic metrics have been used in longitudinal studies to reflect movement quality of post-stroke reaching?'

Chapter III: 'Which metric, identified using systematic review, has a mathematically sound definition, responds as expected to changes in reaching pattern, and is thereby best suited for measuring smoothness of upper limb reaching?'

Our analyses in Chapter II and III provides the basis for future studies and recommendations on stroke research in motor recovery of the upper paretic limb.

### 1.7.2. Section Lower Extremity

Unlike the section above, here we focused on developing novel wearable systems for estimation of relevant gait parameters. Developing wearable systems can help future researchers and clinicians measure more often post stroke which is useful in tracking recovery. These systems will also be useful in exploring remote monitoring, if needed, of the person with stroke. The research questions for each chapter are as follows:

Chapter IV: 'What is the feasibility of pressure insoles in replacing the functionality of the bulky 3D F\&M sensors in the Forceshoes ${ }^{\mathrm{TM}}$ with a focus on estimating gait stability metrics?’

The following chapters aimed at developing the PGL system using three IMUs; one IMU at the pelvis, and one on each foot. The research questions in each of the chapters help make a step towards the development of the system.

Chapter V: 'Can the assumptions of CMP be effectively used as potential biomechanical constraints for estimating relative movement of the feet and CoM?’

Chapter VI: ‘Can the Portable Gait Lab system measure shear and vertical ground reaction forces for variable gait patterns seen in daily life?’

Chapter VII: 'Can only the pelvis IMU of the Portable Gait Lab system measure shear and vertical ground reaction forces for variable gait patterns seen in daily life?'

Chapter VIII: 'Can the Portable Gait Lab system accurately estimate velocity of CoM without drift for variable gait patterns seen in daily life?'

Chapter IX: 'Based on the earlier developments, and the assumptions of CMP, can the Portable Gait Lab system track the relative positions of feet and CoM, and spatiotemporal parameters for variable gait patterns seen in daily life?'

Chapter X: 'Is the Portable Gait Lab system suitable for tracking relative positions of feet and CoM, and spatiotemporal and balance parameters during gait in persons with stroke?'

The principles regarding the development of the PGL were explored in Chapter V. In order to measure the relative positions of the foot and CoM, a few biomechanical parameters are required for applying the CMP assumptions, which were estimated in Chapters VI - VIII. Finally in Chapters IX and $\mathbf{X}$, we validate the system for healthy participants and persons with stroke respectively.

### 1.8. CONTRIBUTIONS OF THE THESIS

The two aspects that this thesis addresses are identifying kinematic and kinetic metrics that measure movement quality and developing wearable systems that can measure them. The chapters in Section Upper Extremity focus on measuring movement quality post stroke and offers recommendations for setting up future studies that can help understand motor recovery better. The chapters in Section Lower Extremity introduces novel techniques in developing wearable systems for measuring gait quality. The impact of the thesis and prospective research directions are addressed in Chapter XI (General Discussion).


## Section Upper Extremity

# Quantifying quality of reaching movements longitudinally post stroke - a systematic review. 

"Because that's what Hermione does. When in doubt, go to the library."

J. K. Rowling, Harry Potter and the Chamber of Secrets

[^1]
#### Abstract

Disambiguation of behavioural restitution from compensation is important to better understand recovery of upper limb motor control post stroke and subsequently design better interventions. Measuring movement quality during standardized performance assays and functional tasks using kinematic and kinetic metrics allows for this disambiguation. Therefore, the objective of this study was to identify longitudinal studies that used kinematic and/or kinetic metrics to investigate post stroke recovery of reaching; and assess whether these metrics distinguish behavioural restitution from compensation. A systematic literature search was conducted using the databases PubMed, EMBASE, Scopus and Wiley/Cochrane Library up to July 1st, 2020. Studies were identified if they performed longitudinal kinematic and/or kinetic measurements during reaching, starting within the first six months post stroke. Thirty-two longitudinal studies were identified, which reported a total of forty-six different kinematic metrics. Although the majority investigated improvements in kinetics or kinematics to quantify recovery of movement quality, none of these studies explicitly addressed the distinction between behavioural restitution and compensation. One study obtained kinematic metrics for both performance assays and a functional task. Despite the growing number of kinematic and kinetic studies on post-stroke recovery, longitudinal studies that explicitly seek to delineate between behavioural restitution and compensation are still lacking. To rectify this situation, future studies should measure kinematics and/or kinetics during performance assays to isolate restitution and during a standardized functional task to determine the contributions of restitution and compensation.


### 2.1. INTRODUCTION

About 80\% of stroke survivors suffer from upper extremity motor impairment (Lawrence et al., 2001), which affects activities of daily living (Langhorne et al., 2011). Therefore, being able to use the arm to complete functional tasks is among the top ten priorities for stroke survivors, caregivers and health care professionals (Pollock et al., 2014). Upper extremity motor impairment after stroke is comprised of weakness, diminished dexterity and abnormal muscle synergies (Jones, 2017).

Most patients exhibit some degree of spontaneous recovery of upper extremity motor impairment, with 80-90\% of clinical improvements occurring within the first 8-10 weeks post stroke (Duncan et al., 1992; Kwakkel et al., 2006; Vliet et al., 2020). Studies suggest that reaching movements tend to converge toward healthy patterns, without necessarily returning fully to pre-stroke patterns (i.e. partial behavioural restitution) (Cortes et al., 2017; van Kordelaar et al., 2014, 2013). The ability to use the upper limb during functional tasks may further improve through the use of compensatory strategies; in which patients accomplish a functional goal in a different way then pre-stroke (i.e. behavioural compensation) (Bernhardt et al., 2017). The ability to distinguish between behavioural restitution and compensation would help to better identify interventions that can influence true neurological recovery.

Movement quality reflects the degree of motor control (Kwakkel et al., 2019). Despite consensus on a standardized set of clinical outcomes in stroke studies (Kwakkel et al., 2017), these clinical measures lack the ability to capture small changes in movement quality (Bernhardt et al., 2016; Kwakkel et al., 2019) and cannot distinguish behavioural restitution from compensation. Longitudinal kinematic studies early after stroke are needed to investigate the time course of movement quality of the upper limb. Recommendations on suitable study designs were provided by the Stroke Recovery and Rehabilitation Roundtable (SRRR) task force (Kwakkel et al., 2019). The SRRR recommends kinematic and/or kinetic measurements during four standardized performance assays for measuring behavioural restitution and a functional task to distinguish true recovery from compensation strategies. Performance assays are needed to quantify the different components of motor
impairment: weakness, diminished dexterity and abnormal muscle synergies. To capture these components of impairment, the SRRR defined the following performance assays: grip strength (Mathiowetz et al., 1985, 1984), precision grip (Mathiowetz et al., 1985), finger individuation (Ejaz et al., 2018; Schieber, 1991) and 2D planar reaching (Alt Murphy et al., 2017; McCrea et al., 2002). It was recommended to perform these measurements repeatedly in the first six months post stroke. Moreover, given the non-linear time course of recovery, these measurements should be repeated more frequently in the first months post stroke, preferably at fixed times (Kwakkel et al., 2017). Investigating these performance assays is not only important to distinguish between behavioural restitution and compensation. The association between performance assays and clinical assessments may elucidate which motor impairment is most strongly represented by a clinical assessment score. This may make clear whether, for example, the Fugl-Meyer motor assessment for Upper Extremity (FM-UE), a clinical assessment commonly used in stroke rehabilitation, truly captures synergy-driven intra-limb coupling or whether it is contaminated by other motor impairment components such as strength (Ellis et al., 2008; McPherson and Dewald, 2019). Furthermore, to determine the degree to which recovery has converged on normal movement, the SRRR recommended that a healthy control group should be included (Kwakkel et al., 2017). A recent review showed that the number of studies that use kinematics and kinetics to investigate reaching performance is growing exponentially (Schwarz et al., 2019). However, the focus of that particular review was not on longitudinal studies, nor on the metrics that distinguish between behavioural restitution and compensation.

Our objective was to review the literature on the use of kinematic and/ or kinetic metrics to measure recovery of movement quality after stroke. We focused on upper limb reaching and pointing tasks, as they require coordination of the elbow and shoulder, which is an important component of many daily activities, and is often limited post-stroke as a result of weakness, loss of motor control and the intrusion of abnormal muscle synergies (Levin et al., 2002; McCrea et al., 2002). We aimed to:
i. identify longitudinal studies which used kinematic and/or kinetic metrics reflecting movement quality to investigate post-stroke recovery of reaching, to show the reported responsiveness of these metrics over time, and their association with clinical measures; and
ii. assess whether these studies have addressed or provided suggestions on how to best track behavioural restitution and distinguish it from compensation.

### 2.2. METHODS

### 2.2.1. Search strategy

A systematic literature search was performed based on the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) statement (Moher et al., 2009) and registered in PROSPERO (number CRD42018100648). To identify all relevant publications, systematic searches were conducted (by MS, MIMR and EJ) in the databases PubMed, EMBASE, Scopus (Elsevier) and the Cochrane Library (Wiley) from inception to July 1st, 2020. Search terms included controlled terms from MeSH in PubMed and EMtree in EMBASE.com as well as free text terms. Free text terms only were used in Scopus and the Cochrane Library. Search terms expressing 'stroke' were used in combination with search terms comprising 'reach and grasp activity' and 'kinematics and kinetics'. Search filters for human studies and English language were used. Reference tracking was performed to identify other relevant publications. Finally, duplicate articles were removed. The full search strategies for all databases can be found in Appendix A.

### 2.2.2. Study selection

After the initial literature search, the titles and abstracts of all papers found were screened independently by two researchers (MS, MIMR). Differences of opinion were discussed, and if no consensus was reached a third reviewer (EW) was approached. Criteria for inclusion were:
i. adult participants who suffered from a cerebral vascular accident,
ii. use of a repeated measures study design with at least two serial within participant measurements starting before the chronic phase (< 6 months) (Bernhardt et al., 2017) post stroke,
iii. at least one kinetic or kinematic outcome metric, measured with any device that does not interfere with movements during an active goaloriented reaching or pointing task.

A study was excluded when:
i. it was a review or conference proceeding, or
ii. the investigated population consisted of less than ten participants, or
iii. it was not written in English. Investigated cohorts were allowed to be part of an intervention study.

A full-text version of all remaining studies was obtained for thorough reviewing by the researchers (MIMR, MS) to establish the definitive inclusion.

### 2.2.3. Data analysis

## Definitions

Behavioural restitution was defined as changes of movement execution patterns that made them more similar to those observed in healthy participants (Bernhardt et al., 2017). Behavioural compensation was defined as regaining the ability to accomplish a goal through substitution with a new movement approach that differs from pre-stroke behaviour (Bernhardt et al., 2017). Performance assays were defined as tests that quantify aspects of affected motor control performance in the absence of compensatory movements and outside the context of a functional task (Kwakkel et al., 2019). Movement quality was defined as a measure of patient's motor task execution in comparison with age-matched normative values of healthy individuals (Kwakkel et al., 2019). Other definitions can be found in the Glossary of Terms.

## Data extraction

The following data were extracted (when applicable): (1) authors and date of publication; (2) sample size; (3) characteristics of included participants; (4)
assessment moments; (5) authors' description of the investigated reaching task; (6) the performed clinical sensory and motor assessments; (7) measurement setup (equipment, segments, sample frequency, dimensions, number of repetitions); (8) definitions of the investigated kinematic and kinetic metrics; (9) the change of the outcome metrics over time; (10) association of metrics with clinical assessments; (11) psychometric properties (validity, reliability, and responsiveness) of these metrics; and (12) investigated performance assays.

## Data interpretation

After summarizing the findings of the systematic review in Section 2.3.1, an overview was provided in Section 2.3.2 regarding the reported metrics, how they are used to quantify movement trajectories, their responsiveness (i.e., change over time) and longitudinal association with clinical measures.

Thereafter, in Section 2.3.3, we described any suggestions made by the authors of the studies on how to track behavioural restitution or distinguish restitution from compensation. We discussed what the reviewed studies reported about kinematics in association with behavioural restitution and/or compensation. We also assessed each study design based on recent recommendations of the SRRR for studying movement quality post-stroke using kinematics and/or kinetics (Kwakkel et al., 2019, 2017). This was only meant as a retrospective review, as most of the studies included in this review were conducted before the task force's recommendations were published. The SRRR recommendations concern measurement time points and measurement methods, such as: (1) performing the first measurement within or before the early sub-acute phase ( $\leqslant 3$ months) post stroke, when changes in movement quality are still to be expected due to spontaneous neurobiological recovery; (2) inclusion $\leqslant 1$ week post stroke, pursuing an inception cohort; (3) perform measurements at fixed time points post-stroke (Duncan et al., 1992; Kwakkel et al., 2006); (4) repeat measurements at least in weeks 1,12 and 26 post stroke; (5) presence of reference data of age-matched non-disabled participants; (6) use highresolution digital optoelectronic systems to capture movements; (7) use a sample frequency $\geqslant 60 \mathrm{~Hz} ;(8) \geqslant 15$ movement repetitions; and (9) investigate performance assays related to motor impairments (Kwakkel et al., 2019) in addition to the reaching task.

### 2.3. RESULTS

### 2.3.1. Study identification

The PRISMA flow diagram of the search and selection process is presented in Fig. 2.1. The literature search generated a total of 17943 references: 6063 in PubMed, 6678 in EMBASE, 1839 in Scopus and 3363 in the Cochrane Library. After removing duplicates, 10712 references remained. Of these articles 10538 were discarded after reviewing title and abstract. The fulltext of the remaining 174 articles was assessed for eligibility (Ouzzani et al., 2016). Thirty-two articles, involving a total of 1259 unique patients with a haemorrhagic or ischemic stroke, met all criteria and were included in the current systematic review. Table 2.1 shows the detailed characteristics of the included studies.

### 2.3.2. Longitudinally investigated kinematic and kinetic metrics

## Kinematic metrics to quantify movement quality

Spontaneous neurological recovery leads to improved movement quality. In healthy individuals the movement trajectory during a standardized reaching task is close to a straight line between the starting position and the target (McCrea et al., 2002; Murphy et al., 2011). The velocity profiles of healthy individuals are smooth and bell-shaped curves with one clear velocity peak (McCrea et al., 2002; Murphy et al., 2011). A pre-planned and well-controlled movement results in a smooth increase of velocity whereby an adequate peak velocity is reached (Thrane et al., 2020). Fig. 2.2 shows 2D movement trajectories during a standardized reaching task and the corresponding velocity profiles of one random patient at different time points post-stroke (Rohrer et al., 2004; van Kordelaar et al., 2014). Through visual inspection, one can clearly conclude that movement quality is affected early after stroke and improves over time, especially in the first weeks.

Fig. 2.2 shows that in addition to visual inspection, movement trajectories can be quantified with many different kinematic metrics, each of which may be affected by different aspects of motor impairment and/or compensation. For instance, patients perform movements slower early after stroke either due to weakness or to compensate for decreased accuracy (Nordin et al., 2014).

Table 2.1 Characteristics of included studies.

| Authors | Objective | Study <br> type and <br> number of <br> participants |  | Participants Stroke |  | Assessment <br> moments | Reaching task; <br> postural restrictions | Additional <br> performance <br> assays <br> investigated |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |

Table 2.1 Continued.

| Lang et al. <br> 2006a; <br> VECTORS | Examine the responsiveness and validity of the Action Research Arm Test (ARAT) in a population of participants with mild-to-moderate hemiparesis within the first few months after stroke. | Interventional; S (51) | $\begin{aligned} & \text { 63.7(13.6); } \\ & 21 / 29 \end{aligned}$ | $\begin{aligned} & \text { 9.5(4.5); 39/11; } \\ & \text { *21/29 } \end{aligned}$ | $\begin{aligned} & 9.5 \pm 4.5 \mathrm{~d} \text { PS, } \\ & 25.9 \pm 10.6 \mathrm{~d} \\ & \text { PS, } \\ & 110.8 \pm 20.7 \mathrm{~d} \\ & \text { PS. } \end{aligned}$ | Move the hand from thigh to the target at $90 \%$ of arm's length in front of the affected shoulder; Yes | x | ARAT, NIHSS, FIM, sensory assessment | 3D; 3; 60 Hz | 6-Camera's; Tr, UE, FA, dorsum of H, Th, IF, T. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Lang et al. 2006b; VECTORS | Examine the relative recovery of reach versus grasp from the acute to chronic phase following stroke. | Interventional; <br> S (23) <br> C (10) | $\begin{aligned} & \text { 64.5(12.8); } \\ & 12 / 11 \\ & \text { 59.1(12.5); } \\ & 5 / 5 \end{aligned}$ | $\begin{aligned} & \text { 9.1(3.5); 10/5; } \\ & \text { *9/14 } \end{aligned}$ | $\begin{aligned} & 9.1 \pm 3.5 \mathrm{~d} \text { PS, } \\ & 105.3 \pm 18.8 \mathrm{~d} \\ & \text { PS, } \\ & 383.4 \pm 16.3 \mathrm{~d} \\ & \text { PS. } \end{aligned}$ | Move the hand from thigh to the target at $90 \%$ of arm's length in front of the affected shoulder; Yes | x | ARAT, sensory assessment, MAS, muscle strength | 3D; 3; 60 Hz | 6-Camera's; Tr, UE, FA, dorsum of $\mathrm{H}, \mathrm{Th}$, IF, T. |
| Wagner et al. 2007; VECTORS ${ }^{1}$ | How do sensorimotor impairments relate to reaching performance in the subacute phase after stroke and how do sensorimotor impairments measured in the acute phase after stroke relate to reaching performance measured several months later. | Interventional; <br> S (39) <br> C (10) | $\begin{aligned} & \text { 63.9(11.5); } \\ & 15 / 24 \\ & \text { 59.1(12.5); } \\ & 5 / 5 \end{aligned}$ | $\begin{aligned} & 8.7(3.6) ; 25 / 8 ; \\ & 18 / 21 \end{aligned}$ | $\begin{aligned} & 8.7 \pm 3.6 \mathrm{~d} \text { PS, } \\ & 108.7 \pm 16.5 \mathrm{~d} \\ & \text { PS } \end{aligned}$ | Forward reaching from thigh to $90 \%$ of arm's length at shoulder height in front of affected shoulder; Yes | Individuation indexes (shoulder, elbow, wrist). Max grip strength, Jamar handheld dynamometer. | ARAT, FM-UE, sensory assessment, MAS, AROM | 3D; 3; 60 Hz | 6-Camera's; Tr, UE, FA, dorsum of $\mathrm{H}, \mathrm{Th}, \mathrm{IF}, \mathrm{T}$. |

Table 2.1 Continued.

| Konczak et <br> al. 2010; <br> NR | How is lesion site and arm dysfunction associated in the acute stage and what is the course of upper limb recovery during the first 4 months. | Observational; <br> S (16) <br> C (10) | $\begin{aligned} & \text { 60.1(14.4); } \\ & 11 / 5 \\ & \text { 59.0(10.3); } \\ & 7 / 4 \end{aligned}$ | $\begin{aligned} & 14.5 \text { range } 1-33 ; \\ & 16 / 0 ; 7 / 9 \end{aligned}$ | 14.5 range 1 33]d PS, 2w after session $1,3 \mathrm{~m}$ after session 1. | 1. Point at a ball suspended from the ceiling in front at $90 \%$ of arm's length at shoulder height, 2. Point at the same location in absence of the target; No | x | MCS, MRI | $\begin{aligned} & \text { 3D; 10; } \\ & 100 \mathrm{~Hz} \end{aligned}$ | 3D ultrasoundbased motion analysis system; Finger |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Dipietro et <br> al. 2012 | Investigate whether untrained and trained movements were characterized by similar changes in smoothness and sub movements. | $\begin{aligned} & \text { Interventional; } \\ & \mathrm{S}_{\text {subacute }}(42) \\ & \mathrm{S}_{\text {chronic }}(116) \end{aligned}$ | $\begin{aligned} & \text { 61.3(1.8); } \\ & 24 / 18 \\ & 58.8(1.2) ; \\ & 73 / 43 \end{aligned}$ | $\begin{aligned} & \text { 19.1(1.2); NR; } \\ & 32 / 10 \\ & 1150(90) ; \text { NR; } \\ & \text { 53/63 } \end{aligned}$ | pre, halfway and post intervention | Eight targets, surrounding a center target, were displayed on a monitor. <br> Participants moved from the center 14 cm to each target, stopped, then returned to the center; No | x | FM-UE | 2D; 80; NR | MIT-Manus and its commercial version InMotion2; H |
| Edwards et <br> al. 2012; <br> VECTORS | Examine the internal consistency, validity, responsiveness, and advantages of the WMFT and compare these results to the ARAT in participants with mild to moderate hemiparesis within the first few months after stroke. | Interventional; S (51) | $\begin{aligned} & \text { 63.7(13.6); } \\ & \text { 21/29 } \end{aligned}$ | $\begin{aligned} & \text { 9.5(4.5); 39/11; } \\ & 21 / 29 \end{aligned}$ | $\begin{aligned} & 9.5 \pm 4.5 \mathrm{~d} \text { PS, } \\ & 25.9 \pm 10.6 \mathrm{~d} \\ & \text { PS, } \\ & 110.8 \pm 20.7 \mathrm{~d} \\ & \text { PS } \end{aligned}$ | Move the hand from thigh to the target at $90 \%$ of arm's length in front of the affected shoulder; Yes |  | WMFT, ARAT, sensorimotor impairments, FA, FIM, NIHSS. | 3D; 3; 60 Hz | 6-Camera's; Tr, UE, FA, dorsum of H, Th, IF, T. |

Table 2.1 Continued.

| $\begin{aligned} & \text { Tan et al. } \\ & \text { 2012; } \\ & \text { NR } \end{aligned}$ | Identify the effects of CIMT on anticipatory hand posture selection and movement time for task-specific reach-tograsp performance. | Interventional; $\mathrm{S}_{\text {СІМТ }}(10)$ $\mathrm{S}_{\text {No сімт }}(10)$ C (6) | $\begin{aligned} & \text { 59.7(11.2); } \\ & 7 / 3 \\ & \text { 58.2(13.4); } \\ & \text { 5/5 } \\ & \text { 43.8(5.0); NR } \end{aligned}$ | $\begin{aligned} & \text { 228(56); NR; 11/9 } \\ & \text { 1191(1225); NR; } \\ & 4 / 6 \end{aligned}$ | Pre and post 2 weeks of intervention | 2 different objects, 2 different grasp types. Grab the object and place it in the hole 15 cm from the edge of the table; Yes | x | WMFT, MAL | 1D; 7; NR | Electric switches at home position, object and target; NA |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Colombo et <br> al. 2013; <br> HUMOUR | We aimed to analyze how time since the acute event may influence the motor recovery process during robot-assisted rehabilitation of the upper limb. | Interventional; $\begin{aligned} & \mathrm{S}_{\text {subacute }}(20) \\ & \mathrm{S}_{\text {chronic }}(21) \end{aligned}$ | $\begin{aligned} & 58.4(12.9) ; \\ & 8 / 12 \\ & 50.7(11.3) ; \\ & 14 / 7 \end{aligned}$ | $\begin{aligned} & 69(42) ; 15 / 5 ; 12 / 8 \\ & 876(1221) ; 17 / 4 ; \\ & 10 / 11 \end{aligned}$ | pre and post $3+$ weeks of intervention | The handle of the robot is grasped by the patient and moved through the workspace of the device (i.e., in the horizontal plane). The task consisted of a sequence of point to point reaching movements in the shape of a geometrical figure; Yes | x | FM-UE, MAS | $\begin{aligned} & \text { 2D; NR; } \\ & 100 \mathrm{~Hz} \end{aligned}$ | 2 DoF elbowshoulder manipulators MEMOS; end effector |
| Duret and <br> Hutin 2013; <br> NR | Analyze clinical and kinematic motor outcomes during an intensive upper limb robot-assisted training program performed as an adjunct to a standard rehabilitation program over an extended period in the subacute phase after stroke in patients with moderate to severe paresis. | Observational; S (10) | $\begin{aligned} & \text { 47.5(19.6); } \\ & 3 / 7 \end{aligned}$ | $\begin{aligned} & 53.5(15.8) ; 8 / 2 ; \\ & 6 / 4 \end{aligned}$ | $\begin{aligned} & 1 \pm 1 \mathrm{~d} ; 40 \pm 4 \mathrm{~d} ; \\ & 80 \pm 6 \mathrm{~d} ; \\ & 120 \pm 13 \mathrm{~d} \text { PI } \end{aligned}$ | Reaching task towards targets set in 4 compass directions. Each movement was 14 cm ; No | x | FM-UE, MSS | 2D; 1-3; NR | InMotion 2.0 <br> robot; End effector |

Table 2.1 Continued.

| Metrot et al. 2013a; <br> $\mathrm{NR}^{2}$ | To assess the natural evolution of reaching kinematics during standard poststroke rehabilitation, focusing on bimanual coordination. | Observational; $\mathrm{S}(12)$ | $\begin{aligned} & \text { 65.6(9.7); } \\ & 9 / 3 \end{aligned}$ | 20.6(7.1); 8/4; 5/7 | inclusion, 1w, 2w, 3w, 4w, 5w, 6w and 12 w PI. | Grasp a ball on the table 25 cm away from the starting position of the hand; Yes | x | FM-UE | 3D; $5 ; 30 \mathrm{~Hz}$ | Electromagnetic motion tracker; H |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| van <br> Kordelaar et <br> al. 2013; <br> EXPLICIT ${ }^{3}$ | Assess longitudinal improvements in dissociated upper limb movements during a standardized reach-tograsp task in patients with a first-ever ischemic stroke. | Observational; S (31) <br> C (12) | $\begin{aligned} & \text { 60.0(11.2); } \\ & \text { 18/13 } \\ & \text { 52.8(5.9); 7/5 } \end{aligned}$ | 14(6); 31/0; 19/12 | 14d, 25d, 38d, 57d, 91d and 189d PS | Move hand from edge of the table in front of affected shoulder to grasp a block at maximum reaching distance of the nonparetic arm; No | x | NIHSS, <br> ARAT, <br> FM-UE, BI | $\begin{aligned} & \text { 3D; 4; } 240 \\ & \text { Hz } \end{aligned}$ | Electromagnetic motion tracker; Tr, Sc, E, W |
| Krebs et al. <br> 2014; NR | Predicting clinical outcomes with robotassisted measurement of kinematic and kinetic with sufficient accuracy to serve as their surrogates. | Observational; <br> S <br> S <br> completers <br> (87) <br> non-completers <br> (121) | $\begin{aligned} & 69.7(13.5) ; \\ & 45 / 42 \\ & 75.7(13.0) ; \\ & 61 / 60 \end{aligned}$ | $\begin{aligned} & 7 ; 87 / 0 ; 44 / 43 \\ & 7 ; 121 / 0 ; 67 / 54 \end{aligned}$ | 7d, 14d, 21d, <br> 30d and 90d PS | Visually guided and visually evoked reaching and circle drawing movements, and attempts to move against resistance; No | x | NIHSS, mRS, FM-UE, MP | 2D; as many as possible; NR | MIT Manus; H |
| Van <br> Dokkum et <br> al. 2014; <br> $\mathrm{NR}^{2}$ | Addressing the link between clinical and kinematic assessment of motor performance during early poststroke recovery. | Observational; <br> S (13) <br> C (12) | $\begin{aligned} & \text { 63.9(9.4); } \\ & 10 / 3 \\ & 32.5(11.4) ; \\ & 0 / 12 \end{aligned}$ | 21.2(7.2); 9/4; 5/8 | 1w, 2w, 3w, 4w, 5w, 6w and 3 m PI | Grasping a ball on the table 20 cm in front of the patient and bring it to a target 5 cm from the edge of the table; Yes |  | FM-UE | 3D; 5; 30 Hz | Electromagnetic motion tracker; H |

Table 2.1 Continued.

| van <br> Kordelaar et <br> al. 2014; <br> EXPLICIT ${ }^{3}$ | Investigate the time course of recovery in terms of smoothness of upper limb movements in the first 6 months post stroke, and assess how progress of time contributes to normalization of this metric | Observational; S (44) | 58(12); 25/19 | $\begin{aligned} & <7(\mathrm{NR}) ; 44 / 0 ; \\ & 27 / 17 \end{aligned}$ | 1w, 2w, 3w, 4w, 5w, 8w, 12 w and 26 w PS | Move hand from edge of the table in front of affected shoulder to grasp a block at maximum reaching distance of the nonparetic arm; No | X | NIHSS, FM-UE, ARAT, BI | $\text { 3D; 7; } 240 \mathrm{~Hz}$ | Electromagnetic motion tracker; $\mathrm{Tr}, \mathrm{Sc}, \mathrm{UA}, \mathrm{FA}$, H, Th, IF. |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{aligned} & \text { Bang et al. } \\ & \text { 2015; NR } \end{aligned}$ | To investigate the effects of a modified constraintinduced movement therapy (mCIMT) with trunk restraint in subacute stroke patients. | $\begin{aligned} & \text { Interventional; } \\ & \mathrm{S}_{\text {exp }}(9) \\ & \mathrm{S}_{\text {control }}(9) \end{aligned}$ | $\begin{aligned} & \text { 60.2(5.8); } 5 / 4 \\ & 59.3(8.2) ; 4 / 5 \end{aligned}$ | $\begin{aligned} & 90(34) ; 6 / 3 ; 6 / 3 \\ & 107(30) ; 5 / 4 ; 4 / 5 \end{aligned}$ | Pre and post 4 weeks of intervention | Reaching forward to grasp a cube, placed in the sagittal plane in the trunk midline at mid-sternal height at arm length; Yes | x | ARAT, <br> FM-UE, BI, MAL | 3D; 3; NR | Dartfish motion analysis software; S, E, W |
| Li et al. 2015; NR | Investigate the concurrent validity of kinematic variables before and after the intervention and the predictive validity after the intervention during reaching tasks with and without a trunk constraint in individuals with stroke. | Interventional; S (95) | $\begin{aligned} & \text { 57.1(10.9); } \\ & \text { 30/65 } \end{aligned}$ | $\begin{aligned} & \text { 519(NR); NR; } \\ & \text { 42/53 } \end{aligned}$ | Pre and post 3-4 weeks of intervention | Reach the index finger towards the bell at $90 \%$ of arm's length; Yes/ No depending on condition. | x | FM-UE, ARAT, MAS | 3D; 3; 120 Hz | 7-camera's (VICON); Tr, Sh, UA, FA, W, IF |

Table 2.1 Continued.

| Prange et <br> al. 2015; <br> Early Arm <br> Support | To examine the effect of weight-supported arm training combined with computerized exercises on arm function and capacity, compared with dose-matched conventional reach training in subacute stroke patients. | $\begin{aligned} & \text { Interventional; } \\ & \mathrm{S}_{\text {exp }}(33) \\ & \mathrm{S}_{\text {control }}(33) \end{aligned}$ | $\begin{aligned} & \text { 60.3(9.7); } \\ & \text { 17/18 } \\ & 58.0(11.4) ; \\ & 24 / 19 \end{aligned}$ | $\begin{aligned} & 51.1(23.8) ; 28 / 7 ; \\ & \text { NR } \\ & \text { 47.6(21.7); 25/8; } \\ & \text { NR } \end{aligned}$ | Pre and post 6 weeks of intervention | Start with hand as close to the sternum as possible and reach forward maximally. Movement was performed in free space to prevent any support; Yes | x | FM-UE, SULCS | 2D; 5; NR | Arm support device (ArmeoBoom); W |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Semrau et <br> al. 2015; <br> NR | Quantify proprioceptive and motor deficits using robotic technology during the first 6 months post stroke to characterize timing and patterns in recovery, and compare robotic assessments with traditional clinical measures. | Observational; S (113) | NR; NR | 10.6(6.6); NR; NR | 1w, 6w, 12w and 26w PS | 8-target center-out reaching task. Each movement was 10 cm ; No | x | TLT, CMSA, FIM, Purdue Pegboard | 2D; NR; NR | Exoskeleton (KINARM); Robot reflects position of H |
| $\begin{aligned} & \text { Yoo et al. } \\ & 2015 ; \\ & \text { NR } \end{aligned}$ | Examine the effects of upper limb robotassisted therapy in the rehabilitation of stroke patients | Interventional; S (15) | $\begin{aligned} & 40-49: 8,50- \\ & 59: 3, \\ & 60+: 4 ; 13 / 2 \end{aligned}$ | $\begin{aligned} & 0-6 \mathrm{~m}: 10,>7 \mathrm{~m}: 5 ; \\ & 11 / 4 ; 7 / 8 \end{aligned}$ | Pre and post 4 weeks of intervention | Move the hand from centre position to targets in each of eight compass directions (distance not clarified); No | x | FM-UE, MBI | 2D; NR; NR | MIT MANUS; Sh, E |

Table 2.1 Continued.

Table 2.1 Continued.

| Pila et al. <br> 2017; <br> EudraCT <br> Trial | Measure overall changes associated with a 3-month robotassisted training program coupled with conventional care, on motor impairment and pointing task kinematics of the upper limb in late subacute stroke. Also, to compare the course of the various kinematic parameters over time, and the associated clinical changes at different joints. | Observational; <br> S (22) <br> C (17) | $\begin{aligned} & 53(18) ; 13 / 9 \\ & 53(18) ; 8 / 9 \end{aligned}$ | $\begin{aligned} & \text { 63(29); 15/7; } \\ & \text { 10/12 } \end{aligned}$ | $\begin{aligned} & 63 \pm 29 \mathrm{~d} \mathrm{PS}, \\ & 98 \pm 32 \mathrm{~d} \mathrm{PS}, \\ & 131 \pm 28 \mathrm{~d} \mathrm{PS}, \\ & 167 \pm 31 \mathrm{~d} \mathrm{PS} \end{aligned}$ | Reaching towards visual targets in 3 directions, each movement was a 14 cm horizontal hand displacement; Yes | x | FM-UE | 2D; >300; NR | InMotion; H |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Palermo et <br> al. 2018; <br> NR | Investigate whether kinematic indices, based on motion capturing a 3D daily-life inspired gesture, improved after the administration of an RMT protocol, which involved an exoskeleton for 3D upper limb rehabilitation, and how these indices are in agreement with patient assessments that have been assessed using the most widely adopted clinical scales for post-stroke motor impairment. | Interventional; S (10) | $\begin{aligned} & \text { 60.1(18.3); } \\ & 8 / 2 \end{aligned}$ | 120(45); NR; 5/5 | Pre and post 4 weeks of intervention | Reach and point at a target, placed on the participant's sagittal plane, at shoulder height, and at a distance from the body equal to the patient's arm length; No | x | FIM, BI, FAT, FM-UE | $\text { 3D; 6; } 120 \mathrm{~Hz}$ | Optoelectronic <br> System (BTS <br> SMART-DX 300) <br> consisting of 6 <br> infrared CCD <br> cameras; Both <br> arms: $\mathrm{F}, \mathrm{H}, \mathrm{W}_{\mathrm{ulna}}$, <br> $\mathrm{W}_{\text {radio }}$, E, C7, <br> Sacrum, targets |

Table 2.1 Continued.

| Mazzoleni et al. 2018; NR | (i) to investigate the relationship between wrist training and proximal segment recovery; (ii) to compare the recovery of subacute and chronic stroke patients after wrist robot-assisted rehabilitation training. | $\begin{aligned} & \text { Interventional; } \\ & \text { 66.4(16.2); } \\ & \mathrm{S}(20) \end{aligned} 9 / 11$ | $\begin{aligned} & \text { 25.4(16.0);17/3; } \\ & 8 / 12 \end{aligned}$ | Pre and post 6 weeks of intervention | Move the cursor from the center of the screen to each of eight peripheral targets. Only N/E/ S/W directions were used for analyses; Yes | x | FM-UE, $\mathrm{FM}_{\text {Shoulder- }}$ $\qquad$ MAS test. , $\mathrm{FM}_{\text {wrist }}$, wrist, MI-UE, Box and Block | 2D; 16; NR | InMotion WRIST robot. 3 DoF (abductionadduction, flexionextension, pronationsupination); W |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Duret et al. 2019; <br> $\mathrm{NR}^{4}$ | examine a range of variables in order to identify reliable indictors of upper-limb motor performance following an intensive rehabilitation program that combined 16 sessions of robot-assisted training (3 days/week) with usual care during the sub-acute phase in patients with moderate-to-severe upper-limb paresis following stroke. | Interventional; 57(17); 25/21 S (46) | $\begin{aligned} & 58(22) ; 32 / 14 ; \\ & 24 / 22 \end{aligned}$ | Pre and post 5 weeks of intervention | 80 point-to-point reaching movements towards 8 visual targets, each 14 cm from the centre position; No | x | $\begin{aligned} & \text { FM-UE, } \\ & \text { FM }_{\text {shoulder-elbow }} \end{aligned}$ | 2D; 80; NR | InMotion 2.0 <br> Arm robot, with two active translational degrees-offreedom to assist shoulder (flexion/ extension) and elbow (flexion/ extension) movements in the horizontal plane; H |

Table 2.1 Continued.

| Mazzoleni <br> et al. 2019; <br> NR | investigate the effectiveness of combining tDCS and wrist robot-assisted rehabilitation in subacute stroke patients and whether this combination therapy would provide additional benefits in comparison with robotic therapy only. | Interventional; $\begin{aligned} & \mathrm{S}_{\text {exp }}(18) \\ & \mathrm{S}_{\text {control }}(16) \end{aligned}$ | $\begin{aligned} & \text { 67.5(16.3), } \\ & 8 / 12 ; \\ & 68.7(15.8), \\ & 7 / 12 \end{aligned}$ | $\begin{aligned} & 25(7) ; 13 / 7 ; 9 / 11 \\ & 25(7) ; 16 / 3 ; 8 / 11 \end{aligned}$ | Pre and post 6 weeks of intervention | Move the cursor from the center of the screen to each of 8 peripheral targets. Only N/E/S/W directions were used for analyses; Yes | x | FM-UE, $\mathrm{FM}_{\text {Shoulder }}$ Elbow, $\mathrm{FM}_{\text {wrist }}$, MAS $S_{\text {wrist }}$, MI-UE, Box and Block test. | 2D; 16; NR | InMotion WRIST robot. 3 DoF (abductionadduction, flexionextension, pronationsupination); W |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Goffredo et al. 2019; NR | Analyse built-in kinematic data registered by a planar end-effector robot for assessing the time course of motor recovery and patient's workspace exploration skills. | Interventional; S (68) | $\begin{aligned} & \text { 65.28(12.71); } \\ & 45 / 23 \end{aligned}$ | NR;49/19;39/29 | Session 1, 5, 10,15 , and 20 of robotic therapy. | point-to-point reaching movements towards a visual target and back, each target 14 cm from the centre position; Yes | x | BI, MI-UE, | $\begin{aligned} & \text { 2D; } 32 \text { per } \\ & \text { target; } 200 \\ & \text { Hz } \end{aligned}$ | InMotion 2.0. Two DoF robotic device; H |
| Hussain et <br> al. 2020; <br> SALGOT ${ }^{5}$ | Determining how the relationship between objective kinematic variables obtained from the target-to-target pointing task and selfreported manual ability varies during the first year after stroke. | Observational; $S(66)$ | $\begin{aligned} & \text { 65.7(13.4); } \\ & 39 / 27 \end{aligned}$ | 9.54d;53/13;29/37 | $10 \mathrm{~d}, 4 \mathrm{w}, 3 \mathrm{~m}$, $6 \mathrm{~m}, 12 \mathrm{mPS}$ | Reach and point at the target using the stylus; No | x | ABILHAND <br> question- <br> naire, <br> FM-UE | 3D; 32; NR | Phantom Omni haptic stylus; H |

Table 2.1 Continued.

| Thrane et al. 2020; SALGOT ${ }^{5}$ | To quantify longitudinal changes and residual deficits in movement performance and quality during the first year after stroke using kinematic analysis of drinking task. | Observational; S(56) C(60) | $\begin{aligned} & \text { 64.0(13.4), } \\ & 35 / 31 ; \\ & 63.4(12.6), \\ & 33 / 27 \end{aligned}$ | NR;NR;30/22 <br> (4other) | 3d, 10d, 4w, $3 \mathrm{~m}, 6 \mathrm{~m}, 12 \mathrm{~m}$ PS | Reach and grasp the glass, lifting the glass and bringing it to the mouth, taking on sip of water, placing the glass back down on the table and return the arm to its initial position; No |  | NIHSS, <br> FM-UE, <br> $\mathrm{FM}_{\text {sensation }}$ | $\text { 3D; 3; } 240 \mathrm{~Hz}$ | motion capture system (ProReflex MCU240 Hz Qualisys) with 5 optoelectronic cameras; H, W, $\mathrm{E}, \mathrm{Sh}_{\mathrm{L}}, \mathrm{Sh}_{\mathrm{H}}, \mathrm{Tr}$, head, top and bottom of the glass |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |

[^2]| A | Hand trajectory <br> Week 1 | Week 5 |
| :---: | :---: | :---: |


| Velocity profile <br> First day of therapy | Velocity profile <br> After 4-6 weeks of therapy |
| :---: | :---: |

Figure 2.2 (a) Reaching trajectories of the hand of one patient in weeks 1, 5, and 26 after stroke onset. Patients move their hand from the start position to a block, in this figure visualized as a black square. Each trace represents one reach-to-grasp movement (Adapted figure (van Kordelaar et al., 2014)). (b) Typical velocity profile of a stroke patient during a point-to-point movement at the first day of therapy and after 4-6 weeks of therapy (Adapted figure (Rohrer et al., 2004)).

## Overview of reported metrics

In total, 46 different kinematic metrics have been investigated during a reaching task in longitudinal studies starting in or before the sub-acute phase post-stroke (Table 2.2). The most frequently investigated metrics were movement time and peak hand velocity (Fig. 2.3). Other metrics investigated in more than $20 \%$ of the studies were: average hand velocity, jerk, speed metric, endpoint accuracy and reach efficiency. None of the studies investigated kinetic metrics during reaching. An overview of the investigated metrics per study, including details on metric definitions as provided by the authors, and when applicable their psychometric properties, can be found in Appendix B.

## Responsiveness and longitudinal association with clinical measures

Here, we report responsiveness of metrics to changes over time, and the longitudinal association between kinematics and the FM-UE, since this particular clinical measure was often reported by the studies. Table 2.2 provides an overview of the responsiveness of all reported kinematic metrics to change over time and the longitudinal association with clinical measures.


Figure 2.3 Percentage of studies that investigated each metric. The most frequently investigated metrics were movement time and peak hand velocity.
Table 2.2 Overview of metrics, their responsiveness to change over time and their clinical association

| Metric in this review | Name of metric used in study (first author, year) | Responsiveness Significant change over time (yes/no); time period post stroke (T1-T2) or passed time (T) | Clinical association <br> Type: longi/cross (time point); clinical measure, correlation coefficient/NR/NS |
| :---: | :---: | :---: | :---: |
| Movement time | Movement time (Platz 2001) | Yes; 3w | x |
|  | Movement duration (Rohrer 2002) | x | x |
|  | Movement time (Lang 2006b) | Yes; 1w-90d | x |
|  | Movement time (Wagner 2007) | Yes; 9d-109d | x |
|  | Total movement time (Konczak 2010) | Yes; 2w-4w | x |
|  | Total movement time (Tan 2012) | Yes; 2w | x |
|  | Movement duration (Dipietro 2012) | Yes; NR | X |
|  | Movement duration (Van Kordelaar 2013) | Yes; 14d-57d | x |
|  | Movement time (Metrot 2013a) | Yes; 2w, 3w | x |
|  | Movement duration (Van Kordelaar 2014) | Yes; 1w-5w | x |
|  | Movement time (Van Dokkum 2014) | x | Longi: FM-UE, $N S$ |
|  | Movement time (Semrau 2015) | x | Cross (all): FIM, PP, CMSA, strength $N R$ |
|  | Movement time (Li 2015) | X | Cross (pre): ARAT, FM-UE, strength $N R$ Cross (post): FM-UE, strength NR |
|  | Movement duration (Buma 2016) | Yes; 6w-29w | x |
|  | Movement time (Palermo 2018) | Yes; 4w | Longi: FIM, BI, FAT, FM-UE; NS |
|  | Task completion time (Goffredo 2019) | Yes, NR | x |
|  | Movement time (Hussain 2020) | X | $\begin{aligned} & \text { Cross }(10 \mathrm{~d} / 4 \mathrm{w}): \text { ABILHAND, NS } \\ & \text { Cross }(3 / 6 / 12 \mathrm{~m}): \text { : ABILHAND, } \\ & \rho:-0.46 /-0.49 /-0.75 \end{aligned}$ |
| Movement distance | Displacement (Yoo 2015) | No; 4w | x |

Table 2.2 Continued.

|  | Endpoint displacement (Li 2015) | x | Cross (pre): ARAT, strength NR Cross (post): ARAT, strength $N R$ |
| :---: | :---: | :---: | :---: |
|  | Reach distance (Prange 2015) | Yes; 6w | x |
| Movement efficacy | Movement efficacy (Duret 2013) | Yes; 40d | x |
| Path error | Root-mean-square (Duret 2013) | No; 80d | x |
|  | Path error (Duret 2016) | Yes; 35d | Cross (pre): FM-UE, $\rho:-0.63$; <br> MSS, $\rho:-0.63$ <br> Longi (correlation between change score): FM-UE, $\rho:-0.51$; MSS, $\rho:-0.49$ |
|  | Movement path error (Duret 2019) | Yes; 5w | x |
| Active movement index | Active movement index (Colombo 2013) | Yes; 3w | x |
| Trajectory length | Trajectory length (Van Dokkum 2014) | x | Longi: FM-UE, NS |
| Trunk displacement | Trunk displacement (Palermo 2018) | Yes; 4w | Longi: FIM, BI, FAT, FM-UE, NS |
| Velocity | Hand velocity (Duret 2013) | Yes; 40d | x |
|  | Posture speed (Semrau 2015) | x | Cross (all): FIM, PP, CMSA; strength $N R$ |
| Average hand velocity | Mean speed (Rohrer 2002) | x | x |
|  | Movement mean speed (Dipietro 2012) | Yes; NR | x |
|  | Mean velocity (Colombo 2013) | Yes; 3w | x |
|  | Average speed (Krebs 2014) | x | x |
|  | Mean velocity (Van Dokkum 2014) | x | x |
|  | Mean movement speed (Duret 2016) | Yes; 35d | Cross (pre): FM-UE, $\rho: 0.73$; <br> MSS, $\rho: 0.73$ <br> Longi (correlation between change score): FM-UE, MSS, reported as weak. |

Table 2.2 Continued.

|  | Mean velocity (Mazzoleni 2018) | Yes (ab/ad component during forward and backward direction, fl/ ex component during left/right direction); 6w | x |
| :---: | :---: | :---: | :---: |
|  | Mean movement speed (Duret 2019) | Yes; 5w | x |
|  | Mean velocity (Mazzoleni 2019) | Yes (forward, backward and left direction); 5w | x |
|  | Movement speed (Goffredo 2019) | Yes, NR | x |
|  | Mean velocity (Hussain 2020) | x | Cross (10d/4w/3m/6m): ABILHAND, NS Cross (12m): ABILHAND, $\rho: 0.54$ |
| Peak velocity | Peak speed (Rohrer 2002) | x | x |
|  | Reach speed (Lang 2006a) | x | *Cross (0d): ARAT, R:0.4 <br> *Cross (14d): ARAT, NS <br> *Cross (90d): ARAT, R:0.55 |
|  | Reach speed (Lang 2006b) | Yes; 1w-90d | x |
|  | Peak wrist velocity (Wagner 2007) | Yes; 9d-109d | Cross (109d): C-STR, $\rho: 0.55$; C-AROM, $\rho: 0.43$ |
|  | Max had velocity (Konczak 2010) | Yes; 2w-4w | x |
|  | Peak wrist velocity (Edwards 2012) | x | *Cross (0/14/90d): WMFT function, R:0.63/0.35/0.45; WMFT time, $R:-0.58 /$ NS/-0.42; WMFT grip, R:0.55/0.42/0.59. |
|  | Movement peak speed (Dipietro 2012) | Yes; NR | x |

Table 2.2 Continued.

|  | Max reaching velocity (Metrot 2013a) | Yes; NR | x |
| :---: | :---: | :---: | :---: |
|  | Peak speed (Krebs 2014) | x | x |
|  | Peak hand velocity (Van Dokkum 2014) | x | Longi: FM-UE, NS |
|  | Max speed (Semrau 2015) | x | Cross (all): FIM, PP, CMSA, strength NR |
|  | Peak velocity (Li 2015) | x | Cross (post): ARAT, (significant for constrained) strength $N R$ |
|  | Peak movement speed (Duret 2016) | Yes; 35d | Cross (pre): MSS, $\rho: 0.60$; FM-UE, $N S$ Longi (correlation between change score): FM-UE, MSS, reported as weak. |
|  | Peak velocity (Palermo 2018) | No | Longi: FIM, BI, FAT, FM-UE, $N S$ |
|  | Peak velocity (Hussain 2020) | $x$ | Cross (all): ABILHAND, NS |
|  | Peak hand velocity (Thrane 2020) | Yes; 3d-6m | x |
| Mix/max speed difference | Mix/max speed difference (Semrau 2015) | $x$ | Cross (all): FIM, PP, CMSA, strength NR |
| Time to peak velocity | Time of max velocity (Van Dokkum 2014) | x | Longi: FM-UE, NS |
|  | Time to peak velocity (Palermo 2018) | No | Longi: FIM, BI, FAT, FM-UE, NS |
|  | Percentage of peak velocity (Li 2015) | x | Cross (post): ARAT (significant for unconstrained); strength $N R$ |
|  | Acceleration time (Konczak 2010) | x | x |
|  | Relative time to peak velocity (Thrane 2020) | Yes; 3d-3m | x |
| Max hand acceleration | Max hand acceleration (Konczak 2010) | Yes; 2w-4w | x |
| Deceleration time | Deceleration time (Konczak 2010) | x | x |
| Number of hand trajectory reversals | Number of hand trajectory reversals (Duret 2013) | Yes; 80d | x |
| Speed maxima count | Speed maxima count (Semrau 2015) | x | Cross (all): FIM, PP, CMSA, strength NR |

Table 2.2 Continued.

| Velocity index | Velocity index (Pila 2017) | Yes; $2 \mathrm{~m}-3 \mathrm{~m}$, <br> $2 \mathrm{~m}-4 \mathrm{~m}, 2 \mathrm{~m}-5 \mathrm{~m}$; <br> 3m-5m | x |
| :---: | :---: | :---: | :---: |
| Normalized reaching speed | Normalized reaching speed (Mazzoleni 2019) | Yes (abduction component during reaching in forward direction); 5 w | x |
| Sub-movements speed profile characteristic | Number, overlap, duration, peak interval, skewness of sub-movements (Krebs 2014) | x | x |
| Jerk | Jerk metric (Rohrer 2002) | x | Longi (correlation between change scores): FM-UE, R:-0.48 |
|  | Jerk (Dipietro 2012) | Yes; NR | x |
|  | Mean magnitude of jerk normalized by peak speed (Krebs 2014) | x | x |
|  | Root mean square of the jerk normalized by the duration of movement (Krebs 2014) | x | x |
|  | Normalized hand displacement jerk (Van Kordelaar 2014) | Yes; 1w-5w | x |
|  | Normalized Jerk (Palermo 2018) | Yes; 4w | Longi: FIM, BI, FAT, FM-UE, NS |
|  | Normalized jerk (Mazzoleni 2018) | Yes (forward and backward direction); 6w | x |
|  | Normalized jerk (Mazzoleni 2019) | Yes (abduction component during reaching in forward direction); 5w | x |

Table 2.2 Continued.

| Speed metric | Speed metric (Rohrer 2002) | X | Longi (correlation between change scores): FM-UE, R:0.40 |
| :---: | :---: | :---: | :---: |
|  | Speed shape (Dipietro 2012) | Yes; NR | x |
|  | Mean over peak speed (Krebs 2014) | x | x |
|  | Movement irregularity (Van Dokkum 2014) | x | Longi: FM-UE, NS |
|  | Smoothness (Yoo 2015) | Yes; 4w | x |
|  | Speed shape (Duret 2016) | Yes; 35d | Cross (pre): FM-UE, $\rho: 0.75$; MSS, $\rho: 0.72$ <br> Longi (correlation between change score): FM-UE, MSS, reported as weak. |
|  | Smoothness (Duret 2019) | Yes; 5w | x |
| Mean arrest period ratio | Mean arrest period ratio (Rohrer 2002) | x | Longi (correlation between change scores): FM-UE, R:0.33 |
| Peaks metric | Peaks metric (Rohrer 2002) | X | Longi (correlation between change scores): FM-UE, NS |
|  | Number of peaks (Dipietro 2012) | Yes; NR | x |
|  | Number of velocity peaks (Metrot 2013a) | Yes; 2w, 3w | x |
|  | Movement smoothness (Colombo 2013) | Yes; 3w | X |
|  | Number of velocity peaks (Van Dokkum 2014) | X | Longi: FM-UE, strength $N R$ |
|  | Number of peak speed (Goffredo 2019) | Yes, NR | x |
|  | Number of velocity peaks (Hussain 2020) | X | Cross ( $10 \mathrm{~d} / 4 \mathrm{w} / 3 \mathrm{~m} / 6 \mathrm{~m} / 12 \mathrm{~m}$ ): <br> ABILHAND, $\rho:-0.45 / \mathrm{NS} / \mathrm{NS} /-0.54 /-0.66$ |
| Tent metric | Tent metric (Rohrer 2002) | X | Longi (correlation between change scores): FM-UE, NS |
| Smoothness index | Smoothness index (Pila 2017) | $\begin{aligned} & \text { Yes; } 2 m-3 m \text {, } \\ & 2 m-4 m, 2 m-5 m \end{aligned}$ | X |

Table 2.2 Continued.

| Endpoint accuracy | Accuracy (Platz 2001) | Yes; 3w | x |
| :---: | :---: | :---: | :---: |
|  | Reach Accuracy (Lang 2006a) | x | $\begin{aligned} & \text { "Cross (0/14/90d): ARAT, } \\ & \text { R:-0.53/-0.50/-0.45 } \end{aligned}$ |
|  | Reach Accuracy (Lang 2006b) | Yes; 1w-90d | x |
|  | Endpoint error (Wagner 2007) | Yes; 9d-109d | $\begin{aligned} & \text { Cross (109d): C-STR, } \rho:-0.34 ; \\ & \text { C-AROM, NS } \end{aligned}$ |
|  | Reach Accuracy (Edwards 2012) | x | *Cross ( $0 / 14 / 90 \mathrm{~d}$ ): WMFT function, $R:-0.65 /-0.72 /-0.50$; WMFT time, $R$ : 0.66/0.66/0.45; WMFT grip, R:-0.52/-0.38/-0.39 |
|  | Reach error (Yoo 2015) | Yes; 4w | x |
|  | Reach error (Duret 2016) | Yes; 35d | Cross (pre): FM-UE, $\rho:-0.79$; MSS, $\rho:-$ 0.79 <br> Longi (correlation between change score): FM-UE, MSS, reported as weak. |
|  | Active range of motion (Duret 2019) | Yes; 5w | x |
| Reach efficiency | Reach efficiency (Lang 2006a) | x | $\begin{aligned} & \text { "Cross (0/14/90d): ARAT, } \\ & \text { R:-0.35/-0.55/-0.43 } \end{aligned}$ |
|  | Reach efficiency (Lang 2006b) | Yes; 1w-90d | x |
|  | Reach path ratio (Wagner 2007) | Yes; 9d-109d | Cross (109d): C-AROM, $\rho:-0.44$; <br> Cross (109d): C-STR, p:-0.47 |
|  | Reach efficiency (Edwards 2012) | x | *Cross ( $0 / 14 / 90 \mathrm{~d}$ ): WMFT function, R:-0.50/-0.43/-0.55; WMFT time, $R$ : 0.56/0.56/0.55; WMFT grip, R:-0.30/-0.48/-0.45 |
|  | Normalized path length (Colombo 2013) | Yes; 3w | x |
|  | Trajectory directness (Metrot 2013a) | Yes; NR | x |

Table 2.2 Continued.

|  | Deviation from Straight line (Krebs 2014) | x | x |
| :---: | :---: | :---: | :---: |
|  | Trajectory directness (Van Dokkum 2014) | x | Longi: FM-UE, NS |
|  | Path length ratio (Semrau 2015) | Yes; NR | Cross (all): FIM, PP, CMSA, strength $N R$ |
|  | Hand path ratio (Palermo 2018) | Yes; 4w | Longi: FAT, strength $N R$ (mentioned as strong); FIM, BI, FM-UE, NS |
|  | Movement accuracy (Goffredo 2019) | No | x |
| Averaged squared Mahalanobis distance | Averaged squared Mahalanobis distance (Cortes 2017) | Yes; 1w-5w | x |
| Distance Index | Distance Index (Pila 2017) | $\begin{aligned} & \text { Yes; } 2 \mathrm{~m}-3 \mathrm{~m}, \\ & 2 \mathrm{~m}-4 \mathrm{~m}, 2 \mathrm{~m}-5 \mathrm{~m} \end{aligned}$ | x |
| Initial direction error | Initial direction error (Semrau 2015) | Yes; NR | Cross (1/6/12/24w): <br> FIM, $\rho:-0.61 /-0.56 /-0.47 /-0.52$ <br> PP, $\rho:-0.79 /-0.73 /-0.72 /-0.77$ <br> CMSA, $\rho:-0.79 /-0.74 /-0.66 /-0.72$ |
| Initial distance ratio | Initial distance ratio (Semrau 2015) | x | Cross (all): FIM, PP, CMSA, strength $N R$ |
| Accuracy index | Accuracy index (Pila 2017) | Yes; 2m-5m | x |
| Quality index | Quality index (Mazzoleni 2018) | Yes (forward, backward and left direction); 6w | x |
|  | Movement error (Mazzoleni 2019) | Yes (forward, backward and left direction); 5w | x |
| Aperture speed | Aperture speed (Lang 2006a) | x | *Cross (0/14/90d): <br> ARAT, R:0.58/0.35/0.39 |
|  | Aperture speed (Lang 2006b) | Yes; 1w-90d | x |

Table 2.2 Continued.
$\left.\begin{array}{llll}\hline & & & \begin{array}{l}\text { *Cross (0/14/90d): } \\ \text { WMFT function, R:0.65/0.40/NS; } \\ \text { WMFT time, } R:-0.55 /-0.38 /-0.39 ; ~ W M F T ~\end{array} \\ \text { grip, R:0.59/0.53/NS: }\end{array}\right]$
Table 2.2 Continued.

|  | Shoulder adduction (Li 2015) | X | Cross (pre): FM-UE (significant for unconstrained), strength $N R$ Cross (post): ARAT (significant for unconstrained), strength NR Cross (post): FM-UE, strength NR |
| :---: | :---: | :---: | :---: |
| Elbow rotation | Elbow rotation (Van Kordelaar 2013) | x | X |
|  | Elbow extension (Li 2015) | x | Cross (pre): ARAT; significant for unconstrained, strength $N R$ |
|  | Maximal elbow extension (Bang 2015) | Yes; 4w | X |
| Peak elbow velocity | Peak angular velocity (Thrane 2020) | Yes; 3d-6m | X |
| Forearm rotation | Forearm rotation (Van Kordelaar 2013) | x | x |
| Wrist rotation | Wrist rotation (Van Kordelaar 2013) | x | x |
| Composite score | Composite score (Semrau 2015) | X | Cross (all): FIM, PP, CMSA, strength $N R$ |
| Reaction time | Reaction time (Semrau 2015) | X | Cross (all): FIM, PP, CMSA, strength $N R$ |
|  | Reaction time (Li 2015) | X | Cross (pre): FM-UE, strength $N R$ Cross (post): FM-UE (significant for unconstrained), strength $N R$ |

[^3]Movement time, average hand velocity and peak hand velocity were shown to significantly change over time, mainly in the early sub-acute phase poststroke. The longitudinal association between movement time and FM-UE was not significant (Palermo et al., 2018; van Dokkum et al., 2014). Average hand velocity showed a poor longitudinal association with FM-UE (Duret et al., 2016). The longitudinal association between peak hand velocity and FM-UE was found to be weak (Duret et al., 2016) or not significant (Palermo et al., 2018; van Dokkum et al., 2014). Time to peak velocity did not change over time (Palermo et al., 2018), nor was it longitudinally associated with FM-UE (Palermo et al., 2018; van Dokkum et al., 2014).

The movement smoothness metrics that were most frequently investigated in longitudinal studies after stroke were: jerk, speed metric and peaks metric (Fig. 2.2). These metrics were shown to change over time post-stroke, mainly in the early sub-acute phase (Colombo et al., 2013; Duret et al., 2016; Mazzoleni et al., 2019, 2018; Metrot et al., 2013; Palermo et al., 2018; van Kordelaar et al., 2014; Yoo and Kim, 2015). Studies showed varying outcomes for the longitudinal association between peaks metric and FM-UE (Rohrer et al., 2002; van Dokkum et al., 2014). Inconclusive results were reported for the longitudinal association between speed metric and FM-UE. One study showed a significant longitudinal association with FM-UE (Pearson's r: 0.40) (Rohrer et al., 2002), while another study found a significant but poor longitudinal association with FM-UE (Duret et al., 2016), and yet another study found no significant longitudinal association (van Dokkum et al., 2014). Rohrer and colleagues (Rohrer et al., 2002) found a significant longitudinal association between jerk and FM-UE (Pearson's r: -0.48), while Palermo and colleagues did not (Palermo et al., 2018). For the smoothness metrics mean arrest period ratio and tent metric, change over time was not investigated. Mean arrest period ratio was longitudinally associated with FM-UE (Pearson's r:0.33), while tent metric was not (Rohrer et al., 2002).

Endpoint accuracy and reach efficiency were both responsive to change over time in the early sub-acute phase post-stroke. Endpoint accuracy was stated to be poorly longitudinally associated with FM-UE (Duret et al., 2016). Reach efficiency showed no significant longitudinal association with FM-UE (Palermo et al., 2018; van Dokkum et al., 2014) Path error was responsive to change over
time and was longitudinally associated with FM-UE (Spearman's $\rho$ : -0.51 ) (Duret et al., 2016).

In 11 out of 32 studies, the reaching task also included grasping. In five of these studies, kinematic metrics for grasping were investigated (Buma et al., 2016; Edwards et al., 2012; Lang et al., 2006a, 2006b; van Kordelaar et al., 2014). Grasp-related metrics such as aperture speed, peak aperture and jerk grasp aperture are responsive to change over time, which was not the case for aperture efficiency or time of peak aperture (Lang et al., 2006b; van Kordelaar et al., 2014).

A combination of simultaneously measured joint rotation metrics reflecting elbow extension and shoulder abduction were stated to be relevant since they are main components of stroke related abnormal muscle synergies (van Kordelaar et al., 2013). In one study, a principal component analysis showed that during a reach-to-grasp task, elbow and shoulder rotations are most associated early after stroke, and become more dissociated mainly within the first 8 weeks post-stroke (van Kordelaar et al., 2013). In the chronic phase post stroke, elbow and shoulder joint rotation during reaching remain more associated compared to healthy individuals (van Kordelaar et al., 2013). The kinematic metric trunk displacement is acknowledged to be a reflection of a compensation strategy to overcome the shoulder-elbow synergy that prevents elbow extension and thereby induces restriction of reaching area. The longitudinal association with clinical measures was not investigated.

### 2.3.3. Metrics reflecting behavioural restitution or compensation strategies

## Attempts to investigate recovery of movement quality by quantifying behavioural restitution and compensation

Trunk movement is a common compensatory strategy shown by stroke patients with any degree of motor impairment (Cirstea and Levin, 2000; Levin et al., 2002). Half of the studies intentionally restricted trunk movement during the reaching task in order to obtain kinematic data of a reaching movement which was not influenced by this form of compensation (Table 2.1). Three studies deliberately sought to measure compensatory movements of the trunk during a reaching task (Li et al., 2015; Palermo et al., 2018; van Kordelaar et al., 2013).

Several studies explicitly addressed whether changes in particular metrics reflect either behavioural restitution or compensation. For example, Konczak and colleagues (Konczak et al., 2010) showed that stroke patients perform pointing movements at a slower speed compared to controls, which was independent of whether the participants had to point in the air or at a target. From this, they concluded that moving slower is not a compensatory strategy per se. Buma and colleagues (Buma et al., 2016) suggested that decreased movement smoothness may result from corrections of deviations from the intended optimal movement pattern. They state that jerk may reflect the control strategy to correct these deviations, which may be interpreted as a quantification of compensation.

Three studies focus on the time period in which behavioural restitution is argued to take place. van Kordelaar and colleagues (van Kordelaar et al., 2013) showed that recovery of the control over Degrees of Freedom (DoF) during a reach-to-grasp task, reflecting the ability to perform movements dissociated from pathological synergies (van Kordelaar et al., 2012a), is restricted to the first five weeks post stroke, while FM-UE increased until eight weeks post stroke. Similar findings were shown for movement smoothness (van Kordelaar et al., 2014). Therefore, they conclude that these kinematic metrics may quantify behavioural restitution of motor control. Cortes and colleagues (Cortes et al., 2017) investigated improvement of motor control of the upper extremity during a 2D reaching task using the Kinereach ${ }^{\text {TM }}$, which is designed to decrease strength requirements by providing gravity support and reducing friction, while the trunk was restricted to limit compensation strategies. Thereby, the reaching task is in line with one of the performance assays suggested by the SRRR (Kwakkel et al., 2019). Cortes and colleagues showed that motor control of horizontal reaching plateaued in the first five weeks post stroke, whereas clinical scores as FM-UE and ARAT continued to show improvements until 14 weeks post stroke (Cortes et al., 2017). They suggest that this difference in time window may be due to strength improvements and learning of compensatory movements contaminating the FM-UE and the ARAT respectively. They concluded that kinematics of performance assays such as 2 D reaching could help isolate the underlying process of spontaneous recovery compared to clinical motor impairment scales such as FM-UE and capacity scores such as ARAT (Cortes et al., 2017).

Lang and colleagues (Lang et al., 2006b) compared recovery of reaching versus grasping after stroke. They showed that reaching accuracy recovered post stroke, while grasping efficiency did not. It is currently unclear what the contribution of different descending pathways is concerning restitution or compensation, and what causes the difference in recovery of reaching versus grasping.

Only one study measured performance assays and a functional task longitudinally (Wagner et al., 2007). In the study, participants performed a reaching task and two performance assays: isolated joint movements and grip strength (Wagner et al., 2007). Deficits in isolated (fractionated) movements were shown to be present by comparing the composite score of the individuation index of the shoulder, elbow and wrist to healthy controls. Also, maximal grip strength was significantly decreased in stroke patients when compared to controls. Both performance assays showed improvement over time from the acute to the subacute phase post-stroke. However, deficits in grip strength and isolated movement control remained. Normal values of kinematic metrics such as reaching accuracy and efficiency were shown during a 3D goal directed forward reaching task, despite the remaining deficits revealed by the performance assays. On the other hand, peak wrist velocity during a reaching task remained deviated from healthy values. From this, they conclude that "performance of functional movement can be normal or near-normal, despite the presence of underlying sensorimotor impairments. This may reflect the idea that not all functional movements require full sensorimotor capacity" (Wagner et al., 2007). This conclusion is in line with the present dichotomy of behavioural recovery, whereby motor function at the activity-level of the ICF is achieved by two components: behavioural restitution and compensation.

## SRRR recommendation compatibility

None of the longitudinal studies met all recommendations provided by the SRRR, one reason of course being that these recommendations were published only recently (Kwakkel et al., 2019). The SRRR recommendations were predicated on the idea that it is important to distinguish between behavioural restitution and compensation. The recommendation to include longitudinal measurements of performance assays besides a functional task was met by one out of 32 studies. In 24 out of 32 studies, the first measurement was performed
after the acute phase post-stroke, and measurements were repeated limited number of times. Furthermore, 24 out of 32 studies did not include healthy reference data and were thereby not able to determine whether observed recovery was complete. An overview of which recommendations of the SRRR were met by the individual studies is provided in Appendix C.

The only study which investigated recovery by performing both a functional task and performance assays (Wagner et al., 2007) met many of the recommendations of the SRRR, except for the minimal number of repetitions within a measurement, and they only performed two measurements per patient.

### 2.4. DISCUSSION

Despite the large number of cross-sectional kinematic post-stroke studies (Schwarz et al., 2019), longitudinal studies that track recovery of quality of upper limb movement remain scarce. Thirty-two longitudinal post stroke studies were found that measured kinematic metrics during a reaching task. A few of these studies addressed the need to distinguish between behavioural restitution and compensation. Only one study investigated the combination of performance assays and a functional task longitudinally (Kwakkel et al., 2019), showing that metrics such as reaching accuracy and reaching efficiency normalized, while peak wrist velocity and performance assays, such as grip strength and isolated movement control, showed recovery but remained impaired. The recommendations recently provided by the SRRR, together with the overview of reported metrics reflecting movement quality, may serve as inspiration and starting point for designing stroke studies which will bring us closer to kinematics that can distinguish between behavioural restitution and compensation.

From a translational perspective, it is of interest to study the longitudinal association between the recommended performance assays and common clinical assessments. For example, in case of FM-UE, such studies would help elucidate precisely what the measure is capturing; whether it mainly quantifies the degree to which out-of-synergy movements can be made as intended (FuglMeyer et al., 1975; Twitchell, 1951), or the degree to which it is contaminated
by other motor impairment components, both neural and musculoskeletal (Ellis et al., 2016, 2008; McPherson and Dewald, 2019). However, although some of the available studies investigated longitudinal associations between kinematics and clinical outcomes (Buma et al., 2016; Duret et al., 2016; Edwards et al., 2012; Hussain et al., 2020; Lang et al., 2006a; Wagner et al., 2007), these analyses did not concern kinematics obtained from performance assays.

A difference in recovery between reaching and grasping was observed by Lang and colleagues (Lang et al., 2006b). It is currently unclear what causes the difference in recovery of reaching versus grasping and what the contribution is of different descending pathways with regard to restitution and compensation. This has to be investigated by obtaining longitudinal neurophysiological data alongside kinematic data within the first months post stroke.

Smoothness is assumed to be a good reflection of movement quality. However, many different kinematic metrics have been used to quantify smoothness, many of which have different mathematical underpinnings and therefore show varying recovery patterns. We explore this issue in Chapter III. Moreover, smoothness of the hand trajectory during a reaching task can be influenced by several components of motor impairment across different joints in the upper extremity. Whether smoothness metrics are able to reflect behavioural restitution remains inconclusive and should be studied in a longitudinal study post-stroke.

In sum, this review shows that despite the growing number of cross-sectional kinematic and kinetic post-stroke studies, there is still a need for longitudinal studies that separate behavioural restitution from compensation over the course of recovery. Thus, measuring movement quality remains in its infancy in stroke recovery and rehabilitation studies. Further research is necessary to provide better means to interpret neuroimaging studies (Krakauer et al., 2012; Kwakkel et al., 2019; Levin et al., 2009), and insight into which aspects of post-stroke arm function deficits are targeted during CIMT (Kwakkel et al., 2015; Wolf et al., 2006) and neuro-modulation therapies such as repetitive Transcranial magnetic stimulation (Edwards et al., 2008) and Transcranial direct current stimulation (Elsner et al., 2018). Finally, understanding recovery
of movement quality may aid in the design of better rehabilitation approaches targeting restitution (Krakauer et al., 2012; Kwakkel and Meskers, 2014).

### 2.4.1. Barriers in kinematic research post-stroke

There are a number of possible explanations for the paucity of longitudinal studies. First, collecting longitudinal datasets in a post-stroke cohort is a challenge when having to adhere to fixed time points, at higher frequency early on; the need to restrict inclusion to those patients that can be captured in the first few weeks post stroke; and losing patients because they often change locations during their clinical trajectory. Second, while there is agreement on movement quality as proxy of true neurological recovery (Krakauer et al., 2012), consensus on which metrics reflect movement quality is lacking. Third, there may be technology-based barriers. High-resolution optical tracking systems (Kwakkel et al., 2019) are typically not portable and pose a challenge for serial assessments as patients need to return to the movement laboratory for follow-up measurements, which increases the chances of drop-out. User-friendly, portable, high-resolution measurement setups or a validated setup of wearables in which inertial measurement units provide information using accelerometers and gyroscopes, would greatly improve feasibility of investigating kinematics post-stroke. An overview of the ease of application and practicality of different motion capture systems to measure kinematic metrics was recently provided (Mesquita et al., 2019). In line with the SRRR task force, authors state that marker-less systems are promising for implementation in hospitals and clinics, yet require validation (Mesquita et al., 2019). Examples of such systems are the Microsoft Kinect, electromagnetic motion capture systems and miniature inertial measurement units (Mesquita et al., 2019).

### 2.4.2. Limitations

Due to our search restrictions regarding databases and language, some relevant studies may have been missed. Studies in which no reaching task was performed were excluded. Studies which measured performance assays but did not include a reaching task will therefore be missed.

### 2.4.3. Future directions

In order to understand what occurs during true recovery from motor impairments after stroke and how innovative therapies may interact with such behavioural restitution, there is an urgent need for longitudinal kinematic and kinetic studies. In line with the SRRR recommendations, future studies should perform frequently repeated measurements in the first three months post stroke, measurement time points should be defined as elapsed time since the moment of stroke onset and healthy reference data should be provided regarding metrics reflecting movement quality. Moreover, studies targeting QoM after stroke should use different performance assays such as strength, dexterity, and the ability to execute isolated movements for quantification of behavioural restitution. The contributions of these different motor impairment components and their relation to underlying mechanisms that drive behavioural restitution and neural repair early post-stroke need further investigation. Besides better understanding of dynamics of the different performance assays and improvements in movement quality, this will also contribute to proper interpretation of observed dynamics in neuroimaging such as EEG (Saes et al., 2020) and fMRI (Desowska and Turner, 2019) obtained early post stroke.

From a technical and practical point of view, there are a number of barriers that hinder the use of high-fidelity systems outside the laboratory. Therefore, we recommend the development of minimal and portable movement analysis systems or validation of existing ones to measure movement quality outside the laboratory. Such portable systems will decrease burden on patients and improve feasibility of longitudinal studies. Moreover, quick and easy to use systems are more likely to ultimately make the transition to routine clinical practice. These systems along with analysis packages that provide a small number of interpretable measures will be essential to make studying recovery using kinematics useful for clinicians.

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## APPENDICES

The following appendices are related to this chapter:

A Search strategy used in Chapter II
B Definitions and psychometric analyses of the metrics identified in Chapter II
C Assessing if the studies identified in Chapter II followed international recommendations

Quality of reaching longitudinally post stroke

# Smoothness metrics for reaching performance after stroke: Which one to choose? 

"All animals are equal, but some animals are more equal than others."
George Orwell, Animal Farm

## Submitted as:

Mohamed Refai, M.I., Saes, M., Scheltinga, B.L., van Kordelaar, J., Bussmann, J.B.J., Veltink, P.H., Buurke, J.H., Meskers, C.G.M., van Wegen, E.E.H., Kwakkel, G., van Beijnum, B.-J.F., Smoothness metrics for reaching performance after stroke. Part 1. Which one to choose?


#### Abstract

Smoothness is commonly used for measuring movement quality of the upper paretic limb during reaching tasks after stroke. Many different smoothness metrics have been used in stroke research, but a 'valid' metric has not been identified. A systematic review, and subsequent rigorous analysis of smoothness metrics used in stroke research, in terms of their mathematical definitions and response to simulated perturbations, is needed to conclude whether they are valid for measuring smoothness. Our objective was to provide a recommendation for metrics that reflect smoothness after stroke, based on: (1) a systematic review of smoothness metrics for reaching used in stroke research, (2) the mathematical description of the metrics, and (3) the response of metrics to simulated changes associated with smoothness deficits in the reaching profile. The systematic review was performed by screening electronic databases using combined keyword groups Stroke, Reaching and Smoothness. Subsequently, each metric identified was assessed with mathematical criteria regarding smoothness: (a) being dimensionless, (b) being reproducible, (c) being based on rate of change of position, and (d) not being a linear transform of other smoothness metrics. The resulting metrics were tested for their response to simulated changes in reaching using models of velocity profiles with varying durations, amplitudes, harmonic disturbances, noises, and submovements. Two reaching tasks were simulated: reach-to-point and reach-tograsp. The metrics that responded as desired in all simulation analyses were considered to be valid.


The systematic review identified 32 different smoothness metrics, 17 of which were excluded based on mathematical criteria, and 13 more as they did not respond as desired in all simulation analyses. Eventually, we found that, for reach-to-point movements, the correlation metric, and the Spectral Arc Length (SPARC) are valid metrics. For reach-to-grasp movements, only SPARC was found to be a valid metric. Based on this systematic review and simulation analyses, we recommend the use of SPARC as a valid smoothness metric in both reach-to-point and reach-to-grasp tasks of the upper limb after stroke. However, further research is needed to understand the time course of smoothness measured with SPARC for the upper limb early post stroke, preferably in a longitudinal study.

### 3.1. INTRODUCTION

Stroke is one of the main causes of adult disability (Feigin et al., 2014; Langhorne et al., 2011; Sacco et al., 2013). Goal-directed upper limb movements after stroke are characterized by slowness, spatial and temporal discontinuity (i.e., lack of smoothness), and abnormal stereotypic patterns of muscle activation or movement synergies (Cirstea and Levin, 2000; Twitchell, 1951).

Improved smoothness during reaching, pointing or grasping using the upper paretic limb reflects improvement in the movement quality early after stroke (Balasubramanian et al., 2015; van Kordelaar et al., 2014). The Stroke Recovery and Rehabilitation Roundtable (SRRR) task force identified standardized measurement of upper limb movement quality as an important target in recovery research (Bernhardt et al., 2019). Smoothness of movement is regarded as the result of 'learned, coordinative processes in sensorimotor control', although the underlying neuronal and mechanical substrates that cause lack of smoothness in motor control are still poorly understood (Reinkensmeyer et al., 2016; Rohrer et al., 2002). Smoothness is therefore interpreted as a reflection of the level of sensorimotor coordination and movement proficiency (Hogan and Sternad, 2009; Kiely et al., 2019).

Balasubramanian and colleagues defined movement smoothness as continuity or non-intermittency of a movement, independent of its amplitude and duration (Balasubramanian et al., 2015). Maximizing the smoothness of a movement is considered to be prioritized by the neuro-muscular system, as it reduces the control burden on the brain (Schwartz, 2016). Nonetheless, the neurophysiological mechanisms of smoothness deficits after stroke are yet to be understood. Muscle activity patterns observed during reaching after stroke have been shown to be impaired (Shumway-Cook and Woollacott, 2007). Smoothness deficits could, for example, be caused by the inability to synchronize motor units or control agonists and antagonists in the right proportions (Krylow and Zev Rymer, 1997; Rohrer et al., 2002), or may be due to changes in Corticospinal tract (CST) excitability following stroke (Talelli et al., 2006).

A prerequisite for investigating smoothness deficits after stroke is identifying a valid smoothness metric. Unfortunately, there is currently no commonly accepted metric for quantifying movement smoothness, and many types have been used in the literature to investigate smoothness of reaching movements post stroke. The use of many smoothness metrics in clinical research is limited by several methodological concerns. For instance, some metrics are not clearly described and therefore not reproducible. Other metrics depend on the duration or distance of reaching or are not dimensionless. In both cases, they could be confounded by the shape, i.e., the duration and amplitude, of the movement (Hogan and Sternad, 2009). Some proposed smoothness metrics are based on position, and do not truly reflect smoothness per se (Balasubramanian et al., 2015; Melendez-Calderon et al., 2021) as they do not measure the rate of change of position. Furthermore, some metrics are linear transformations of other smoothness metrics, and are therefore proxies of existing metrics. Finally, some metrics lack robustness against measurement noise (Balasubramanian et al., 2015).

Several narrative reviews about smoothness have discussed the strengths and weaknesses of a limited set of available metrics (Balasubramanian et al., 2015; Hogan and Sternad, 2009; Rohrer et al., 2002). The relations between these metrics and smoothness were assessed either by using simulation models, or by studying post-stroke correlations with clinical scales. However, these studies reviewed the literature narratively, rather than systematically. Therefore, a comprehensive overview of metrics used to measure smoothness after stroke is lacking. Furthermore, these metrics have not been validated in terms of whether they reflect smoothness (Feinstein and Cannon, 2001). As a result, proper recommendations for a valid smoothness metric are currently lacking in the literature.

Our goal was to identify the most valid metrics for quantifying smoothness of upper paretic limb movement after stroke during reaching tasks, specifically the reach-to-point and reach-to-grasp tasks. To this end, several subsidiary questions were formulated. Firstly, to identify available metrics, we addressed the question 'Which metrics have been used in the literature to assess movement smoothness in reaching by persons with stroke?'. Secondly, we filtered metrics sequentially, using a set of criteria derived from the literature to assess
whether their mathematical definitions regarding smoothness were sound (Balasubramanian et al., 2015; Hogan and Sternad, 2009; Rohrer et al., 2002). This was done to answer the question 'Which of the available metrics are mathematically defined, reproducible, not linear transforms of another metric, dimensionless, and defined using the rate of change in position?'. Thirdly, we assessed how each metric responds to smoothness deficits in the reaching task, to answer the question 'How does each smoothness metric respond to a simulated change in the velocity profile of a reaching task?’

### 3.2. METHODS

### 3.2.1 Systematic Literature Review

The literature search was performed in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement, using keyword groups 'Stroke', 'Reaching’ and ‘Smoothness' (Moher et al., 2009) (Full search query in Appendix D). PubMed, Scopus, Cochrane Library, EMBASE and CINAHL databases were searched for all records up to October 2019. The screening of the literature was performed by one author (BLS) and ambiguities were resolved with another author (MRMI). Articles were excluded if they were in a language other than English, or if they were reviews or conference proceedings. Eventually, we included articles in which (1) reaching or aiming movements of persons with stroke were studied and (2) a metric was used to determine the smoothness of a reaching movement. The International Classification of Functioning, Disability, and Health (ICF) definition of a reaching movement (code: d 4452 ) is 'Using the hands and arms to extend outwards and touch and grasp something, such as when reaching across a table or desk for a book' (WHO, 2017). The references of the included articles were scanned for additional suitable articles. The review has been registered in the PROSPERO registry under CRD42020173211.

### 3.2.2. Metrics mathematically reflecting smoothness

Metrics should reflect the definition of movement smoothness, i.e., the continuity or non-intermittency of the movement profile, independent of its amplitude and duration (Balasubramanian et al., 2015). Based on the requirements stated in the introduction above, the definition of a metric was not sound if:

E1. the units contained $m$ and/or $s$,
E2. the metric was not reproducible from the literature,
E3. the metric was not based on velocity or a derivative of velocity, or
E4. the metric was linearly related to another metric by (a) scaling or (b) addition of a constant.

### 3.2.3 Response of metrics to changes in velocity profile

The response of each metric to four different types of simulated perturbations, applied to two reaching velocity profiles, viz. reach-to-point and reach-tograsp, were studied. A reach-to-point movement was simulated using a minimal jerk model (Flash and Hogan, 1985):

$$
\begin{equation*}
v_{\mathrm{mj}}(t)=\mathrm{d}_{\mathrm{t}}\left(\frac{30 t^{4}}{T^{5}}-\frac{60 t^{3}}{T^{4}}+\frac{30 t^{2}}{T^{3}}\right) \tag{3.1}
\end{equation*}
$$

where $v_{m j}$ is the minimal jerk velocity profile, $\mathrm{d}_{\mathrm{t}}$ is the total reaching distance, $T$ is the total movement time and $t$ is the time scale from 0 to $T$. Using this, a symmetrical velocity profile $\left(\mathrm{v}_{\text {symm }}\right)$ was created with a $\mathrm{d}_{\mathrm{t}}$ of 0.3 m , and a $T$ of 1 s . While this velocity profile reflects a reach-to-point movement, it does not truly reflect reach-to-grasp movements (Hughes et al., 2013), as the latter movements have to account for a higher accuracy when nearing the target position (Hughes et al., 2013). An initial analysis on healthy participants showed that an asymmetrical velocity profile $\left(\mathrm{V}_{\text {asymm }}\right)$ was better suited for this purpose. This was modelled using a polynomial curve (Appendix E). Both velocity profiles are shown in Appendix F and have been further investigated in this chapter.

Of the four simulated perturbations, the first three are analytical evaluations of the smoothness metrics, and the last one is specifically based on theories regarding recovery of movement after stroke (Rohrer et al., 2002).

- Shape Simulation (SS): The movement duration and distance of the base velocity profiles were varied. The smoothness metric must not depend on either of these parameters. The durations and distances of both velocity profiles were varied from 0.5 to 6.0 s in steps of 0.1 s , and from 0.2 to
0.7 m in steps of 0.01 m . A total of 2856 combinations were used to calculate the outcomes of the metrics. The ranges for movement duration and distance were chosen such that they were within the physiological range of human reaching.
- Harmonic Disturbances (HD): In this analysis, tremor or weak control of reaching movement was simulated using harmonic disturbances added to the base velocity profiles (Elias et al., 2018). This included sinusoids with varying amplitude and frequency. The relation between frequency or amplitude and the metric should be monotonic. Smoothness is expected to decrease with increasing amplitude for a given frequency, and also with increasing frequency for a given amplitude.
Sinusoids of frequencies between 2 and 25 Hz in steps of 0.5 Hz , and amplitudes between 0 and $0.2 \mathrm{~m} / \mathrm{s}$ in steps of $0.005 \mathrm{~m} / \mathrm{s}$ were added to the base velocity profile. A total of 1927 unique combinations were explored. The ranges chosen were within the physiological ranges of movement (Balasubramanian et al., 2012; Lang et al., 2006b).
- Measurement noise (MN): A more robust smoothness metric is less sensitive to measurement noise (Balasubramanian et al., 2015). The noise was modelled as normally distributed white noise (mean $=0$, standard deviation $=1$ ) and added to the base velocity profiles.
The root mean square (RMS) of the noise was varied from 0 to $0.08 \mathrm{~m} / \mathrm{s}$ in steps of $0.002 \mathrm{~m} / \mathrm{s}$. Twenty-five different realizations for each RMS were generated, and the metrics were estimated for each realization. The minimum, maximum, mean and standard deviation of the metrics were calculated and reported. In an additional analysis of noise we filtered the noise-added velocity profile using a zero phase 4th order low pass Butterworth filter with cut off of 20 Hz (Balasubramanian et al., 2015). The mean of the metric outcome across the 25 realizations after filtering was determined.
- Sub-movement Simulation (SMS): A smoothness metric must reflect the change in the progressive blending of sub-movements (Rohrer et al., 2004). The smoothness metric should decrease monotonically with increasingly distinct sub-movements, and increasing delays between each sub-movement (Rohrer et al., 2002).

This study is an extension of previous work applied to a set of metrics (Balasubramanian et al., 2012; Rohrer et al., 2002). The reaching profiles were modelled as a composition of two or more sub-movements, each defined as the base velocity profile with a duration of 1 s . The sub-movements were separated by a varying lag, denoted as $K s$. Ks ranged from 0 s, were the sub-movements fully overlap, to 1.2 s , where there was 1.2 s between the starting points of the two sub-movements. The lag was increased in steps of 0.02 s . Note that when the lag was greater than 1 s , there were instances of zero velocity between subsequent sub-movements. The total duration of the movement increased with Ks. Simulations were performed with two, three and four sub-movements.

## Analysis of the simulations

The responses of each metric to the four different types of simulated perturbations were individually assessed. For the Shape Simulation, the percentage of change $(\% \Delta)$ from the metric value for base profile was estimated, and in this study, a change of more than $10 \%$ was considered to be meaningful.

The Combinations Exceeded (CE) parameter was introduced in order to quantify how each metric responded to the Harmonic Disturbances. The $\% \Delta$ was estimated for each combination of frequency and amplitude. CE was marked as the percentage of the combinations that exceeded $10 \%$. Hence, a higher value of CE meant that there were more combinations of frequency and amplitude that caused a meaningful change in the value of the metric from its base velocity profile.

For the Measurement Noise simulation, the ratio of signal-to-noise power (SNR) was estimated, to quantify the robustness to noise. First the power of the measurement noise was estimated. Then, the power of the signal was estimated as the power of the base velocity profile with added measurement noise. The lowest RMS of added noise was $0.002 \mathrm{~m} / \mathrm{s}$, which corresponds to SNRs of 45.0 dB for $\mathrm{v}_{\text {symm }}$ and 45.4 dB for $\mathrm{v}_{\text {asymm }}$. Subsequently, the highest noise RMS added was $0.08 \mathrm{~m} / \mathrm{s}$, which corresponded to SNRs of 13.2 dB for $\mathrm{v}_{\text {symm }}$ and 13.6 dB for $\mathrm{v}_{\text {asymm }}$. The SNR at which the mean value of the metric differed from the base velocity profile by at least $10 \%$ is reported. Metrics that reached a $10 \%$ threshold only at a high RMS of added measurement noise, and
therefore a low SNR, were deemed to be more robust to noise. On the other hand, metrics that crossed the threshold at lower RMS values, and therefore a higher SNR, are highly sensitive to noise. An SNR threshold to distinguish between high and low robustness was determined using the distribution of the SNR values obtained at the $10 \%$ cut-off for each metric. The SNR values that fell in the interquartile range of the distribution were deemed to have low robustness to noise. All metrics with an SNR lower than the 25th percentile were considered to have high robustness to noise.

Finally, in the Sub-movements Simulations, monotonicity was assessed using visual inspection, and in case of ambiguities, the slope of the resulting graph was assessed. Metrics that did not change monotonically were considered invalid for measuring smoothness. All computations were performed using MATLAB ${ }^{\circledR}$ 2015b Mathworks, Natick, MA, USA).

### 3.3. RESULTS

### 3.3.1 Systematic Literature Review

A total of 476 unique articles were identified, 102 of which were found to be eligible for inclusion using Rayyan (Ouzzani et al., 2016). A total of 32 different metrics (see Appendix G) were identified (Fig. 3.1 shows the PRISMA flow chart).

### 3.3.2 Metrics mathematically reflecting smoothness

Table 3.1 shows an overview of all metrics identified from the literature, and the ones that did not meet the four exclusion criteria (E1-E4). The metrics identified in the systematic review were classified into categories based on their mathematical definitions. Metrics defined in the time domain were classified as 'Trajectory metrics', or 'Velocity metrics', or 'Acceleration metrics', or 'Jerk metrics'. Metrics defined in the frequency domain were classified as 'Frequency metrics'. Metrics that did not fit in any of these categories, or fitted in more than one category, were classified as 'Other metrics'.


Figure 3.1 PRISMA Flow diagram summarises the number of studies filtered during the review. A total of 102 studies met all inclusion criteria.

Trajectory-based smoothness metrics: The Index of Curvature (IC) (Bigoni et al., 2016) and the standard deviation of the position perpendicular to the movement direction ( $S D_{-} X Y$ ) measured smoothness using only the discrete position information of the reaching movement. As these are not based on the rate of change of position, they do not reflect smoothness of reaching (criterion E3). This holds for any proposed metric that belongs to this category.

Velocity-based smoothness metrics: Of the seven velocity-based metrics, Movement Arrest Period Ratio (MAPR), Speed Metric (SM), Number of Submovements (NOS), Velocity Arc Length (VAL) and Correlation Metric (CM) were found to be mathematically sound for measuring smoothness and were used for further analysis.
Table 3.1 Overview of Smoothness metrics identified from the literature.

| Metric (Abbreviation) | Units | Used $\mathrm{in}^{\text {a }}$ | Exclusions | Category | Earliest Citation |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Index of curvature (IC) | [] | 1 | E3 | Trajectory | (Bigoni et al., 2016) |
| Standard deviation in 2D plane (SD_XY) | [] | 1 | E3 | Trajectory | (Simonsen et al., 2017) |
| Number of sub-movements (NOS) | [] | 1 |  | Velocity | (Liebermann et al., 2010) |
| Speed metric (SM) | [] | 15 |  | Velocity | (Rohrer et al., 2002) |
| Normalized reaching speed (NRS) | [] | 2 | E4 (SM) | Velocity | (Mazzoleni et al., 2011) |
| Movement arrest period ratio (MAPR) | [] | 3 |  | Velocity | (Beppu et al., 1984) |
| Tent Metric (TM) | [] | 1 | E2 | Velocity | (Rohrer et al., 2002) |
| Velocity Arc Length (VAL) | [] | 1 |  | Velocity | (Balasubramanian et al., 2012) |
| Correlation Metric (CM) | [] | 2 |  | Velocity | (Krebs et al., 2001) |
| Peaks Metric (Peaks) | [] | 61 |  | Acceleration | (Brooks, 1974) |
| Number of Movement Units (NMU) | [] | 3 | E4a (Peaks) | Acceleration | (Menegoni et al., 2009) |
| Number of peaks normalized by movement duration (NPt) | $\mathrm{s}^{-1}$ | 1 | E1 | Acceleration | (Kahn et al., 2006) |
| Number of peaks normalized by movement distance (NPd) | $\mathrm{m}^{-1}$ | 4 | E1 | Acceleration | (Abdul Rahman et al., 2017) |
| Inverse number of peaks and valleys (IPV) | [] | 1 |  | Acceleration | (Pila et al., 2017) |
| Acceleration metric (AM) | [] | 2 | E1 | Acceleration | (Mazzoleni et al., 2011) |
| Integrated absolute jerk (IAJ) | $\mathrm{ms}^{-2}$ | 2 | E1 | Jerk | (Duff et al., 2010) |
| Mean absolute jerk (MAJ) | $\mathrm{ms}^{-3}$ | 2 | E1 | Jerk | (Bigoni et al., 2016) |
| Mean absolute jerk normalized by peak speed (MAJPS) | $\mathrm{s}^{-2}$ | 6 | E1 | Jerk | (Rohrer et al., 2002) |

Table 3.1Continued.

| Metric (Abbreviation) | Units | Used in ${ }^{\text {a }}$ | Exclusions | Category | Earliest Citation |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Integrated squared jerk (ISJ) | $\mathrm{m}^{2} \mathrm{~s}^{-5}$ | 1 | E1 | Jerk | (Laczko et al., 2017) |
| Root mean squared jerk metric (RMSJ) | $\mathrm{ms}^{-3}$ | 1 | E1 | Jerk | (Young and Marteniuk, 1997) |
| Normalized integrated jerk (NIJ) | $\mathrm{ms}^{-3} \sqrt{\mathrm{~s}}$ | 1 | E1 | Jerk | (Adamovich et al., 2009) |
| Dimensionless squared jerk (DSJt) | [] | 12 |  | Jerk | (Teulings et al., 1997) |
| Log dimensionless squared jerk (LDSJt) | [] | 1 |  | Jerk | (van Kordelaar et al., 2014) |
| Dimensionless squared jerk (DSJm) | [] | 1 | E4a (DSJt) | Jerk | (Marini et al., 2017) |
| Dimensionless squared jerk (DSJb) | [] | 1 |  | Jerk | (Balasubramanian et al., 2012) |
| Log dimensionless squared jerk (LDSJb) | [] | 1 |  | Jerk | (Balasubramanian et al., 2012) |
| Rotational jerk (RJ) | [] | 1 | E3 | Jerk | (Repnik et al., 2018) |
| Spectral metric (SPMR) | [] | 1 |  | Frequency | (Strohrmann et al., 2013) |
| Spectral method (SPM) | [] | 1 |  | Frequency | (Balasubramanian et al., 2009) |
| Spectral arc length 2012 (SPAL) | [] | 8 |  | Frequency | (Balasubramanian et al., 2012) |
| Spectral arc length (SPARC) | [] | 1 |  | Frequency | (Balasubramanian et al., 2015) |
| Combined smoothness metric (CSM) | --b | 1 | E1 | Other | (Popović et al., 2014) |

[^4]$M A P R$ is the proportion of time that the movement speed exceeds a given percentage of the peak speed (Beppu et al., 1984). SM, defined as the mean speed of the whole movement normalized by the peak speed, was found to decrease with the severity of the stroke (Rohrer et al., 2002). Normalized Reaching Speed (NRS) is the ratio of the difference in peak and mean speed over the peak speed (Mazzoleni et al., 2011). As $N R S=1-S M$, it is a linear transform of the $S M$ metric, and is expected to behave congruently. Therefore, $N R S$ was excluded from further analysis (criterion E4). The definition and mathematical description of the Tent Metric (TM) was incomplete in the study (Rohrer et al., 2002), and therefore could not be evaluated further (criterion E2). NOS counts the sub-movements that make up the tangential velocity profile (Rohrer and Hogan, 2006) and has been used to assess smoothness in persons with stroke (Liebermann et al., 2010). VAL (Balasubramanian et al., 2012) is based on the arc length of the speed profile normalized by the peak speed. It assumes that a bell-shaped velocity profile has a shorter arc length than one with velocity fluctuations. CM determines the correlation between the velocity profile extracted from the minimal jerk model and the actual hand velocity profile during reaching (Krebs et al., 2001).

Acceleration-based smoothness metrics: In this category, six metrics were identified, of which peaks (Peaks) and Inverse Number of Peaks and Valleys (IPV) were analysed further.

Peaks was the most frequently used metric (61 citations). The metric reflects the number of local maxima in the velocity profile for a given movement (Brooks, 1974), which is inversely proportional to the smoothness of a movement. Peaks can also be defined as zero crossings in the acceleration domain. Peaks were additionally normalized either to the movement duration (NPt) (Kahn et al., 2006) or to the movement distance (NPd) (Abdul Rahman et al., 2017). However, doing so causes the metric to be dependent on movement duration or movement distance. Therefore, these adapted definitions of Peaks (NPt and NPd) were excluded (criterion E1). Smoothness was also estimated using the Number of Valleys (Bermúdez i Badia and Cameirão, 2012) or the Number of Valleys and Peaks (Mohapatra et al., 2016). Since these definitions are linear transforms of Peaks, they are assumed to show congruent behaviour to Peaks, and were excluded from further analysis (criterion E4). IPV, on the other hand, is not a linear transform of Peaks, and was included in further analysis (Pila et al.,
2017). Although a few studies employed additional criteria for peak detection (Casadio et al., 2009; Hussain et al., 2018), the choices for these criteria were not motivated, and they were not considered for the present study. The Acceleration Metric $(A M)$ is the ratio between the mean acceleration and the peak acceleration (Mazzoleni et al., 2011). A point-to-point reaching movement should have zero velocity both at the beginning and end of the movement, which implies that the mean acceleration over this movement must be zero. However, this was not the case in the referenced studies, suggesting that some aspect of its definition is missing (Mazzoleni et al., 2013, 2011). According to the textual description, the metric definition is not face-valid, and it was therefore excluded (criterion E2).

Jerk-based smoothness metrics: There were a total of 12 different jerk-based metrics, of which only two types of dimensionless squared jerk metrics, DSJt and $D S J b$, and their respective log transformations, $L D S J t$, and $L D S J b$, were further analysed.

Jerk, the third derivative of position, has often been used as a measure of smoothness in different ways; either as the integral of the squared jerk or the integral of the absolute jerk (Hogan and Sternad, 2009; Rohrer et al., 2002; Teulings et al., 1997). Furthermore, the results were scaled using different terms, which introduces a unit to the metric. As smoothness metrics have to be dimensionless (criterion E1), only the dimensionless jerk metrics were considered. Three types of dimensionless squared jerk metrics, DSJt (Teulings et al., 1997), DSJb (Balasubramanian et al., 2012), and DSJm (Marini et al., 2017), were introduced to measure smoothness. The suffixed letter corresponds to the author's name. These jerk metrics differ in the normalizations used in their definitions. As DSJm is a linear transform of DSJt, it was excluded (criterion E4a). A natural logarithm transform of the DSJb metric was performed to improve its sensitivity (LDSJb) (Balasubramanian et al., 2012). The same was applied to DSJt, thereby introducing LDSJt (van Kordelaar et al., 2014). LDSJb and LDSJt employ the peak velocity, and the average velocity respectively in their equations and are not linear transformations of each. Rotational Jerk $(R J)$ measures movement smoothness using the orientations of the wrist during the movement (Repnik et al., 2018). This form of smoothness quantifies the variability of hand orientation. However, as we analysed changes to a tangential velocity profile, we have no models for the changes in orientation during the reaching movement. Therefore, this metric was not analysed further.

Frequency-based smoothness metrics: All four metrics from this category, including Spectral Method (SPM), Spectral Arc Length 2012 (SPAL), Spectral Arc Length (SPARC), and Spectral Metric (SPMR), were analysed further.

The SPM, SPAL, and SPARC were developed by the same authors (Balasubramanian et al., 2015, 2012, 2009), and are directly proportional to the increase in smoothness of the movement. The SPM measures smoothness as the sum of all peaks in the amplitude-normalized Fourier transform of the velocity profile (Balasubramanian et al., 2009). The SPAL uses the negative arc length of the amplitude and the frequency-normalized Fourier transform of the velocity profile (Balasubramanian et al., 2012). The frequency range used in SPAL was further limited in order to define SPARC (Balasubramanian et al., 2015). Finally, $S P M R$ expresses smoothness using the energy within a 0.2 Hz bin around the dominant frequency in the Fourier transform of the accelerations normalized by the entire energy (Strohrmann et al., 2013).

Other metrics: Kostić and Popović (Kostić and Popović, 2013) defined Combined Smoothness Metric (CSM) in the context of a drawing task in which a patient, while seated at a desk, draws a pre-defined square. The smoothness metric uses information from the movement velocity and jerk, and consists of four different terms. As the formula uses different dimensions incorrectly, the metric was excluded (criterion E1).

### 3.3.3 Response of metrics to changes in velocity profile

## Metrics used in the simulation analyses

In the previous section, fifteen metrics were identified as mathematically sound, and therefore subjected to further analysis: NOS, SM, MAPR, VAL, Peaks, IPV, DSJt, LDSJt, DSJb, LDSJb, CM, SPMR, SPM, SPAL and SPARC. Table 3.2 describes the selected metrics' range of feasible mathematical values obtained for each type of perturbation. Finally, it shows the parameters used to interpret the response of metrics to the simulations $\% \Delta$, CE, and SNR. Note that SM, MAPR, IPV, CM, SPM, SPMR, SPAL and SPARC should decrease with decreasing smoothness of movement, while the other metrics (i.e., NOS, VAL, Peaks, DSJt, LDSJt, DSJb, and LDSJb) should increase with decreasing smoothness. In this section, we discuss the results of the simulation analyses using $\mathrm{v}_{\text {symm }}$ as the base velocity profile.
Table 3.2 Simulation Analysis for each metric and its changes.

| Metric <br> (Feasible <br> Range) | Base <br> Velocity Profile | Shape |  |  | Sinus |  |  | Noise |  |  | Filtered noise |  |  | Sub-movements$(\mathrm{N}=2)$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Min | Max | \% ${ }^{(\%)}$ | Min | Max | CE <br> (\%) | Min | Max | SNR <br> (dB) | Min | Max | SNR <br> (dB) | Min | Max |
| NOS | $\mathrm{V}_{\text {symm }}$ | 1 | 2 | 100 | 1 | 7 | 10.7 | 1 | 7 | N.A. | 1 | 7 | N.A. | 1 | 3 |
| (1-7) | $\mathrm{V}_{\text {asymm }}$ | 3 | 7 | 133.3 | 3 | 7 | 4.9 | 4 | 7 | N.A. | 3 | 7 | N.A. | 3 | 7 |
| SM | $\mathrm{V}_{\text {symm }}$ | 0.53 | 0.53 | 0 | 0.39 | 0.56 | 63.6 | 0.38 | 0.53 | 18.6 | 0.43 | 0.55 | 18.6 | 0.5 | 0.7 |
| (0-1) | $\mathrm{V}_{\text {asymm }}$ | 0.45 | 0.45 | 0 | 0.35 | 0.51 | 55.9 | 0.32 | 0.46 | 18.6 | 0.36 | 0.46 | - | 0.4 | 0.5 |
| MAPR | $\mathrm{V}_{\text {symm }}$ | 0.82 | 0.83 | 1.22 | 0.75 | 0.96 | 3.2 | 0.8 | 0.9 | - | 0.75 | 0.88 | - | 0.75 | 0.9 |
| (0-1) | $\mathrm{V}_{\text {asymm }}$ | 0.8 | 0.8 | 0 | 0.73 | 0.92 | 0.6 | 0.67 | 0.85 | - | 0.66 | 0.86 | - | 0.7 | 0.9 |
| VAL | $\mathrm{v}_{\text {symm }}$ | -2E-03 | -1.6E-04 | 92 | -9.9E-04 | -5.1E-03 | 21.6 | -9.7E-03 | 5.6E-03 | 25 | -9.7E-03 | -7.2E-03 | 25 | -4.9E-03 | -2E-03 |
| $(-\infty-\infty)$ | $\mathrm{V}_{\text {asymm }}$ | -2E-03 | -1.6E-04 | 92 | -9.9E-04 | -6.6E-04 | 16.2 | -9.7E-03 | 4.2E-03 | 24.6 | -9.7E-03 | -7.9E-03 | 14 | -4.9E-03 | -1.9E-04 |
| Peaks | $\mathrm{V}_{\text {symm }}$ | 1 | 1 | 0 | 1 | 25 | 78.2 | 1 | 36 | 45 | 1 | 16 | 45 | 1 | 3 |
| ( $1-\infty$ ) | $\mathrm{V}_{\text {asymm }}$ | 1 | 1 | 0 | 1 | 25 | 79.1 | 1 | 35 | 27.4 | 1 | 16 | 21.9 | 1 | 5 |
| IPV | $\mathrm{V}_{\text {symm }}$ | 1 | 1 | 0 | 0.02 | 1 | 78.2 | 0.01 | 1 | 45 | 0.03 | 1 | 45 | 0.2 | 1 |
| $(-\infty-1)$ | $\mathrm{V}_{\text {asymm }}$ | 1 | 1 | 0 | 0.02 | 1 | 79.1 | 0.01 | 1 | 27.4 | 0.06 | 1 | 21.9 | 0.1 | 1 |
| DSJt | $\mathrm{V}_{\text {symm }}$ | 18.92 | 18.97 | 0.26 | 17.4 | 8216 | 96.3 | 18.7 | $5.2 \mathrm{E}+03$ | 45 | 18.5 | 885.6 | 45 | 18.8 | 95.6 |
| (0-m) | $\mathrm{V}_{\text {asymm }}$ | 41.7 | 61.8 | 32 | 54.72 | 8214.7 | 92.6 | 34.4 | 5230 | 45.4 | 32.8 | 889.6 | 45.4 | 36.3 | 188.4 |
| LDSJt | $\mathrm{v}_{\text {symm }}$ | 2.94 | 2.94 | 0 | 2.85 | 9.01 | 95.1 | 2.9 | 8.6 | 45 | 2.9 | 6.8 | 45 | 2.9 | 4.6 |
| (0-m) | $\mathrm{V}_{\text {asymm }}$ | 3.7 | 4.1 | 9.5 | 4 | 9.01 | 87.4 | 3.5 | 8.6 | 45.4 | 3.5 | 6.79 | 39.4 | 3.6 | 5.2 |
| DSJb | $\mathrm{v}_{\text {symm }}$ | 203 | 205 | 0.98 | 162.5 | $2.1 \mathrm{E}+07$ | 96.9 | 194.8 | $9.9 \mathrm{E}+06$ | 45 | 191.4 | 3.7E+05 | 45 | 199.7 | $4.2 \mathrm{E}+03$ |
| (0- ${ }^{\text {) }}$ | $\mathrm{V}_{\text {asymm }}$ | 718.6 | $1.6 \mathrm{E}+03$ | 54 | $1.2 \mathrm{E}+03$ | $1.5 \mathrm{E}+07$ | 94.6 | 489.3 | $8.5 \mathrm{E}+06$ | 45.4 | 443.9 | $2.7 \mathrm{E}+05$ | 45.4 | 479.4 | $1.2 \mathrm{E}+04$ |

Table 3.2 Continued.

| Metric <br> (Feasible <br> Range) | Base <br> Velocity <br> Profile | Shape |  |  | Sinus |  |  | Noise |  |  | Filtered noise |  |  | Sub-movements$(\mathrm{N}=2)$ |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | Min | Max | $\% \Delta$ <br> (\%) | Min | Max | CE <br> (\%) | Min | Max | SNR <br> (dB) | Min | Max | SNR <br> (dB) | Min | Max |
| LDSJb | $\mathrm{V}_{\text {symm }}$ | 5.31 | 5.32 | 0.19 | 5.1 | 16.9 | 95.1 | 5.3 | 16.1 | 45 | 5.3 | 12.9 | 45 | 5.3 | 8.4 |
| (0- ${ }^{\text {a }}$ | $\mathrm{V}_{\text {asymm }}$ | 6.6 | 7.4 | 11 | 7.12 | 16.61 | 87.9 | 6.19 | 15.96 | 45.4 | 6.1 | 12.5 | 39.4 | 6.2 | 9.4 |
| CM | $\mathrm{V}_{\text {symm }}$ | 1 | 1 | 0 | 0.75 | 1.00 | 34.5 | 0.92 | 1 | - | 0.96 | 1 | - | -0.16 | 1 |
| (-1-1) | $\mathrm{V}_{\text {asymm }}$ | 0.637 | 0.641 | 0.6 | 0.43 | 0.64 | 26.7 | 0.57 | 0.67 | - | 0.58 | 0.69 | - | -0.14 | 0.83 |
| SPMR | $\mathrm{v}_{\text {symm }}$ | 0.11 | 0.99 | 600 | 0.11 | 0.23 | 93.5 | 0.02 | 0.23 | 39 | 0.03 | 0.23 | 31.1 | 0.22 | 0.45 |
| (0-1) | $\mathrm{v}_{\text {asymm }}$ | 0.08 | 0.9 | 1014 | 0.1 | 0.2 | 76.9 | 0.02 | 0.16 | 39.4 | 0.03 | 0.16 | 28.5 | 0.14 | 0.30 |
| SPM | $\mathrm{v}_{\text {symm }}$ | -1 | -1 | 0 | -1.4 | -1 | 57.0 | -2.11 | -1.03 | 26.9 | -1.6 | -1.04 | 21.5 | -1.8 | -1 |
| (0- ${ }^{\text {( }}$ | $\mathrm{V}_{\text {asymm }}$ | -1 | -1 | 0 | -1.35 | -1 | 54.9 | -2.09 | -1 | 27.4 | -1.57 | -1 | 22.5 | -1.97 | -1 |
| SPAL | $\mathrm{v}_{\text {symm }}$ | -2.08 | -1.87 | 11.23 | -3.01 | -1.9 | 50.0 | -2.33 | -1.95 | - | -2.28 | -1.95 | - | -3.4 | -1.9 |
| $(0-\infty)$ | $\mathrm{V}_{\text {asymm }}$ | -1.96 | -1.74 | 12 | -2.9 | -1.8 | 54.7 | -2.2 | -1.9 | - | -2.2 | -1.8 | - | -3.7 | -1.84 |
| SPARC | $\mathrm{v}_{\text {symm }}$ | -1.39 | -1.4 | 0.71 | -2.9 | -1.4 | 66.9 | -2.2 | -1.4 | 15.1 | -2.2 | -1.4 | 14.8 | -2.7 | -1.4 |
| (0- ${ }^{\text {( }}$ | $\mathrm{v}_{\text {asymm }}$ | -1.43 | -1.42 | 0.1 | -2.8 | -1.4 | 66.3 | -2.1 | -1.4 | 14.7 | -2.1 | -1.4 | 14 | -3.1 | -1.4 |

Assessing the response of each metric by comparing the effect of perturbation against the base velocity profile: $\Delta \%$ : percentage difference in metric value from the base velocity profiles (instances where the metric depends on the shape are in bold), CE (\%): percentage of combinations where the metric value differs by at least $10 \%$ from base velocity profiles, SNR (dB): the signal-to-noise ratio at which the metric differs by at least $10 \%$ from the base profile. Note that a higher added RMS noise value corresponds to a lower SNR value, and hence to a greater robustness to noise. Metrics included are NOS (number of sub-movements), $S M$ (speed metric), $M A P R$ (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), $D S J t$ and $D S J b$ (Dimensionless squared jerk), LDSJb and LDSJt (log of DSJt and DSJb), CM (correlation metric), SPMR (spectral metric), SPM (spectral method), SPAL (spectral arc length 2012), and SPARC (spectral arc length).

As we found that the changes in the values of the smoothness metrics for the $\mathrm{v}_{\text {asymm }}$ were similar, their results have been placed in Appendix H. The main difference between using the two base velocity profiles was the magnitude of the resulting values, as shown in Table 3.2. Where other differences in the response to the simulation analyses were found, they are addressed in the following sections.

## Shape Simulation (SS)

Fig. 3.2 shows the response of each metric to changes in movement duration and movement distance for the symmetric velocity profile. The percentage of change $(\% \Delta)$ shows that $N O S, V A L, S P M R$, and $S P A L$ were sensitive to changes in this simulation for both velocity profiles (Table 3.2). DSJt, DSJb and LDSJb showed significant changes only for the $\mathrm{v}_{\text {asymm }}$. SM, Peaks, IPV, and SPM were truly insensitive to changes in movement duration and distance for both base velocity profiles. The other metrics showed a $\% \Delta$ less than $10 \%$.

## Harmonic Disturbances (HD)

Fig. 3.3 shows the metric outcomes with added sines of varying frequencies and amplitudes. The algorithm used to estimate NOS failed to converge to an optimal solution for higher frequencies (shown as missing data in Fig. 3.3). It can be seen that all metrics show a lower smoothness outcome as the amplitude of the added sine increases. All metrics except $S M, M A P R$ and $C M$ showed lower smoothness outcomes at higher frequencies for the same amplitude. SPAL and SPARC were insensitive to sine disturbances with frequencies higher than 20 Hz , as their definitions include the use of a cutoff frequency. Table 3.2 shows that the CE parameter values for $M A P R, V A L$, and $C M$ are less than $50 \%$, suggesting that these metrics are relatively less sensitive to harmonic disturbances.

## Measurement Noise (MN)

NOS is only capable of analysing the smoothness at low noise powers, up to an RMS of $0.008 \mathrm{~m} / \mathrm{s}$ (Fig. 3.4). For higher noise powers, the algorithm that counts NOS fails to converge to an optimal solution (indicated by N.A. in Table 3.2 in the SNR column). The other metrics show lower outcomes of smoothness as the RMS of the noise is increased (Fig. 3.4).





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Figure 3.2 Shape simulation (SS): The vertical axis represents the metric value, going from yellow to blue in descending order. The horizontal axes represent the movement duration and movement distance. Metrics included are NOS (number of sub-movements), SM (speed metric), MAPR (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), DSJt and DSJb (Dimensionless squared jerk), LDSJb and LDSJt (log of DSJt and DSJb), CM (correlation metric), SPMR (spectral metric), SPM (spectral method), SPAL (spectral arc length 2012), and SPARC (spectral arc length). SM, MAPR, IPV, CM, SPM, SPMR, SPAL and SPARC should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. $S M$, Peaks, $I P V$, and $S P M$ were truly insensitive to changes in movement duration and distance for both base velocity profiles.

Figure 3.3 Harmonic Disturbances simulation: The colour represents the value on the z-axis, with yellow being the highest value. Metrics included are NOS (number of sub-movements), $S M$ (speed metric), $M A P R$ (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), DSJt and DSJb (Dimensionless squared jerk), LDSJb and LDSJt (log of DSJt and DSJb), CM (correlation metric), SPMR (spectral metric), $S P M$ (spectral method), $S P A L$ (spectral arc length 2012), and $S P A R C$ (spectral arc length). $S M, M A P R, I P V, C M, S P M, S P M R, S P A L$ and $S P A R C$ should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. MAPR, VAL, and CM were relatively less sensitive to harmonic disturbances.
$M A P R, C M$, and SPAL did not cross the $10 \%$ threshold for any noise power included in the simulation (unfilled entries '-' in Table 3.2). This indicates that these metrics are robust to the range of measurement noise added in this study. All jerk-based smoothness metrics were highly sensitive to measurement noise. Peaks and IPV were more sensitive to measurement noise when the base velocity profile was $\mathrm{v}_{\text {symm }}$ rather than $\mathrm{v}_{\text {asymm }}$.

## Sub-movements Simulation (SMS)

The algorithm used to estimate NOS calculated incorrect values at certain instances when the algorithm failed to converge to a solution (Fig. 3.5). For all numbers of sub-movements evaluated, the changes in the values of $S M$ and MAPR were non-monotonic. VAL, CM, SPM, SPAL, and SPARC showed monotonic increases with increasing lag. Surprisingly, $S P M R$ showed a higher outcome of smoothness with increasing numbers of sub-movements, which shows that the metric fails in this analysis. All other metrics showed a lower outcome for smoothness with increasing lag. For Peaks and IPV, a third peak was detected at 0.3 and 0.5 s , respectively (Fig. 3.5).

None of the dimensionless jerk metrics changed monotonically in this simulation, and they also showed a dip at $K s=1.0$ s. Additionally, the monotonicity of jerk-based metrics depended on the base velocity profile model used for the $\mathrm{v}_{\text {symm }}$ (Appendix I). For CM, we found that the changes in values were monotonic only for $\mathrm{v}_{\text {symm }}$, and not for $\mathrm{v}_{\text {asymm }}$.

### 3.3.4 Summary of findings

Table 3.3 summarizes the simulation analysis results and indicates whether the responses of each metric were as desired. For the measurement noise analysis, it describes the robustness of each metric to added noise. Descriptive statistics of the SNR values as shown in Table 3.2 were used to divide the metrics into two groups: high and low robustness to measurement noise. Note that a higher added RMS noise value corresponds to a lower SNR value, and hence to greater robustness to noise.

From Table 3.3, we find that the CM and SPARC metrics responded as desired to all simulation analyses for the symmetrical profile and were also most robust to added values of measurement noise. On the other hand, only SPARC satisfied all desirable properties for the asymmetric velocity profile.


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Noise RMS
Figure 3.4 Measurement Noise simulation: The thick blue line represents the mean value of 25 different realizations of the noise for each measurement noise level added, and the shaded area is the corresponding standard deviation. The dotted black lines denote the minimum and maximum values of the metric found at that RMS value. The dashed blue line shows mean values of the filtered noise sets. Metrics included are NOS (number of sub-movements), $S M$ (speed metric), MAPR (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), IPV (inverse of number of peaks and valleys), $D S S t$ and $D S J b$ (Dimensionless squared jerk), $L D S J b$ and $L D S J t$ (log of DSSt and DSJb), CM (correlation metric), SPMR (spectral metric), SPM (spectral method), SPAL (spectral arc length 2012), and SPARC (spectral arc length). SM, MAPR, IPV, CM, SPM, SPMR, SPAL and SPARC should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. MAPR, CM, and SPAL did not change more than $10 \%$ for any power of added noise.


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[-] Figure 3.5 Sub-movements simulation: The colours denote the number of sub-movements. The horizontal axis represents the lag between two sub-movements. Metrics included are $N O S$ (number of sub-movements), $S M$ (speed metric), MAPR (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), $D S J t$ and $D S J b$ (Dimensionless squared jerk), LDSJb and LDSSIt (log of DSJt and DSJb), CM (correlation metric), $S P M R$ (spectral metric), $S P M$ (spectral method), $S P A L$ (spectral arc length 2012), and $S P A R C$ (spectral arc length). SM, MAPR, IPV, CM, $S P M, S P M R, S P A L$ and SPARC should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. $V A L, C M, S P M, S P A L$, and SPARC showed monotonic increases with increasing lag. However, CM changed monotonically only for $\mathrm{v}_{\text {symm }}$, and not for $\mathrm{v}_{\text {asymm }}$.

Table 3.3 Summary of the analysis results.

| Metric | Duration/Distance independence |  | Harmonic Disturbances |  | Submovements |  | Robustness |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{V}_{\text {symm }}$ | $\mathrm{V}_{\text {asymm }}$ | $\mathrm{V}_{\text {symm }}$ | $\mathrm{V}_{\text {asymm }}$ | $\mathrm{V}_{\text {symm }}$ | $\mathrm{V}_{\text {asymm }}$ | $\mathrm{V}_{\text {symm }}$ | $\mathrm{V}_{\text {asymm }}$ |
| CM | Yes ${ }^{+}$ | Yes | Yes | Yes | Yes | No | High* | High* |
| SPAL | No | No | Yes | Yes | Yes | Yes | High* | High* |
| MAPR | Yes | Yes ${ }^{+}$ | Yes | Yes | No | No | High* | High* |
| VAL | No | No | Yes | Yes | Yes | Yes | High | High |
| SM | Yes ${ }^{+}$ | Yes ${ }^{+}$ | Yes | Yes | No | No | High | High |
| SPM | Yes | Yes | Yes | Yes | Yes | Yes | Low | Low |
| SPMR | No | No | Yes | Yes | No | No | Low | Low |
| NOS | No | No | No Data ${ }^{+}$ |  | No | No | No Data ${ }^{+}$ |  |
| SPARC | Yes | Yes | Yes | Yes | Yes | Yes | High | High |
| Peaks | Yes ${ }^{+}$ | Yes ${ }^{+}$ | Yes | Yes | No | No | Low | Low |
| IPV | Yes | Yes | Yes | Yes | No | No | Low | Low |
| DSJt | Yes | No | Yes | Yes | No | Yes | Low | Low |
| LDSJt | Yes ${ }^{+}$ | Yes | Yes | Yes | No | Yes | Low | Low |
| DSJb | Yes | No | Yes | Yes | No | Yes | Low | Low |
| LDSJb | Yes | No | Yes | Yes | No | Yes | Low | Low |

'Yes' means that the metric responded to the perturbations as desired, whereas 'No' means otherwise. ${ }^{+}$There was no instance in the analysis where the metric value crossed the $10 \%$ threshold. * The metric was robust to all noise values added in the simulation. ${ }^{+}$Incomplete data. Metrics included are NOS (number of sub-movements), SM (speed metric), MAPR (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), IPV (inverse of number of peaks and valleys), DSJt and DSJb (Dimensionless squared jerk), LDSJb and LDSJt (log of DSJt and DSJb), $C M$ (correlation metric), $S P M R$ (spectral metric), $S P M$ (spectral method), $S P A L$ (spectral arc length 2012), and SPARC (spectral arc length).

### 3.4. DISCUSSION

The aim of the present study was to identify valid smoothness metrics to investigate the movement quality of the upper paretic limb during reaching tasks by persons with stroke. A metric was determined to be valid if it is mathematically sound and responds to the simulation analyses as desired. The systematic literature review revealed 32 different metrics used in stroke research. However, only 15 unique metrics had a sound mathematical definition
relating to smoothness (Hogan and Sternad, 2009). Furthermore, many metrics failed to respond as desired to the sub-movement simulations and were not robust to added measurement noise. Our simulation analyses showed that the Correlation Metric (CM) responded as desired in all simulations for the symmetric velocity profile but failed to respond as desired to the submovement simulations for the asymmetric velocity profile. Spectral Arc Length (SPARC), by contrast, responded as desired in all simulation analyses, for both base velocity profiles. This finding suggests that both CM and SPARC are valid metrics reflecting the smoothness of reach-to-point movement, whereas only SPARC seems to be valid for measuring smoothness in a reach-to-grasp movement post stroke.

### 3.4.1. Clinical Relevance

The present study showed that in spite of the plethora of smoothness metrics available in the literature, only SPARC and CM are valid, given the reaching task performed. Smoothness is considered a result of learned coordinative processes, and increased motor control results in improved smoothness during reaching, pointing and grasping (Balasubramanian et al., 2015; Rohrer et al., 2002; van Kordelaar et al., 2014). Identifying and using valid smoothness metrics is essential for proper clinical research, and results in accurate observations of the recovery of motor control while improving the identification of true treatment effects on movement quality.

Clinical assessments which are most closely related to behavioural restitution, and thereby neurological recovery, take into account the ability to perform movements outside the pathologic synergies (See et al., 2013). Whether smoothness metrics reflect neurological recovery after stroke can be determined by investigating the longitudinal association between smoothness metrics and assessments closely related to behavioural restitution. Furthermore, studying the associations between the recovery of neurological pathways and changes in movement smoothness will reveal the influence of behavioural restitution and compensation on smoothness. These smoothness values must be compared with reference values from healthy age- and gendermatched individuals. Identifying these associations with smoothness during recovery, and eventually the underlying physiology that governs smoothness, will provide an indication whether smoothness can be used as a target or
outcome measure in training and, for example, in designing rehabilitation robots.

### 3.4.2. Practical Barriers

Practical requirements need to be considered when the metrics are applied in either a clinical setting or an ambulatory or daily life setting. When measuring the smoothness of reach-to-point movements using motion tracking systems or high-end kinematic measurement sensors, the simplest and most robust metric is $C M$, due to its low sensitivity to noise. For ambulatory or daily life settings, metrics that can be estimated using wearable on-body sensors are preferred. Inertial and Magnetic Measurement Units (IMUs) are commonly used as wearable sensors for measuring the kinematics of movement. However, as an IMU measures accelerations, estimating velocity from it would require additional processing and is usually prone to drift (Woodman, 2007). In a recent study, Melendez-Calderon and colleagues suggest that SPARC should not be applied to linear velocities obtained from IMUs, and an alternative definition based on angular velocities may be of interest (Melendez-Calderon et al., 2021). However, techniques to correct drift due to strapdown integration (Woodman, 2007) were not employed in their study, as the authors suggest that it warrants a systematic analysis of the errors introduced in the smoothness estimate (Melendez-Calderon et al., 2021). Therefore, if the errors are accounted for, it should be possible to reliably measure SPARC using corrected linear velocities obtained from IMUs for a standardized pre-defined movement with a clear start and end posture. Given the advantages of using IMUs, their validity in measuring movement quality after stroke requires further research (Mesquita et al., 2019).

### 3.4.3. Generalizability of current findings

Besides populations with stroke, smoothness is highly relevant to studying the impact of neurological disease in other populations, such as those with Huntington's disease and with Parkinson's disease (Hogan and Sternad, 2009). For instance, smoothness has been used to study fluidity of movement in the upper limb, reflecting bradykinesia and rigidity in patients with Parkinson's disease (di Biase et al., 2018). Furthermore, smoothness has been used to differentiate between affected and healthy gait, as well as to examine effects of medications, and to identify fall risk (Beck et al., 2018). In addition, the
level of smoothness is highly relevant in sports, as a measure of proficiency (Choi et al., 2014; Hreljac, 2000). The present findings emphasize the need for metrics that truly reflect smoothness and may serve as inspiration for related fields to determine which smoothness metric is valid for the movement task they analyse.

### 3.4.4. Limitations and future directions

The first limitation of the current review was that it was restricted to smoothness metrics investigated in stroke, focusing on post-stroke reaching. Generalization to other neurological diseases is therefore limited. The same is true for other movement tasks such as rhythmic drinking tasks (Osu et al., 2011) or self-paced, isolated elbow flexion movements (Wininger et al., 2012). Secondly, only English language articles were considered for our systematic review. Thirdly, our simulations are not real movements, instead they offer a systematic analysis of changes in an ideal movement. For instance, our noise simulation analysis considered the robustness of metrics to added measurement noise. However, if the noise is a result of weak human control, the resulting movement would be less smooth, as reflected by the smoothness metric. Therefore, efforts to distinguish between measurement noise and perturbations due to actual human motion control must be undertaken in order to distinguish abnormal, pathologically reduced movement smoothness from that seen in healthy, age- and gender-matched participants. Fourthly, we see that different reaching tasks result in different velocity profiles; reach-topoint or aiming movements are associated with symmetrical velocity profiles (Flash and Hogan, 1985), while reach-to-grasp movement is associated with an asymmetrical velocity profile (Hughes et al., 2013). We found CM to be highly dependent on the symmetry of the profile, as it estimates the correlation with a minimal jerk profile. Therefore, it might be of interest to consider a $C M$ measure that takes account of correlation with a velocity profile that models the reaching task, for instance the asymmetric profile for reach-tograsp movements. This would require knowledge of the intended reaching task beforehand, which could be solved by testing using standardized pre-defined movements. Fifthly, smoothness metrics such as $R J$ are based on rotational movements and had to be rejected as they could not be tested with the current simulations. Finally, smoothness metrics have been designed so as not to be influenced by the movement duration or distance (Balasubramanian et al.,

2015; Hogan and Sternad, 2009; Rohrer et al., 2002). The impact of additional factors such as anthropometric differences in arm thickness or length, etc., on smoothness is unknown and requires further investigation.

Although our simulations mimicked features of reaching movements of persons with stroke, such as varying duration or distance, and sub-movement segmentation (Cirstea and Levin, 2000), they cannot truly replace actual reaching by participants who have suffered a stroke. Additionally, longitudinal studies of patterns of smoothness metrics in patients early post stroke will show which metric is sensitive to changes in the values of smoothness over time and how these values relate to values measured in healthy age- and gender-matched participants. Therefore, the next step (not part of this thesis) would be to investigate the time courses of CM and SPARC and their associations with upper limb motor recovery early post stroke (Saes et al., n.d.).

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## APPENDICES

The following appendices are related to this chapter:

D Search strategy used
E Modelling reach-to-grasp movement in healthy participants
F Models for reach-to-point and reach-to-grasp movements
G Mathematical definition of selected smoothness metrics
H Simulation analyses performed for reach-to-grasp movement
I Influence of the velocity profile model on monotonicity in the submovement simulation

Smoothness metrics for reaching performance after stroke


## Section

## Lower Extremity

# Gait and Dynamic Balance Sensing Using Wearable Foot Sensors 

"Simplicity is a matter of taste."
Stephen Hawking, The Grand Design

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#### Abstract

Remote monitoring of gait performance offers possibilities for objective evaluation, and tackling impairment in motor ability, gait, and balance in populations such as elderly, stroke, multiple sclerosis, Parkinson's, etc. This requires a wearable and unobtrusive system capable of estimating ambulatory gait and balance measures, such as Extrapolated Centre of Mass (XCoM) and dynamic Margin of Stability (MoS). These estimations require knowledge of 3D Forces and Moments (F\&M), and accurate foot positions. Though an existing Ambulatory Gait and Balance System (AGBS) consisting of 3D F\&M sensors, and Inertial Measurement Units (IMUs) can be used for the purpose, it is bulky and conspicuous. Resistive pressure sensors were investigated as an alternative to the on-board 3D F\&M sensors. Subject specific regression models were built to estimate 3D F\&M from 1D plantar pressures. The model was applicable for different walking speeds. Different pressure sensor configurations were studied to optimise system complexity and accuracy. Using resistive sensors only under the toe and heel, we were able to estimate the XCoM with a mean absolute RMS error of $2.2 \pm 0.3 \mathrm{~cm}$ in the walking direction while walking at a preferred speed, when compared to the AGBS. For the same case, the XCoM was classified as ahead or behind the Base of Support correctly at $97.7 \pm 1.7 \%$. In conclusion, the study shows that pressure sensors, minimally under the heel and toe, offer a lightweight and inconspicuous alternative for $\mathrm{F} \& \mathrm{M}$ sensing, towards estimating ambulatory gait and dynamic balance.


### 4.1. INTRODUCTION

Assessment of motor impairment periodically during rehabilitation is crucial in understanding recovery. This is feasible via clinical outcome measures, and instrumented laboratory facilities, particularly in participants with motor impairment, such as stroke, Parkinson's, multiple sclerosis, etc., and also others prone to instability such as frail elderly. Clinical outcomes indicate a subjective change in capacity or function of given tasks whereas instrumented systems offer objective quantification of kinematic and kinetic changes on impairment level of said tasks. Once the patient is discharged from the clinic, she/he is expected to continue functional training to maintain recovery and increase independence in Activities of Daily Life (ADL) (Dobkin, 2005). Continuing objective monitoring after discharge helps quantify recovery, and identify compensatory patterns if present (Kwakkel et al., 2017; World Health Organization, 2002). As instrumented laboratory facilities are expensive and restrictive in measurement space, wearable systems can be explored as alternatives.

ForceShoes ${ }^{\mathrm{TM}}$ (Xsens Technologies B.V., Enschede, The Netherlands) is a shoe with on-board sensors and was developed as an ambulatory gait lab (Veltink et al., 2005; Weenk et al., 2015). It consists of two Inertial Measurement Units (IMUs) and two 3D Force and Moment (F\&M) sensors on each foot. It has been validated against commonly used systems, such as force plates (AMTI®) and motion capture (VICON©), for measurement of contact forces and foot position estimations respectively (Liedtke et al., 2007; Schepers et al., 2009; Weenk et al., 2015). Unlike these systems, ForceShoes ${ }^{\text {TM }}$ has the advantage of being portable, and not restricted by area of measurement setup or marker placement. It is used to reconstruct the kinematics and kinetics of the feet during walking (Schepers et al., 2007; van Meulen et al., 2016c, 2016b).

Gait measures such as step length and width, and foot positions can be estimated using IMUs on the ForceShoes ${ }^{\mathrm{TM}}$. Weenk and colleagues (Weenk et al., 2015) reduced the drift in position estimation using an Extended Kalman Filter (EKF), and validated it with motion capture. The EKF fused foot positions from the IMUs, and relative foot distance from an ultrasound
sensor. The ForceShoes ${ }^{\text {TM }}$, along with ultrasound sensor, EKF, and additional processing will be referred to as Ambulatory Gait and Balance System (AGBS).

Using the AGBS, Schepers and colleagues (Schepers et al., 2009) derived Centre of Mass (CoM) of the body during gait. Subsequently, van Meulen and colleagues (van Meulen et al., 2016b) estimated the Extrapolated CoM (XCoM), which is the CoM extrapolated in the direction of the walking velocity. The trajectory of the XCoM projected on the ground with respect to the Base of Support (BoS), which is the region between two feet when they are in contact with the ground, is an indication of dynamic stability (Hof et al., 2005). van Meulen and colleagues (van Meulen et al., 2016b) used the shortest distance from the XCoM and the frontline of the BoS as a condition of stability during continuous gait, called as the dynamic Margin of Stability (MoS) (Hof et al., 2005). Bruijn and colleagues (Bruijn et al., 2013), suggested that XCoM (and eventually MoS) can objectively indicate balance quality, and van Meulen and colleagues (van Meulen et al., 2016c) showed that MoS varies with differences in participant's balance impairments. Balance quality is otherwise estimated using clinical outcomes such as Berg Balance Scale, Dynamic Gait Index, Tinetti Falls Scale, etc. However, the construct of these outcomes show that they are subjective to the assessor. Using a system like AGBS, one can objectively evaluate gait and dynamic balance in an ambulatory or home setting for different populations including stroke, multiple sclerosis, Becker's Muscle Dystrophy, Parkinson's, elderly, etc.

However, the system has its limitations. Liedtke and colleagues (Liedtke et al., 2007), showed that gait pattern is slightly modified when wearing the AGBS. Moreover, it is not practical to use them every day due to the bulky 3D F\&M sensors. These make each shoe weigh close to 1 kg and increases the sole height by 2.5 cm (van Meulen et al., 2016b), increasing discomfort and chances of tripping, especially for people with gait impairments. Alternative systems for ambulatory estimation of 3D F\&M can be achieved by using an IMU-only setup. Karatsidis and colleagues solved this using 17 IMUs placed in a full body suit (Karatsidis et al., 2016). However, the system requires a full body setup and the effect of a reduced IMU setup for this purpose has not yet been studied.

Insoles with pressure sensors can be used as an alternative to the bulky 3D F\&M sensors. They can be slipped into everyday use shoes, are lightweight, and inconspicuous. They provide 1D plantar pressures under the feet during walking and can be used for estimating a range of gait parameters (Abdul Razak et al., 2012; Hegde et al., 2016; Koch et al., 2016).

Pressure insoles can only provide the vertical plantar pressure. However, 3D F\&M of the feet (along with its positions) are required to estimate the CoM (Schepers et al., 2009), XCoM and MoS. Studies have shown estimations of 3D F\&M from 1D plantar pressures by using analytic and machine learning methods. Forner-Cardeno and colleagues (Forner Cordero et al., 2004) showed analytic derivation of 3D forces from 1D plantar pressure data, but their method relies on force plate data. Sim and colleagues (Sim et al., 2015), showed the use of a wavelet neural network to estimate time-normalised 3D F\&M from 1D plantar pressure. Other studies use other machine learning methods to achieve the same (Fong et al., 2008; Rouhani et al., 2010; Savelberg and de Lange, 1999). In spite of a few disadvantages, such as the need for training data, or possible failure in untrained scenarios, machine learning methods have some potential use in this study.

The goal of this study is to evaluate 1D plantar pressure sensing as a lightweight alternative to the 3D F\&M sensors in AGBS for estimating dynamic balance measures. To do so, linear regression models were built to predict 3D F\&M from 1D plantar pressures. The models are subject specific and independent of walking speeds. The predicted 3D F\&M along with foot positions are used to estimate CoM, XCoM, and MoS. The estimations are compared with those of the AGBS for different pressure sensor configurations. The study throws light on pressure sensors as a replacement to the 3D F\&M sensors, the influence of the number of sensors on the estimation of XCoM and MoS, and insights on the algorithms used during the process.

### 4.2. METHODS



Figure 4.1 (a) Side view of right ForceShoes ${ }^{\mathrm{TM}}$. The shoe consists of an ultrasound system (US), 3D Force \& Moment sensors (F\&M), and Inertial Measuring Units (IMUs) as seen on the side. Each shoe weighs close to 1 kg and is about 2.5 cm thick making it uncomfortable to walk with. (b) Pressure insoles are placed within the ForceShoes ${ }^{\mathrm{TM}}$ to study if they are a feasible alternative to the 3D F\&M sensors.

### 4.2.1. Measurement System

Fig. 4.1a shows the ForceShoes ${ }^{\text {TM }}$ containing two 3D F\&M sensors, two IMUs, and an ultrasound. Only the IMU located at the forefoot was used for analysis. The data from the 3D F\&M sensors and IMUs were sent to an Xbus that transmits data wirelessly to a PC. The transmitter and receiver of the ultrasound system was placed on the right and left foot respectively. They were synchronized and the data were transmitted via Bluetooth to a PC. Fig. 4.1b shows the pressure insole system (medilogic ${ }^{\circledR}$ insoles, T\&T medilogic Medizintechnik GmbH, Germany) placed in the ForceShoes ${ }^{\mathrm{TM}}$. It has 151 resistive pressure sensors and was held in place using tape to eliminate slippage. The wireless transmitters of the pressure insoles and ForceShoes ${ }^{\mathrm{TM}}$ were worn as a belt around the waist. The 3D F\&M sensors, IMUs, and the pressure insoles were sampled at 50 Hz . The data was then low pass filtered twice at 10 Hz using second order Butterworth filter to ensure zero-phase lag. The data was then transformed to the global coordinate frame, where X axis is along the walking direction and Z axis is the vertical axis pointing upwards.

### 4.2.2. Participants

Six healthy participants were recruited for the study. All participants signed an informed consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved
by the Ethical Committee of the faculty. The inclusion criteria included participants with no history of impaired gait or leg injury. Five participants were males and the size of the shoe used was 44 (European Size Chart). The average and standard deviation of the height, weight, and age was $1.81 \pm 0.06 \mathrm{~m}$, $81 \pm 9 \mathrm{~kg}$, and $25 \pm 1$ years respectively. Leg length was measured from the greater trochanter to the ground (Hof, 1996) and was $1.04 \pm 0.05 \mathrm{~m}$.

### 4.2.3. Experimental Protocol

The ultrasound system and 3D F\&M sensors were calibrated before each measurement. The participants were then asked to perform different walking tasks. In each of the walking tasks, the participant was asked to walk for 10 m along a straight unobstructed path. The participant was instructed to begin with their feet placed parallel. Once the researcher gave the start sign, the participant walked along a straight line. The time taken between start and stop of the walking was measured using a stopwatch. This activity was repeated six times. The walking tasks were performed in four different scenarios which are as follows:

- Normal walking: During this task, the participant was asked to walk at his preferred walking speed.
- Slow walking: During this task, the participant was asked to walk at a slower pace. The speed was guided by the use of a metronome that beat at a frequency of 37 beats per minute. Each beat corresponds to heel strike of the same foot on the ground. The frequency was found using trial and error such that the participants reduced their walking speed to $0.8 \mathrm{~m} / \mathrm{s}$.
- Very Slow walking: During this task, the participant was asked to walk at a much slower pace. The frequency of the metronome was set at 27 beats per minute. This frequency was found so as to reduce the walking speed to $0.4 \mathrm{~m} / \mathrm{s}$.
- Bag walking: During this task, the participant was asked to walk at his preferred walking speed while wearing a backpack weighing 5 kg . This is to represent an extra, yet minimal load people may carry during daily life tasks, such as a shopping bag.


### 4.2.4 Objective Evaluation of Gait and Dynamic Balance

## Gait

Ultrasound and IMUs were used for estimating foot positions, from which gait parameters such as step length, and step width were obtained. The EKF predicted states of position, instantaneous velocity, orientation error and gyroscope bias error (Weenk et al., 2015, Fig. 3). Error between predicted and measured data was used to correct the states for every measurement sample. Measurement updates included foot position and instantaneous velocity measured from the IMU, zero velocity instances, height of IMU during zero velocity and relative feet distance from the ultrasound system (Weenk et al., 2015). The ultrasound updates were used in the EKF at an update frequency of 13 Hz (van Meulen et al., 2016b).

## Dynamic Balance

Estimation of CoM is the first step towards evaluating dynamic balance. Low and high frequency components of CoM were estimated using two separate algorithms and fused using a complementary filter, to improve estimation accuracy (Schepers et al., 2009). The first stage estimates CoM from both foot kinetic and kinematic information by low pass filtering the Centre of Pressure (CoP) to estimate the position of CoM, referred to as Stage Low Frequency (Stage LF). Here, the CoP for each foot $\left(\mathbf{x}_{\text {CoP,foot }}\right)$ is estimated as:

$$
\begin{equation*}
\mathbf{x}_{C o P, f o o t}=\left(-\frac{M_{Y}}{F_{Z}} ; \frac{M_{X}}{F_{Z}} ; 0\right) \tag{4.1}
\end{equation*}
$$

where $F_{Z}$ is the vertical Ground Reaction Force (GRF), and $M_{Y}$ and $M_{X}$ denote the moments in the respective axes. The CoP trajectory over the walking trial was weighted with the relative magnitude of the vertical GRF under each foot and is given as

$$
\begin{equation*}
\mathbf{x}_{C o P}=\frac{F_{l}}{F_{l}+F_{r}} \cdot \mathbf{x}_{C o P, l}+\frac{F_{r}}{F_{l}+F_{r}} \cdot \mathbf{x}_{C o P, r} \tag{4.2}
\end{equation*}
$$

where $F_{l}$ and $F_{r}$ represent the vertical GRF in the left and right foot respectively. The $\mathbf{x}_{\text {CoP }}$ was then low pass filtered at 0.4 Hz to obtain the $\mathbf{x}_{\text {CoM,LF }}$. The cut off was found to be optimal for continuous walking (Schepers et al., 2009). The Stage LF CoM is estimated from both foot kinetic and kinematic information.

The second algorithm estimates CoM from kinetic information alone by double integration of the net forces based on Newton's second law, referred hereafter as Stage High Frequency (Stage HF). The body mass $m_{\text {body }}$ can be embodied at the CoM and it's acceleration is given as

$$
\begin{equation*}
\mathbf{a}_{\mathrm{CoM}}=\frac{\mathbf{F}_{t}}{m_{b o d y}}+\mathbf{g} \tag{4.3}
\end{equation*}
$$

where $\mathbf{F}_{t}$ is the net force acting on the body, and $\mathbf{g}$ is the gravitational acceleration ( $9.8 \mathrm{~m} / \mathrm{s}^{2}$ positive downwards). The CoM position was derived from integrating the $\mathbf{a}_{\text {Сом }}$ twice. This results in $\mathbf{x}_{\text {Сом, int }}$ which was high pass filtered with a cut off at 0.4 Hz to obtain $\mathbf{x}_{\text {Com, } \mathrm{HF}}$. This is the same cut off as that of Stage LF low pass filter. The $\mathbf{x}_{\text {CoM,LF }}$ and $\mathbf{x}_{\text {CoM, } \mathrm{HF}}$ were fused using a complementary filter to obtain the trajectory of CoM. Fig. 1.3 shows the Extrapolated CoM (XCoM) that can be obtained by

$$
\begin{equation*}
X C o M=\operatorname{CoM}+\frac{\mathbf{v}_{\mathrm{CoM}}}{\omega_{0}} \tag{4.4}
\end{equation*}
$$

where $\mathbf{v}_{\mathrm{CoM}}$ is the velocity of CoM and an indicator of the direction of movement, $\omega_{0}$ is given as $\sqrt{\mathbf{g} / l_{0}}$, and $l_{0}$ is the vertical CoM position (Hof et al., 2005; van Meulen et al., 2016b). In Fig. 1.3, we see that the MoS is the shortest distance between the vertical projection of XCoM on the ground (XCoM') from the frontline of BoS (van Meulen et al., 2016b).

### 4.2.5. Estimation of 3D F\&M from Pressure Insoles

The AGBS provides positions, and 3D F\&M of the feet. This is used to estimate CoM, XCoM, and MoS as shown earlier. However, pressure insoles are only able to provide the 1D plantar pressures. Therefore, Subject Specific Regression Models (SSRM) were created to estimate 3D F\&M from 1D plantar pressure data.

First, the data from IMUs, 3D F\&M, and pressure insoles were synchronized. Trials that had sensor issues or measurement errors were removed. It was made sure that each participant had at least three trials for each walking task.

Chapter 4


Fig. 4.2a shows the workflow of building an SSRM. First, all walking trials from the 'Normal', 'Slow', and 'Very Slow' tasks are appended. This forms one extended dataset containing 1D pressures for all walking trials with all speeds as inputs for the SSRM. Then, the SSRM is built as a linear regression model fitted between the inputs and targets (3D F\&M) using least squares method. This results in six different models, one for each dimension of the F\&M. The SSRM built using the walking profiles for three different speeds is then used to estimate the 3D F\&M for each walking speed separately, and also for the Bag task which was not included in building the SSRM. Walking velocity was not used as an input to the SSRM. The same model can predict forces and moments during quiet standing, initiation of walking, cyclical walking and deceleration of walking and stopping for different walking speeds. The modelling process was repeated to create SSRMs for each participant. Fig. 4.2b shows the sensors used for the two stages, Stage LF and HF, and how the 3D F\&M estimated using the SSRMs was used to calculate the CoM (along with foot positions), XCoM, and MoS. These measures were then compared with the measurements from the AGBS.

### 4.2.6. Influence of Sensor Choice

The influence of the sensor configuration on the estimation of CoM, XCoM, and MoS was studied next. By reducing the number of pressure sensors used, the contribution of foot kinematics and kinetics can be understood better. Additionally, this could serve as a reference to design sensor setups with required error margins of stability parameters. Therefore, the number of pressure inputs used in building the SSRMs is varied. Fig. 4.3 shows the overlap between the 151 medilogic ${ }^{\circledR}$ pressure sensors, and that of the IEE (IEE S.A, Luxembourg) sensors. The IEE sensors (green regions in Fig. 4.3) were used to determine specific foot regions. The IEE insole has 8 sensors placed strategically under four foot regions: two under the toe, three under the metatarsal, one covering the arch, and two under the heel. The different configurations used are described as follows.

- All: All 151 sensors were used to build the SSRM.
- FF: The pressure sensors in the medilogic ${ }^{\circledR}$ insole that corresponded to the 8 sensor locations were used for building the SSRMs. This covered the four foot regions.


Figure 4.3 Pressure sensor configurations used to build the SSRM based on the four foot regions are depicted here. The pluses denote the placement of the 151 medilogic ${ }^{\circledR}$ pressure sensors. The shaded regions denote the overlap with the sensors of IEE. The sensors of the medilogic ${ }^{\circledR}$ insole that correspond to the shaded regions were used for analysis. The different sensor configurations used: 'All', where all 151 sensors were used, 'FF', where only the medilogic ${ }^{\circledR}$ pressure sensors that overlapped with the IEE sensor locations were used, 'T+H', where the medilogic ${ }^{\circledR}$ pressure sensors only under the toe and heel regions were used, ' T ', which covered only the toe region, and ' H ', which covered only the heel region.

- $\quad \mathrm{T}+\mathrm{H}$ : This configuration covered only the toe and heel regions.
- T: This configuration covered the toe region alone.
- H: This configuration covered the heel region alone.
- None: In this the accuracy of estimating CoM, XCoM, and MoS is studied under the absence of any force or moment information. Therefore, only foot positions are used in this configuration. In order to proceed, a few assumptions were made. First, the position of the CoP during standing is assumed to lie equidistant from the centre of two feet. Secondly, during single stance, the CoP lies entirely at the centre of the foot in contact with the ground. Thirdly, during double stance phase, a smooth transition assumption (using spline interpolation) is used to smoothly shift weight from the lagging to the leading foot (Ren et al., 2008). These assumptions were used in Stage LF to obtain CoM. The Stage HF estimation of the CoM was not performed as there is no data about the force acting on the body in this configuration.


### 4.2.7. Classification of Stability

The MoS, an indication of dynamic balance, both in anterior-posterior as well as medio-lateral directions, gives information about walking stability (Hof et al., 2005; van Meulen et al., 2016c). However, here only the gross placement of the projection of XCoM ( XCoM ') in 2D with respect to the frontline of the BoS is studied. The BoS is estimated using the AGBS setup. The XCoM' could then be classified as either ahead or behind the BoS. Instances when the XCoM' is ahead of the BoS can be termed as unstable. This is compared between the SSRM and AGBS estimated XCoM'. This exercise is done to study how closely the SSRM based system can identify instances of instability as compared to the AGBS.

### 4.2.8. Analysis of Results

The Root Mean Square (RMS) of the differences normalised to the range of measured values was calculated between estimations by SSRMs and results obtained from the AGBS. This is done for the 3D forces ( $r r m s d F$ ) and moments (rrmsdM) and compared with results seen in literature. This is an estimation of the error margin present when the 3D F\&M are predicted by the SSRMs. Following this, the absolute RMS of the differences (rmsdX) for the XCoM was found, which quantifies the uncertainty in measurement. Then, a study of the contribution by the two stages, Stage LF and HF, to the accuracy of the XCoM was done. In this case, the Mean Absolute Distance (madt), the 2D distance in the XY plane, is calculated. Finally, the Percentage of Correctly Classified (PCC) samples of stability by the SSRMs was studied.

### 4.3. RESULTS

### 4.3.1. Forces and Moments

The average walking speeds of the participants for the Normal, Slow, V Slow, and Bag walking tasks are $1.03 \pm 0.15,0.6 \pm 0.1,0.42 \pm 0.05$, and $0.98 \pm 0.2 \mathrm{~m} / \mathrm{s}$ respectively. The regression models were built using walking trials in the Normal, Slow, and Very Slow tasks. The total number of steps (averaged between left and right) for each of the six participants used in building the SSRMs were $97,100,116,133,162$, and 200. The number of steps vary as each participant differed in number of valid trials used, and also step sizes. Fig. 4.4a shows the comparison between the 3D forces estimated by the SSRM and
measured by the 3D F\&M sensors (of the AGBS). The mean value for each participant is displayed as a boxplot. The distributions are shown for the different walking tasks for each sensor configuration ('All', 'T+H', 'H', 'T') used in the SSRM. The values are averaged over the left and right leg. In Fig 4.4, the white filled circle denotes the inter-participant mean of the distribution. The filled box contains the distribution that lies between $25 \%$ to $75 \%$ of the data. The outliers of the distribution beyond 1.5 times the interquartile range is denoted by stars.

In Fig. 4.4a, the forces estimated by the SSRM built with 'All' sensors shows relatively small error margins with the AGBS measured forces. This is seen to be the case for Normal, Slow, and Very Slow tasks. This shows that the model can be applied to different walking speeds, making it robust to changes in walking speeds. The SSRMs were used to estimate the forces in the Bag walking task to test its validity in an untrained scenario. The Bag task involves walking at the preferred walking speed while carrying a bag weighing 5 kg . Fig. 4.4a shows that when using 'All' sensors, the forces can be estimated accurately for the untrained Bag task. The rrmsdF in all three axes is $6 \%$ or less. This shows that the model is not only capable of reproducing the forces during an untrained walking profile but can also be used when the participant is carrying a small additional load. This could be due to the participant specificity of the SSRMs, enabling it to map the walking profile of each participant under different conditions.

The estimations remain relatively accurate when we consider the 'FF' sensor configuration. The rrmsdF is below $12 \%$ in all the three axes, for all walking tasks. Other sensor configurations show decreasing correlation coefficients and increasing RMS errors when reducing number of sensors for all walking tasks. When considering the ' T ' or ' H ' sensor configuration, we see that the error margin in $r r m s d F$ increases to $20 \%$. This is expected as these configurations do not contain pressure profile during either the toe off or heel strike. Additionally, as the number of sensors is reduced, the regression model uses lesser sensors to estimate the forces. Moments, however, show larger errors than forces as they are a cross product of distance and forces in the two orthogonal axes. Subsequently, the estimation worsens as the number of sensors are reduced. In both Fig. 4.4a and b, the results for 'None' sensor configuration is not shown as there is no force or moment information in these cases.
Figure 4.4 (a) shows the range normalised Root Mean Square (RMS) of the differences (rrmsdF) between the forces, and (b) the range normalised RMS (rrms $d M$ ) between the moments, estimated using SSRMs and measured from AGBS. Box plots of the mean values are shown for the different walking tasks for each sensor configuration used: All sensors ('All'), Four foot regions ('FF'), Toe +Heel ('T+H'), Toe ('T'), and Heel ('H'). In both (a) and (b), we see low errors when using the 'All' configuration which increases as the number of sensors used are reduced.

### 4.3.2. Dynamic Balance

The 3D F\&M from AGBS and SSRM are then used to estimate the CoM using Stage LF and Stage HF. Fig. 4.5 shows representative trajectories of the CoM and XCoM for a Normal task. The CoM fluctuates between the two feet as the stance changes. Simultaneously, in Fig. 4.5b the XCoM can be seen to oscillate with changes in the instantaneous velocity of the CoM. The SSRM trajectories deviate from the reference trajectory estimated by the AGBS, as they have different accuracies in estimating the forces and moments. Fig. 4.6 shows the comparison of XCoM in only the X and Y axes as we are interested only in the projection of XCoM , i.e., XCoM ' on the ground as rmsdX. When using 'All' sensors, the accuracy of estimating XCoM' for all walking tasks is high. The $r m s d X$ is less than 2 cm for the X and Y axes respectively. This is the case for all walking tasks. For other sensor configurations ('T+H', 'T', and 'H'), the $r m s d X$ does not change drastically as seen with 3D F\&M in Fig. 4.4a or b. Although there is no force or moment information of the feet in the 'None' configuration, the XCoM' has low errors in both X and Y axes. The rmsdX for the X and Y axis is less than 12 and 8 cm respectively. Assuming step width during quiet stance as 15 cm , maximum step width and length as 40 cm and 70 cm respectively, the BoS can range between $700 \mathrm{~cm}^{2}$ to a maximum of $2400 \mathrm{~cm}^{2}$. Comparing error margins of XCoM with respect to the BoS gives an idea about the relative magnitude of the error.

The previous paragraph threw light on the influence of 3D F\&M estimation accuracy on the estimation of XCoM. Next, the contribution of Stage HF on the estimation of XCoM is studied. Here, we hypothesize that for lower walking speeds, there is lesser useful information in the higher frequencies. This is acceptable as our primary applications are towards people with gait impairment. Also, the Stage HF relies on the need for good kinetic information. Lesser reliance on this translates to the possibility of eliminating kinetic sensors. Therefore, the XCoM' with and without the Stage HF is considered. Then, the madt is calculated between the estimations by the SSRMs and AGBS. Fig. 4.7 shows the distribution of madt in two cases during the Slow task. One case (XCoM Fused) contains the madt between the fused XCoM' from the SSRM from the AGBS. The second case (XCoM LF) contains the madt between the XCoM' with only low frequency information and the fused XCoM' of the AGBS.


Figure 4.5 Representative trajectory of (a) CoM and (b) XCoM from a Normal walking task when the participant moves from the left to the right. The black line shows the reference trajectory estimated using the AGBS. The other dotted lines show the trajectory with respect to different sensor configurations used: All sensors ('All’), Four foot regions ('FF'), Toe + Heel ('T+H’), Toe ('T’), Heel ('H'), and No pressure sensors ('None').

In Fig. 4.7, the XCoM Fused shows lower madt than XCoM LF when compared with the estimations from the AGBS. The average madt for XCoM LF in all sensor configurations (except 'None') is about 3 cm . The distribution of the madt for XCoM LF shows larger variance but remains robust with reduction in sensor configuration. This suggests that for walking at low speeds, the low frequency information of CoM is sufficient to estimate XCoM given an error margin of 3 cm . This could translate to advantages in terms of lower sampling rates of sensors, which may influence power consumption, or the possibility to eliminate kinetic sensors. Note that in case of 'None', the XCoM LF and XCoM Fused distributions are similar as this sensor configuration does not have any Stage HF information.


Figure 4.6 Average root mean square of the differences between the XCoM estimated using regression model and measured from AGBS (rmsdX) in the X and Y axes. Box plots of the mean values shown for the different walking tasks for each sensor configuration used: All sensors ('All'), Four foot regions ('FF'), Toe+Heel ('T+H'), Toe ('T'), Heel ('H’), and No pressure sensors ('None'). For the 'All' configuration, the rmsdX is less than 2 cm for both the X and Y axes, which increases to 12 cm and 8 cm respective axes in the 'None' configuration.

### 4.3.3. Classification of Stability

Once the XCoM' estimated by the SSRMs is classified as ahead or behind the frontline of the BoS, it is compared with the classifications done by the AGBS, which is assumed to be the ground truth. Fig. 4.8 shows the percentage of sample points rightly classified as ahead (PCC Ahead) or behind (PCC Behind) the frontline of the BoS.

In order to classify, the frontline of the BoS is needed, which is measured only during quiet standing or instances of double support. During quiet standing, the XCoM ' lies well within the BoS, as there is no movement. During these instances, XCoM ' is most correctly classified.


Figure 4.7 The mean absolute distance (madt) between XCoM with both low and high frequency (XCoM fused) and XCoM with only low frequency content (XCoM LF) for the Slow task for each sensor configuration used: All sensors ('All'), Four foot regions ('FF'), Toe+Heel ('T+H'), Toe ('T'), Heel ('H'), and No pressure sensors ('None'). We see that the madt is larger for the XCoM LF.

It can be seen from Fig. 4.8a that the percentages are very high for any sensor configuration in all walking tasks. The inset table shows the percentage of actual time behind or ahead the BoS. Simultaneously, during double support phase the XCoM' is usually 'ahead' of the BoS in healthy people. However, as double support phases are very short in a gait cycle, the number of samples where the XCoM ' is ahead of the BoS is limited. Subsequently, there is a higher chance of error or mismatch in the placement of XCoM' ahead of the BoS. Fig. 4.8 b shows that the distributions are wider, and the mean PCC is lower as compared to Fig. 4.8a. For 'All' sensors, the figure shows that the SSRMs has high PCC in estimating the dynamic stability. The mean PCC is above $95 \%$ (for both ahead and behind) for all four walking tasks. In Fig. 4.8, the PCC reduces as the number of sensors are reduced.

### 4.4. DISCUSSION

In this study, subject specific models were built instead of a generic model for all participants. This choice was made as preliminary studies showed poor performance of a generic regression model built using trials from different participants.


Figure 4.8 The percentage of samples when XCoM' was rightly classified (PCC) as (a) Behind or (b) Ahead of the BoS is shown as box plot distributions. The classifications by the AGBS were considered to be true and was used as the reference. The percentage of time during gait when the XCoM' was ahead or behind the BoS as measured by AGBS is shown in the inset table. The sensor configurations used: All sensors ('All'), Four foot regions ('FF'), Toe+Heel ('T+H'), Toe ('T'), Heel ('H'), and No pressure sensors ('None').

Additionally, this method could be expected to perform better for people with gait impairment. Correlations between the estimated and measured 3D F\&M as average percentages among both foot were estimated, and compared with Sim and colleagues (Sim et al., 2015) and tabulated in Table 4.1. Their study used fast, normal, and slow walking speeds for training a wavelet neural network that estimated the 3D F\&M from plantar pressures. It is seen that in both, this study and Sim and colleagues, forces in the Z axis show the highest correlation, followed by the X axis. This is expected as plantar pressures are defined by the vertical ground reaction force. In case of moments, Z axis showed the least correlation. Comparatively, except for forces in X axis, this study shows slightly higher correlations with the reference, than that in Sim and colleagues (Sim et al., 2015). Note that the current study doesn't use a normalised gait cycle for building the SSRMs, as Sim and colleagues (Sim et al., 2015) does. Therefore, the SSRMs contain information of the gait cycle during initiation and decelerations, allowing better prediction even when making short steps or shuffling at home.

Table 4.1 Comparison of the correlations found in this study and Sim and colleagues (Sim et al., 2015).

| -- | This Study (\%) | Sim and colleagues (\%) |
| :--- | :---: | :---: |
| $\mathbf{F}_{\mathrm{X}}$ | 95.5 | 97.6 |
| $\mathbf{F}_{\mathrm{Y}}$ | 95.3 | 85.3 |
| $\mathbf{F}_{\mathrm{Z}}$ | 99.6 | 98.8 |
| $\mathbf{M}_{\mathrm{X}}$ | 97.9 | 87 |
| $\mathbf{M}_{\mathrm{Y}}$ | 96.3 | 88.1 |
| $\mathbf{M}_{\mathbf{Z}}$ | 87.1 | 84.7 |

The most interesting observation is found when we study the influence of F\&M estimation on the estimation of XCoM'. We know from Fig. 4.4, that the estimation of F\&M deteriorates as we reduce the number of sensors. However, Fig. 4.6 shows that this has little effect on the estimation of XCoM'. It has to be noted that the foot position used is the same for all sensor configurations. This could give rise to the argument that accuracy of foot position is more important than force or moment sensing, highlighting the relative influence of foot kinetics and kinematics towards accuracy of XCoM. This argument is strengthened when considering the 'None' configuration. We see low rmsdX values in Fig. 4.6 for this configuration. However, it must be noted that some of the assumptions, especially the smooth transition assumption, in 'None' may fail during instances of daily life such as shuffling of feet, or while turning. Nonetheless, the comparisons show that in order to identify the XCoM', we must have good accuracy in estimating the foot position. Currently, EKF and ultrasound range updates are used to improve the foot position estimation provided by the IMUs.

Fig. 4.8 can serve as a reference for choosing the right sensor configuration based on the required task. If we are to consider an 'optimal' case that has fewer number of sensors while providing good accuracy, the 'FF' sensor configuration seems to be the right choice. However, the ' $\mathrm{T}+\mathrm{H}$ ' sensor configuration can be used if a more minimal setup is preferred. This configuration has only sensors under the heel and toe, but the model shows good accuracy in estimating the XCoM'. This shows that for minimal sensing of ADL, a simple sensor set with at least two pressure sensors (one under the heel and other under the toe), IMUs
on the forefoot, and updates of the distance between the two feet is required for a confident estimation of the XCoM and dynamic stability.

## Limitations and Future Work

Though the recruitment was not selective to sole size or gender, the participating group is not very diverse. There is only one shoe size tested and only one female participant in the study. However, this would not have any effect on validity of the method as the models are participant specific. Also, as the study was performed on healthy participants, the results might vary in populations with gait impairment.

Walking trajectories were required to create the SSRMs, which in practice, would translate to a calibration phase where the participant should walk a few times using the measurement setups. As seen earlier, an average of 134 steps is needed to achieve the results shown. Though this is an extra effort, it eliminates the use of bulky 3D F\&M sensors in daily life which can modify gait pattern and cause discomfort during extended wear (Liedtke et al., 2007; van Meulen et al., 2016c). Alternatives to create participant specific models could be building models generic to any participant and calibrating them before use.

In this study, the SSRMs are linear regression models. Studies have shown other possibilities for improving accuracy in predicting 3D forces/moments (Fong et al., 2008; Rouhani et al., 2010; Savelberg and de Lange, 1999). Further, this study finds that Stage LF is sufficient for CoM estimation. Therefore the CoP, essential for estimating CoM in Stage LF, can be found using only the pressure sensors (Mohamed Refai et al., 2018). This eliminates the conversion from 1D pressure to 3D F\&M, thereby reducing the complexity in generating SSRMs.

The participants were asked to walk in straight lines in this study. Shuffling or turning can introduce shear forces directed towards the direction of turning. The accuracy of the SSRMs in these conditions should be studied further. Additionally, the study is missing assessments of MoS in the mediolateral direction as it is highly relevant in understanding gait stability (Bruijn et al., 2013). This study shows the feasibility of pressure sensors over 3D F\&M sensors. The IMUs can be embedded inside the insoles, as designed by

Moticon ${ }^{\circledR}$ (Moticon GmbH , 2018), allowing design for a thinner, and wearable AGBS. However, the ultrasound range estimator requires further improvement. The range estimator requires synchronized receiver and transmitter placed in a direct line of sight. Alternatives, such as using infrared, may contribute towards the design of an inconspicuous AGBS (Bertuletti et al., 2016).

### 4.5. CONCLUSIONS

The AGBS in this study can thus be replaced with a setup containing pressure sensors and IMUs on each foot, and an ultrasound range estimator. During straight line walking, pressure sensors under the toe and heel can be sufficient (along with foot positions), to study the XCoM and dynamic stability of a healthy participant. Also, low frequency information of the CoM is sufficient for estimating the XCoM trajectory. Using a few assumptions, XCoM could also be estimated using only the estimations of foot position, ignoring any kinetic information. In addition, the current study highlights the contribution of foot kinematics and kinetics while estimating XCoM. These results could be used in the design of a lighter and wearable AGBS system. Such a system can contribute towards objective quantification of gait and balance quality in an ambulatory setup. This, unlike current clinical outcomes, can help monitor functional recovery.

# Portable Gait Lab: Centroidal Moment Pivot Point for Minimal Sensing of Gait 

"First, principles; second, hypotheses; third, models; then last, complete theories."

Lee Smolin, Einstein's Unfinished Revolution

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#### Abstract

Ambulatory sensing of gait kinematics using Inertial Measurement Units (IMUs) usually uses sensor fusion filters. These algorithms require measurement updates to reduce drift between segments. A full body IMU suit can use biomechanical relations between body segments to solve this. However, when minimising the sensor set, we lose a lot of this information. In this chapter, we explore the assumptions of Centroidal Moment Pivot point (CMP) as a possible source of measurement updates for the sensor fusion filters. CMP is otherwise utilised for humanoid gait in robots. First, the relation between the CMP and Centre of Pressure (CoP) was studied using a GRAIL system, consisting of optokinetic measurements. We found that the mean distance over the gait cycle between CMP and CoP was $10.5 \pm 1.2 \%$ of the foot length. Following this, we show how these results could be used to improve measurements in a minimal IMU based sensing setup.


### 5.1. INTRODUCTION

Ambulatory estimation of gait measures is useful in understanding gait patterns in healthy participants, and also recovery in people with gait impairment (Bruijn et al., 2013). One possible ambulatory method is to use Inertial Measurement Units (IMUs). IMUs consists of 3D accelerometers, and 3D gyroscopes, and are small and wearable. They can be used to estimate full body kinematics, and also kinetics, if a full body suit of IMUs is used (Karatsidis et al., 2016; Roetenberg et al., 2009).

IMUs have also been widely explored for minimal sensing of gait (Wouda et al., 2018). Several algorithms including machine learning and sensor fusion approaches have been applied in order to estimate spatial and temporal parameters from a small set of IMUs (Pacini Panebianco et al., 2018; Zhao et al., 2018). Sensor fusion approaches derive movement velocity and position of the segment they are attached to. However, they are affected by drift. Additionally, the IMUs do not have a sense of relative distance between each segment. In a full body setup, biomechanical constraints are used to solve this issue (Roetenberg et al., 2009). However, in a minimal sensing setup, such as IMUs on the feet, this may cause the two feet to drift apart from each other. This issue has been solved either as a problem with inequality constraints (Skog et al., 2012), or using biomechanical constraints based on the inverted pendulum model of human motion (Zhao et al., 2018).

The Zero moment point (ZMP) and Centroidal Moment Pivot (CMP) point have been extensively used to balance gait in humanoid systems (Popovic et al., 2005; Sorao et al., 1997). These ground reference points are addressed in Chapter I. The CMP point assumes that for a stable gait pattern, the moments around the Centre of Mass (CoM) are zero. Assuming this to be true for gait in healthy individuals, we can derive relations between CMP, CoM, and distances between the feet. This could be potential information that would reduce drift in the sensor fusion approaches. Therefore, in this study, we explore the assumptions of CMP to identify biomechanical constraints that would be useful as a measurement update for sensor fusion filters. First, we study the differences between CMP and the reference Centre of Pressure (CoP) for walking in two conditions: normal and a casted condition.

This is measured in an optoelectronic setup. Using the same setup, we test a relation derived from the CMP that could provide relative distances between each foot and CoM. Further, we show an IMU example to describe steps to implement the CMP in IMU based sensor fusion approaches.

### 5.2. METHODS

### 5.2.1. Measurement Setup

Seven healthy female participants were asked to walk on the GRAIL (Motekforce Link, The Netherlands). As can be seen in Fig. 5.1a, the GRAIL was used to collect gait biomechanics. The setup measured the 3D ground reaction forces and also the 3D kinematics of the body positions. The participants' average age was $22.9 \pm 1.4$ years, height was $1.78 \pm 0.06 \mathrm{~m}$, and weight was $73.4 \pm 5.4 \mathrm{~kg}$. The participants were asked to walk for 5 minutes on the treadmill at $1.2 \mathrm{~m} / \mathrm{s}$. After this, a plaster technician casted the right foot of the participant and they were asked to walk again for 5 minutes at the same speed on the treadmill. Casting was done to induce asymmetry in gait. The institutional ethical review board of the Vrij University Amsterdam approved the experimental procedure in this study. All participants provided written informed consent.

### 5.2.2. Centre of Mass

Schepers et al. (Schepers et al., 2009) used a complementary filter algorithm to estimate low and high frequency components of CoM from the 3D forces and moments measured from the Forceshoes ${ }^{\mathrm{TM}}$ (Fig. 5.1b). Here, we apply the algorithms to measurements from the GRAIL, as it has been validated against the CoM estimations using segmental kinematics (Schepers et al., 2009). Additionally, as we use the Forceshoes ${ }^{\mathrm{TM}}$ in the later part of the study, the same algorithms are applied here. The first stage estimates CoM from both foot kinetic and kinematic information by low pass filtering the CoP to estimate the position of CoM. The total body CoP is estimated from the force measurements on the GRAIL as

$$
\begin{equation*}
\operatorname{CoP} P_{a x}=\frac{F_{Z, l} \cdot \operatorname{CoP}_{a x, l}}{F_{Z, l}+F_{Z, r}}+\frac{F_{Z, r} \cdot \operatorname{CoP}_{a x, r}}{F_{Z, l}+F_{Z, r}} \tag{5.1}
\end{equation*}
$$



Figure 5.1 Measurement setups used in this study. Gait data was collected using the (a) GRAIL platform which consists of a split belt treadmill with force plates and ten VICON motion capture cameras. (b) The Forceshoes ${ }^{\mathrm{TM}}$ can be used as an ambulatory system for measuring gait parameters. The shoe consists of an Ultrasound System (US), 3D Force \& Moment sensors (F\&M), and Inertial Measuring Units (IMU) as seen on the side.
where $C o P_{a x}$ is the CoP. All variables in (5.1) are expressed in a global frame with Z axis positive upwards along the vertical, and X positive along the walking direction. This coordinate frame is used throughout this chapter. All variables are a function of time. Here, subscripts $r$ and $l$ stand for the right and left foot respectively, and subscript $a x$ corresponds to either X or Y axes. $F$ refers to the force in a particular axis. The $\mathrm{CoP}_{a x}$ is then low pass filtered at 0.4 Hz to obtain the $\mathrm{CoM}_{a x, L F}$ (Schepers et al., 2009).

The second algorithm estimates CoM from kinetic information alone by double integration of the net forces based on Newton's second law. The acceleration of the body mass $m_{\text {body }}$ at the CoM is

$$
\begin{equation*}
\boldsymbol{a}_{C o M}=\frac{\boldsymbol{F}}{m_{\text {bod } y}}+\mathbf{g} \tag{5.2}
\end{equation*}
$$

where $\boldsymbol{F}$ is the net force acting on the body, and $\mathbf{g}$ is the gravitational acceleration. The change in CoM position over time was derived from integrating the $\boldsymbol{a}_{C o M}$ twice. This results in $\boldsymbol{x}_{C o M}$ which was high pass filtered with a cut off at 0.4 Hz to obtain $C o M_{a x, H F}$. This is the same cut off as that of $C o M_{a x, L F}$ 's low pass filter. The $C o M_{a x, L F}$ and $C o M_{a x, H F}$ are fused using a complementary filter to obtain the trajectory of CoM.

### 5.2.3. Centroidal Moment Point (CMP)

In Chapter I (Section 1.5 .3 (Centroidal Moment Pivot)), the ground reference points including the CMP are defined. During 'stable' gait, we assume that the whole body angular momentum is constant, and thereby the net moment around the CoM is zero. Therefore, CMP is a virtual point of contact on the ground, such that the cross product of the vector $(\boldsymbol{r})$ joining the CoM and CMP and the ground reaction force vector $(\boldsymbol{F})$ is zero. This gives us the following equations:

$$
\begin{align*}
& \boldsymbol{r} \times \boldsymbol{F}=0  \tag{5.3}\\
& (\operatorname{CoM}-C M P)_{a x} \cdot F_{Z}=(\operatorname{CoM}-C M P)_{z} \cdot F_{a x}  \tag{5.4}\\
& C M P_{a x}=\operatorname{CoM}_{a x}-\left(\operatorname{CoM}_{z} \cdot \frac{F_{a x}}{F_{Z}}\right) . \tag{5.5}
\end{align*}
$$

In (5.4), $\mathrm{CMP}_{Z}$ is zero as it lies on the floor, and $\mathrm{CoM}_{Z}$ is the height of pelvis from the GRAIL system. Therefore, (5.5) provides CMP positions in X and Y axes. This is then compared with the CoP estimated from the treadmill force plates using (5.1).

### 5.2.4. Application of Centroidal Moment Pivot Point

The relation between CMP and CoM as shown in (5.5) can be utilised as additional information about relative distance between the feet and CoM. Therefore, they can be used as measurement updates for a sensor fusion filter, if the other variables are known. For example, during swing phase of the left foot, the CoP of the body will lie under the right foot. Without pressure insoles, it is not straight forward to measure CoP of each foot. However, the foot positions can be estimated using an IMU on each foot (Weenk et al., 2015), and CoM can be tracked using a pelvis IMU (Floor-Westerdijk et al., 2012). Here, we can provide an estimate for the right foot during left foot swing phase as

$$
\begin{equation*}
\operatorname{pos}_{a x, r}=\operatorname{CoM}_{a x, s l}-\left(\operatorname{CoM}_{z} \cdot \frac{F_{a x}}{F_{Z}}\right) \tag{5.6}
\end{equation*}
$$

where $p o s_{a x, r}$ is position of the right foot, and subscript $s l$ denotes instances of left foot swing phase. We have assumed that the differences in CMP and foot position is trivial. Subsequently, we can derive an estimate for the left foot during the swing phase of the right foot ( $s r$ ) as

$$
\begin{equation*}
\operatorname{pos}_{a x, l}=\operatorname{CoM}_{a x, s r}-\left(\operatorname{CoM}_{z} \cdot \frac{F_{a x}}{F_{Z}}\right) \tag{5.7}
\end{equation*}
$$

and then compare $\operatorname{pos}_{a x, r}$ and $\operatorname{pos}_{a x, l}$ with the true foot positions at the respective instances ( $s l$ and $s r$ ).

### 5.2.5. Example using IMUs

We show a possible application of (5.6) and (5.7) in practice by describing an example measurement. A participant (male, $71 \mathrm{~kg}, 1.78 \mathrm{~m}$ tall, and 25 years old) is asked to walk with the Forceshoes ${ }^{\mathrm{TM}}$ for 10 m in a straight line. There is an IMU on each foot. We apply the sensor fusion filter of Weenk and colleagues (Weenk et al., 2015) to the measurements by the IMU. This includes their prediction models, and measurement updates such as zero velocity update, and zero height update. However, we skip the measurement updates from the ultrasound sensor, as this includes relative foot distance information. Therefore, we obtain foot positions, $\operatorname{pos}_{a x, r}^{w k}$ and $\operatorname{pos}_{a x, l}^{w k}$. Here, the superscript $w k$ refers to the method of Weenk and colleagues (Weenk et al., 2015) and the subscript $a x$ refers to either the X or Y axis. The subscripts $r / l$ refer to either the right or left foot. These position estimates will have drifted due to noise, due to absence of any relative distance information. Then, we estimate reference CoM trajectory using forces measured by the Forceshoes ${ }^{\mathrm{TM}}$ (Schepers et al., 2009). Further, we apply (5.6) and (5.7) to the CoM estimated, in order to estimate $\operatorname{pos}_{a x, r}^{c m}$ and $\operatorname{pos}_{a x, l}^{c m}$ respectively. Here, the superscript $c m$ refers to the CMP method. Further, we assume $\mathrm{CoM}_{Z}$ is a constant line, with a value equal to the participant's pelvis height during quiet standing. We plot the trajectories of interesting parameters and comment on how this could be used in a sensor fusion setup.

### 5.2.6. Analysis of Results

We compare the $C M P_{a x}$ measured in (5.5) with the CoP measured from the treadmill force plates in GRAIL. Then, we compare the error as a percentage of participant's foot length $\beta \%$ with Herr et al (Herr and Popovic, 2008). Following this, we compare $\operatorname{pos}_{a x, r}$ and $\operatorname{pos}_{a x, l}$ from (5.6) and (5.7) with foot positions measured by VICON in GRAIL. For each of these, we test if the differences are statistically significant using a two tailed t-test. Following this, we plot the trajectories of the interesting parameters in our example (Section 5.2.5) with the IMUs.


$\begin{array}{lllllll}40 & 50 & 60 & 70 & 80 & 90 & 100\end{array}$
Figure 5.2 Comparison of the mean trajectories of the Centroidal Moment Pivot point (CMP) in dashed line and Centre of Pressure (CoP) in solid line for a normalised gait cycle. The cycle begins with right heel strike and ends with the subsequent right heel strike. The cycle is the average cycle for all participants. The shaded regions show the standard deviation. The left column shows the normal condition, and the right column shows the casted condition. The first row shows the trajectory in the X axis and the bottom row shows the trajectory in the Y axis.

### 5.3. RESULTS

Fig. 5.2 shows the normalised trajectories of CMP and CoP in the X and Y axes for both conditions: normal and casted. The graph shows the normalised gait cycle averaged over all participants. The shaded regions show the standard deviation of the trajectories. The first column denotes the normal condition, and the second column denotes the casted condition. Each row corresponds to one axis in the global frame. The mean absolute Root Mean Square (RMS) of the differences between the CMP and CoP over the complete cycle is shown in Table 5.1 for both conditions. No statistically significant difference was found between the two variables. In Table 5.2, we compare the mean RMS of the distance between the CMP and CoP across the gait cycle normalised by foot length ( $\beta \%$ ) with that of Herr et al (Herr and Popovic, 2008). Further, in Table 5.3, the mean RMS of the differences between the $\operatorname{pos}_{a x, r}$ and $\operatorname{pos}_{a x, l}$ and respective foot positions from GRAIL is shown for normal and casted walking conditions. It was found that during casted walking only $p o s_{Y, r}$ was not significantly different from the respective reference foot positions. Finally, in Fig. 5.3, we see a top view of a walking trajectory, and the potential estimates of relative distances using the assumptions of CMP.

Table 5.1 Mean RMS of the differences between CMP point and CoP over a gait cycle.

| - | X Axis | Y Axis |
| :--- | :---: | :---: |
| Normal (cm) | $2.8 \pm 0.3$ | $0.8 \pm 0.2$ |
| Casted (cm) | $3.6 \pm 0.4$ | $1.4 \pm 0.3$ |

Table 5.2 Mean distance between CMP and CoP across gait cycle normalised by foot length ( $\beta \%$ ).

| - | (Herr and Popovic, 2008) | This study |
| :--- | :---: | :---: |
| Normal (\%) | $14 \pm 2$ | $10.5 \pm 1.2$ |
| Casted (\%) | - | $13.5 \pm 1.5$ |

Table 5.3 Mean RMS of difference between $\operatorname{pos}_{a x}$ and reference foot positions at respective instances. ( ${ }^{*} p<0.05$ ).

|  | $\operatorname{pos}_{X, l}$ | $\operatorname{pos}_{Y, l}$ | $\operatorname{pos}_{X, r}$ | $\operatorname{pos}_{Y, r}$ |
| :--- | :---: | :---: | :---: | :---: |
| Normal (cm) | $9.5 \pm 0.8^{*}$ | $1.3 \pm 0.3^{*}$ | $9.3 \pm 0.6^{*}$ | $1.9 \pm 0.5^{*}$ |
| Casted (cm) | $8.9 \pm 1.4^{*}$ | $1.5 \pm 0.4^{*}$ | $12.8 \pm 1.8^{*}$ | $2.8 \pm 0.9$ |

Chapter 5

Figure 5.3 Top view of the trajectories from the example in Section 5.2.5. The participant starts walking at 0 m in the walking direction. The triangles denote the starting position of the two feet. The dark green dotted line and blue dotted lines are the left ( $p_{o s} s_{a x, l}{ }^{w k}$ ) and right ( $p_{0} s_{a x, r}$ ) foot trajectories respectively, estimated from the algorithm of Weenk and colleagues (Weenk et al., 2015) from the foot IMUs. The red dotted line is the reference centre of mass ( CoM ) estimated by the Forceshoes ${ }^{\mathrm{TM}}$. The solid yellow lines and green lines are possible estimates for left foot during right swing phase ( $\mathrm{pos}_{a x, l}^{c m}$ ), and the right foot during left swing phase ( $p o s_{a x, r}^{c m}$ ) respectively. These are estimated using the CMP point assumptions.

### 5.4. DISCUSSION

In practice (5.3) is not valid. Although the whole body angular momentum is regulated, the moments around the CoM oscillate around zero in healthy gait (Herr and Popovic, 2008, Fig. 3). Upper body angular rotations also cause moments around the CoM. This is a missing component in (5.3). However, here we look at how the CMP and CoP agree, during straight walking, where the moments around the CoM may be really small.

Fig. 5.2 shows that there is close overlap between the trajectories of CMP and CoP for the normalised gait cycle. The gait cycle begins with right heel strike, and we can see the transition of the CoP from left to the right foot. The CoP falls completely under the right foot around $15 \%$ of the gait cycle. Following the left swing phase, we notice the left heel strike around $50 \%$ of the gait cycle, as the CoP starts to move towards the left foot. The trajectory continues to the next right heel strike which is the end of the gait cycle. Further, we observe that the standard deviation of the trajectories (both CMP and CoP) is smaller during the transition from one foot to the other. In both normal and casted conditions, the trajectory of CMP is closer to the CoP in the Y axis during these transition (double stance) phases, when compared to the swing phases. This could suggest that the moments around the CoM are smaller during double stance phase, thereby showing lower differences in the CMP and CoP trajectories during these instances.

Table 5.1 shows these differences as mean RMS of the differences between CMP and CoP over the whole gait cycle. It is seen that the casting increases the error margins of the differences. The influence of casting on asymmetry of gait was verified by studying the step length. It was found that there were significant differences in the step lengths on the restricted foot before and after casting. Casting therefore, could induce asymmetry, causing increased rotation of the upper body to compensate for the change in walking pattern, and therefore, we see the differences in Table 5.1. Table 5.2 shows the mean distance between CMP and CoP across the gait cycle, normalised by foot length of the participants. The lower errors in this study could be due to the use of the method of Schepers et al. (Schepers et al., 2009), for estimating CoM , as both the low and high frequency information are present. However, this inference should be tested.

Table 5.3 shows the differences between foot positions estimated from CoM using CMP assumptions and true foot positions from GRAIL system. The larger errors can be explained by the fact that we are actually comparing CMP estimates from CoM with foot positions. We assume CMP to lie close to CoP for each foot, and in turn, assume differences between CoP and foot positions to be trivial. Therefore, the Table 5.3 shows the error margins associated with these assumptions. The table shows that the error margins are around 9.5 cm in X axis, and about 1.6 cm in the Y axis, for the normal walking condition. They show larger deviations in case of casting. These margins give us an idea of the feasibility of using CMP based assumptions for estimating foot positions from CoM.

In Fig. 5.3, we see the different trajectories of interest, during an overground walking situation. Here, we see that the feet drift away from each other as there is no relative distance information. Therefore, we could use the estimates of right and left feet from CoM and CMP to reduce this drift. Fig. 5.3 shows these estimates, $p o s_{a x, r}^{c m}$ and $\operatorname{pos}_{a x, l}^{c m}$ (denoted as solid green and yellow lines) oscillating on either side of the CoM. These lines are present only at the respective gait phases, either during left swing, or during right swing. This information could be used as a measurement update in a sensor fusion filter, at the right instances. As these filters, such as Kalman Filter, work with uncertainty margins, the error margins (Table 5.3) could be accommodated for.

Thus, this shows that a minimal sensing system could consist of three IMUs; one on each foot, and one at the pelvis. The foot IMUs could track the movement of the feet in 3D. Measurement updates such as zero velocity update will minimise the drift in the X and Z directions (Weenk et al., 2015). The CoM can be tracked using a pelvis IMU (Floor-Westerdijk et al., 2012). The CMP assumptions shown in this study could be used during left swing to estimate relative position of CoM relative to right foot. Additionally, during right swing phase, we can estimate CoM relative to left foot. If we fuse all this information, we can estimate the relative positions between the two feet during subsequent stance phases. This removes the need for full body sensing (Roetenberg et al., 2009), or an inter-foot distance sensor (Bertuletti et al., 2016; Weenk et al., 2015). However, these assumptions need to be validated using a separate study.

Equation (5.5) also requires knowledge of the height of the CoM and forces in 3D. CoM height can be measured by the pelvis IMU, with appropriate measurement updates (Floor-Westerdijk et al., 2012). Estimating forces in 3D could be solved by either using pressure insoles, or a sensor fusion approach that measures the rotations of the pelvis in 3D. If we assume that the body is only in contact with the ground, then the accelerations of the pelvis could be similar to the accelerations at the CoM. This is simply the specific ground reaction forces in 3D.

The current method assumes that the CoM position is used as a reference, and the estimates of the two feet could be corrected based on (5.6) and (5.7). An alternative method is to assume the right foot to be a reference point and then estimate the CoM, and subsequently, left foot position.

## Limitations and Conclusions

The measurements were done on a treadmill which result in repetitive gait patterns. These are suitable for analysis, although, these patterns are not present in daily life. It is interesting to study the validity of CMP assumptions during over ground walking, and while performing tasks of daily life, and also asymmetric gait patterns. These evaluations would provide some indication about its use in minimal sensing of gait in a remote setting, or people with impaired gait. Asymmetrical walking may require the use of a sternum IMU to measure rotations of the upper body, to account for possible additional moments during walking.

The errors in Table 5.3 are majorly present as we compare CMP with reference foot positions. Therefore, a possible solution could be to measure CoP during walking, as they show lower errors with CMP, as can be seen in Table 5.1. In an ambulatory sensing setup, these errors could be solved by using a pressure insole to measure CoP providing more accurate relative distances between CoM and either foot.

This study shows possible applications of using CMP assumptions to reduce the lateral drift during minimal sensing of gait using IMUs. The next step is indeed to build a sensor fusion algorithm (with a setup similar to that shown in Section 5.2.5) that can implement these updates iteratively. It is advised that the assumptions are studied for different walking patterns.

# Portable Gait Lab: Estimating 3D GRF using a Pelvis IMU in a foot IMU defined frame 

"Life is about making the right things and going on."<br>R. K. Narayan, Malgudi Days

[^5]In IEEE Transactions on Neural Systems and Rehabilitation Engineering. 28, 1308-1316.


#### Abstract

Ground Reaction Forces (GRF) during gait are measured using expensive laboratory setups such as in-floor or treadmill force plates. Ambulatory measurement of GRF using wearables enables remote monitoring of gait and balance. Here, we propose using an Inertial Measurement Unit (IMU) mounted on the pelvis to estimate the GRF during gait in daily life. Calibration procedures and an Error State Extended Kalman filter (EEKF) were used to transform the accelerations at the Centre of Mass (CoM) to the 3D GRF. The instantaneous 3D GRF was estimated for different over ground walking patterns and compared with the 3D GRF measured using the reference ForceShoes ${ }^{\mathrm{TM}}$ system. Furthermore, we introduce a changing reference frame called the current step frame that followed the direction of each step made. The frame was defined using movement of the feet, and the estimated GRF were expressed in this new frame. This allowed direct comparison and validation with the reference. The mean and standard deviation of error between the estimated instantaneous 3D GRF and the reference, normalized against the range of the reference, was $12.1 \pm 3.3 \%$ across all walking tasks, in the horizontal plane. The error margins show that a single pelvis IMU could be a minimal and ambulatory sensing alternative for estimating the instantaneous 3D components of GRF during over ground gait.


### 6.1. INTRODUCTION

Whole body Ground Reaction Forces (GRF) are used to evaluate gait kinetics and balance measures (Schepers et al., 2009; van Meulen et al., 2016c). Traditionally, GRF are measured using force plates installed under either the floor, or special treadmills. These, indeed, cannot be used in an ambulatory manner.

If a simple inverted pendulum model of gait is assumed (Hof et al., 2005), the GRF is equal and opposite the sum of accelerations at the Centre of Mass (CoM); and accelerations can be directly measured by Inertial Measurement Units (IMUs). Ancillao and colleagues (Ancillao et al., 2018) reviewed several approaches where IMUs were used to estimate the GRF using either biomechanical models or machine learning methods. For instance, Karatsidis and colleagues (Karatsidis et al., 2016) used several IMUs placed in a full body suit and applied inverse dynamics to obtain GRF. Others attempted to estimate GRF using a single sensor (Kiernan et al., 2018; Neugebauer et al., 2012). However, these studies only assessed the vertical GRF (vGRF). Other studies estimated the 3D GRF using machine learning methods (Leporace et al., 2015; Wouda et al., 2018). These showed good estimates using models for straight line walking but can be limited for variable gait. Gurchiek and colleagues (Gurchiek et al., 2017) estimated the 3D GRF with only one pelvis IMU, but only during specific steps where the GRF vector changes its direction. A later study (Shahabpoor and Pavic, 2018) used dynamic time warping to estimate an average progression of only the vGRF. To summarize, most studies reviewed measured only the vGRF using a single pelvis IMU, or the 3D GRF using machine learning methods or additional ancillary IMUs (Ancillao et al., 2018). Estimating the lateral components of GRF is a critical aspect when using a one IMU approach (Ancillao et al., 2018). It is therefore, of interest to estimate the instantaneous 3D GRF using a single IMU during variable gait.

A commonly used biomechanical assumption is that the CoM is encompassed by the rigid pelvis (Floor-Westerdijk et al., 2012; Schepers et al., 2009), and thereby, an IMU at the pelvis could measure the CoM accelerations. Using Newton's law, the product of body mass and CoM accelerations provides the whole body GRF. This is a simplification of the inverted pendulum model of gait
and errors are expected (Ancillao et al., 2018; Shahabpoor and Pavic, 2018). However, this allows us to minimize the measurement setup for ambulatory estimation of GRF. The challenge here is to estimate the CoM accelerations measured at the pelvis IMU in the three axes that correspond to the anterioposterior, medio-lateral, and vertical axes of the GRF.

Gait kinematics and kinetics are usually expressed in a fixed global frame, defined using the non-portable measurement setup or certain pre-defined initializations. However, this can be restrictive in understanding GRF in an ambulatory manner. Expressing these forces along the changing walking direction can provide a more functional representation, which is body-centric, especially during shuffling or turns. It is therefore, also of interest to define a changing reference frame, expressed along the direction of each step being made. This changing reference frame is referred to hereon as the current step frame.

Thus, the main goal in this study is to evaluate the feasibility of estimating 3D GRF from a pelvis IMU, for different walking patterns seen in daily life for the complete gait. A calibration procedure, and an Error State Extended Kalman Filter (EEKF) were used to estimate body orientation, in order to determine the 3D components of the pelvis acceleration in a certain reference frame. Two additional IMUs were placed, one on each foot, and were used to define the current step frame. This frame was based on the direction of each step being made, and the GRF was then expressed in this frame. The estimates of the GRF were derived from the pelvis IMU, and the foot IMUs were only used to define the changing current step frame. Introducing this new frame is the second goal of this paper. The instantaneous 3D GRF was then compared with the reference system, the ForceShoes ${ }^{\mathrm{TM}}$, and also with results from literature.

### 6.2. METHODS

In this section, the methodology used to estimate 3D GRF from a pelvis IMU in the current step frame is explained. First, in Section 6.2.1, the definition of reference frames used in this study are described. Section 6.2.2 summarizes the assumptions considered for the models that will be described. Section 6.2.3 describes the IMU models used for the following sections. In Section 6.2.4, the
algorithms used for foot contact detection is explained. Using the IMU models described, and foot contact instances, Section 6.2.5 describes the estimation of the different reference frames as mentioned in Section 6.2.1, and also the 3D GRF. Section 6.2.6 describes the measurement system used, and Sections 6.2.7 and 6.2.8 describe the participants, and the experimental protocol used to validate this study respectively. Finally, Section 6.2 .9 describes the analysis of the results.


Figure 6.1 Graphical interpretation of the reference frames used. The left foot is in light blue, and the CoM trajectory is the thin grey line. Instead of a fixed global frame $\psi_{g}$, a current step frame of reference $\psi_{C S(k)}$ is used for step $k$ which changes for each step. The frame is defined using the movement of the feet. Segment frames used are $\psi_{f l}$ and $\psi_{f r}$ for foot frames, and $\psi_{p}$ for the pelvis frame.

### 6.2.1. Reference Frames used

The use of a fixed global frame of reference for gait analysis could be attributed to the fixed nature of force plates or optical motion capture systems. As shown in Fig. 6.1, the global frame $\psi_{g}$ has a predefined and fixed frame throughout the measurement. However, wearable setups allow us to define frames that are associated with the direction of gait. For instance, pressure profiles, and centre of pressure patterns are expressed in foot frames. Similarly, here we can define reference frames that are attached to the moving body.

There are two possible options to define a body-centric reference frame. One option is to have a reference frame defined by the heading of the body. This would be based on the measurements of the pelvis IMU and tracking CoM positions. Alternatively, we could define reference frames based on the direction of each step. Estimating changes in foot positions is feasible using strapdown inertial navigation, and zero velocity updates (Sabatini et al., 2005).


Figure 6.2 Rotations from sensor $\left(\psi_{s}\right)$ to current step $\left(\psi_{c s}\right)$ frame. Sensor data is first calibrated to segment frame (pelvis ( $p$ ), left foot ( $f$ l), or right foot ( $f r$ )). Then, during a step $k$, they are first transformed to a previous step frame $\psi_{c s(k-1)}$, for each sample $i$. At the end of this step, the change in foot positions is used to build the current step frame $\psi_{c s(k)}$.

Further, the reference system used in this study, the ForceShoes ${ }^{\text {TM }}$, can track changes in foot positions (Weenk et al., 2015). Therefore, the second method is preferred. This is made feasible by one additional IMU placed on each foot.

The current step frame is denoted as $\psi_{c s(k)}$ and defined graphically in Fig. 6.1. It depends on the direction of the step $k$, and thus, changes for each step. Although this is similar to the local foot frame defined by other studies (Fino et al., 2020; Rebula et al., 2013), $\psi_{c s(k)}$ is defined for each step. We define the X axis of this frame as positive in the forward direction, defined by the line between the beginning and end of a step. The Z axis is positive upwards along the vertical. This is the $\psi_{c s(k)}$ for the current step $k$, and is redefined for the next step.

The sensors of the IMUs measure in their respective sensor frames denoted by $\psi_{s}$. This has to be transformed to the $\psi_{c s}$ per step. The transformation between frames is shown in Fig. 6.2. First, each sensor was transformed to their respective segment (seg) frames $\psi_{\text {seg }}$ using a simple calibration method. The segments of interest in this study are the pelvis $(p)$, left foot ( $f l$ ), and the right foot ( $f r$ ). Then, during step $k$, the orientation of these segments was expressed in the current step frame of the previous step $\psi_{c s(k-1)}$, as this frame was already defined. EEKFs were used to estimate the change in orientation of the segments during this phase. At the end of step $k$, the change in position of the moving foot was used to estimate the orientation from $\psi_{c s(k-1)}$ to $\psi_{c s(k)}$ as
$\boldsymbol{R}^{c s(k), c s(k-1)}$ allowing transforming to $\psi_{c s(k)}$. This was redefined for each step, resulting in a $\psi_{c s(s t e p)}$ per step. In short, four frames of reference were used in this study: sensor frame $\left(\psi_{s}\right)$, segment frames (pelvis $\psi_{p}$, right foot $\psi_{f r}$ and left foot $\psi_{f l}$ ), current step frame of the previous step $\left(\psi_{c s(k-1)}\right)$, and that of the current step $k\left(\psi_{c s(k)}\right)$. The notations used in this study are listed in Table 6.1.

### 6.2.2. Assumptions considered

As mentioned earlier, an inverted pendulum model of gait was considered in this study. The GRF accelerates the CoM and opposes gravity. Also, we assume that all mass is concentrated at the CoM, which is located within the pelvis. Additionally, the feet are the only contact with the external world, and no additional load is carried by the body. Therefore, the accelerations measured by the IMU at the pelvis are similar to the CoM accelerations, and eventually reflects the GRF.

### 6.2.3. Inertial Measurement Unit Model

The 3D accelerometer and 3D rate gyroscope present in the IMU provides the acceleration and angular velocities in the sensor frame $\psi_{s}$ respectively, and can be modelled as

$$
\begin{align*}
\boldsymbol{y}_{A}^{s} & =\boldsymbol{a}^{s}-\mathbf{g}^{s}+\boldsymbol{e}_{A}  \tag{6.1}\\
\text { and, } \boldsymbol{y}_{G}^{s} & =\boldsymbol{\omega}^{s}+\boldsymbol{b}^{s}+\boldsymbol{e}_{G} \tag{6.2}
\end{align*}
$$

where $\boldsymbol{y}_{A}^{s}$, and $\boldsymbol{y}_{G}^{s}$ denote the accelerometer and gyroscope signals respectively from the IMU. They are measured in the $\psi_{s}$ reference frame denoted by the superscript $s . \boldsymbol{a}$ is the linear acceleration of the sensor, $\mathbf{g}$ is gravity, and $\boldsymbol{e}_{A}$ is Gaussian white noise. Also, $\boldsymbol{\omega}$ is the angular velocity, $\boldsymbol{b}$ is a slowly varying offset, and $\boldsymbol{e}_{G}$ is the Gaussian white noise. Both (6.1) and (6.2) are discrete time equations and are expressed for a given time instance $i$.

### 6.2.4. Foot Contact and Step Detection

Step detection is important in estimating the current step frame. Here, the method of Skog and colleagues (Skog et al., 2010) was used to estimate the foot contact instances for the two feet. As the IMUs are synchronized in time, the double stance instances can be estimated. A step is defined as the instance
between the heel strike of one foot to that of the other. However, as we are using IMUs to track the foot as one rigid body, we do not model the rolling of the foot during the stance phase. Therefore, it becomes less important to identify the different gait events during stance. Hence, we define a step as the instance between the midpoint of a double stance event to the midpoint of the next double stance.

### 6.2.5. Orientation in the different reference frames

The transformation between different frames is explained in the following sections. Static calibrations used to transform the sensor data to the respective segment frame is first described. Following this, the structure of the fusion filter, used to estimate changes in orientation of the segment during a step, expressed in the previous step frame is described. Finally, the estimation and transformation to the current step frame is explained.

## Sensor to Segment Calibration

The orientation of the sensor $\psi_{s}$ in segment frame $\psi_{\text {seg }}$ written as $\boldsymbol{R}^{\text {seg,s }}$ was estimated using the mounting frame calibration techniques described by Bonnet and colleagues (Bonnet et al., 2009):

$$
\begin{align*}
& a x_{Z}=\frac{y_{A}^{s}}{\left\|y_{A}^{s}\right\|}  \tag{6.3a}\\
& a x_{Y, p}=P C A\left(\boldsymbol{y}_{G}^{s}\right)  \tag{6.3b}\\
& a x_{X}=a x_{Y} \times a x_{Z}  \tag{6.3c}\\
& a x_{Y}=a x_{Z} \times a x_{X}  \tag{6.3d}\\
& \boldsymbol{R}^{s e g, s}=\left[\begin{array}{lll}
a x_{X} & a x_{Y} & a x_{Z}
\end{array}\right] \tag{6.3e}
\end{align*}
$$

For all three segments, the inclination estimate was estimated by measuring the magnitude of the accelerometer signal using (6.3a) during an initial standing still phase, during which the 3D accelerometer is expected to measure only gravity. The Y axis of the pelvis was estimated by asking the participant to bend forward. Principal component analysis was applied to the gyroscope output to find the axis measuring largest angular rotation. The X axis of the
pelvis was estimated using right hand thumb rule, as seen in (6.3c). The Y axis was then updated using (6.3d). The orientation is given in (6.3e).

Alternatively, the heading (X axis) for the feet was estimated by running the filter once with arbitrary values for three steps. Then, the change in position between the start and the third step was used to estimate the X axis. The third step was arbitrarily chosen. Drift during these steps were removed using Zero Velocity (ZV) and Zero Height (ZH) updates (Weenk et al., 2015). The Y axis was estimated using (6.3d), and the X axis was updated using (6.3c). Again, the rotation matrix was given as the $3 x 3$ matrix in (6.3e).

Table 6.1 Notations used, shown for an arbitrary vector $\boldsymbol{a}$.

| Notation | Definition |
| :--- | :--- |
| $\boldsymbol{a}_{k}$ | $\boldsymbol{a}$ at k-th instant |
| $\boldsymbol{a}^{s}$ | $\boldsymbol{a}$ expressed in frame $\psi_{s}$ |
| $\dot{\boldsymbol{a}}$ | derivative of $\boldsymbol{a}$ |
| $\hat{\boldsymbol{a}}$ | a-posteriori estimate of $\boldsymbol{a}$ |
| $\boldsymbol{a}^{-}$ | a-priori estimate of $\boldsymbol{a}$ |
| $\boldsymbol{e}_{\boldsymbol{a}}$ | Gaussian white noise associated with $\boldsymbol{a}$ |

## Error State Extended Kalman Filter

Now, the change in orientation of the segments during each step has to be estimated. The current step frame $\psi_{c s(k)}$ can only be defined at the end of the step $k$ as it requires the change in foot positions during that step. However, the previous current step frame $\psi_{c s(k-1)}$ has already been defined. Therefore, the change in orientation of the segment during step $k$ was first expressed in $\psi_{c s(k-1)}$ using an EEKF. The EEKF tracked the $\boldsymbol{R}_{i}^{c s(k-1), s e g}$, i.e., the orientation of the segment $\psi_{\text {seg }}$ with respect to $\psi_{c s(k-1)}$ for given instance $i$. Here, $i$ denotes the samples of the current step $k$.


Figure 6.3 Block representation of the Error State Extended Kalman filter for the pelvis IMU. The state vector consists of orientation error $\boldsymbol{\theta}_{\epsilon}$ and gyroscope bias error $\boldsymbol{b}_{\epsilon}$. The updated states are used to estimate the $\boldsymbol{R}_{i}^{C S(k-1), p}$ for each step. Using information from the foot IMUs, $\boldsymbol{R}_{\text {step }}^{C S(k), c s(k-1)}$ was estimated, and then the GRF was transformed to frame $\psi_{c s(k)}$ for the step $k$.

The EEKF filter used for the pelvis orientation is shown in Fig. 6.3 and was based on Kortier and colleagues (Kortier et al., 2014), and Luinge and colleagues (Luinge and Veltink, 2005). The states included in the state vector $(\boldsymbol{x})$ of the EEKF were orientation error $\boldsymbol{\theta}_{\epsilon}$ and gyroscope bias error $\boldsymbol{b}_{\epsilon}$. The state vector was thus $\boldsymbol{x}=\left(\boldsymbol{\theta}_{\epsilon} \boldsymbol{b}_{\epsilon}\right)^{T}$, and its covariance matrix was denoted as $\boldsymbol{P}$. The advantage of using an EEKF for estimating orientation errors is that the inertial processes can be considered linear, if the errors are assumed to be small. Similar EEKFs were built for the other segments.

## Prediction

Prediction models were defined for each state. First, the gyroscope bias (b) was modelled as a first-order Markov process as

$$
\begin{equation*}
\boldsymbol{b}_{i}=\boldsymbol{b}_{i-1}+\boldsymbol{e}_{b, i} \tag{6.4}
\end{equation*}
$$

where $\boldsymbol{e}_{b, i}$ is white Gaussian noise associated with the process. Then, the gyroscope bias was predicted as

$$
\begin{equation*}
\widehat{\boldsymbol{b}}_{i}^{-}=\widehat{\boldsymbol{b}}_{i-1} . \tag{6.5}
\end{equation*}
$$

The gyroscope bias error $\boldsymbol{b}_{\epsilon}$ can be modelled as

$$
\begin{equation*}
\boldsymbol{b}_{\epsilon, i}=\widehat{\boldsymbol{b}}_{i}-\boldsymbol{b}_{i} . \tag{6.6}
\end{equation*}
$$

Using equations (6.4), (6.5), and (6.6), we get

$$
\begin{equation*}
\boldsymbol{b}_{\epsilon, i}=\boldsymbol{b}_{\epsilon, i-1}-\boldsymbol{e}_{b, i} . \tag{6.7}
\end{equation*}
$$

Next, orientation can be estimated from orientation error $\left(\boldsymbol{\theta}_{\epsilon}\right)$ :

$$
\begin{equation*}
\widehat{\boldsymbol{R}}_{i}^{c s(k-1), \text { seg }} \approx \boldsymbol{R}_{i}^{c s(k-1), \text { seg }}\left(\mathbf{I}+\widetilde{\boldsymbol{\theta}}_{\epsilon, i}\right) . \tag{6.8}
\end{equation*}
$$

For any vector $\boldsymbol{V},[\widetilde{\boldsymbol{V}}]=\left(\begin{array}{ccc}0 & -v_{z} & v_{y} \\ v_{z} & 0 & -v_{x} \\ -v_{y} & v_{x} & 0\end{array}\right)$. Note that (6.8) is valid when orientation errors are assumed to be small.

Furthermore, we can derive orientation from angular velocity using (Schepers et al., 2010a):

$$
\begin{equation*}
\dot{\boldsymbol{R}}_{i}^{c s(k-1), \text { seg }}=\boldsymbol{R}_{i}^{c s(k-1), s e g} \cdot(\widetilde{\boldsymbol{\omega}}) \tag{6.9}
\end{equation*}
$$

Based on (Schepers et al., 2010a), we have the derivative of orientation error and its discretised form (Gustafsson, 2018) as

$$
\begin{equation*}
\dot{\boldsymbol{\theta}}_{\epsilon}=\widetilde{\boldsymbol{\omega}} \cdot \boldsymbol{\theta}_{\epsilon}-\boldsymbol{b}_{\epsilon} \tag{6.10}
\end{equation*}
$$

and $\boldsymbol{\theta}_{\epsilon, i}=\left(\mathbf{I}_{3}+T \cdot \widetilde{\boldsymbol{\omega}}+\frac{T^{2}}{2} \cdot \widetilde{\boldsymbol{\omega}}^{2}\right) \boldsymbol{\theta}_{\epsilon, i-1}+\left(-T \cdot \mathbf{I}_{3}-\frac{T^{2}}{2} \cdot \widetilde{\boldsymbol{\omega}}\right) \boldsymbol{b}_{\epsilon, i-1}$.
The Kalman filter prediction equation is given as (Welch and Bishop, 2006):

$$
\begin{align*}
\widehat{\boldsymbol{x}}_{i}^{-} & =\boldsymbol{F} \cdot \widehat{\boldsymbol{x}}_{i-1}  \tag{6.12}\\
\text { where } \boldsymbol{F} & =\left(\begin{array}{cc}
\mathbf{I}_{3}+T \cdot \widetilde{\boldsymbol{\omega}}+\frac{T^{2}}{2} \cdot \widetilde{\boldsymbol{\omega}}^{2} & -T \cdot \mathbf{I}_{3}-\frac{T^{2}}{2} \cdot \widetilde{\boldsymbol{\omega}} \\
\mathbf{0}_{3} & \mathbf{I}_{3}
\end{array}\right) . \tag{6.13}
\end{align*}
$$

The covariance matrix is predicted using

$$
\begin{equation*}
\widehat{\boldsymbol{P}}_{i}^{-}=\boldsymbol{F} \cdot \widehat{\boldsymbol{P}}_{i-1}^{-} \cdot \boldsymbol{F}^{T}+\boldsymbol{Q} \tag{6.14}
\end{equation*}
$$

where $Q$ is the process noise covariance matrix.

## Measurement Update

It was assumed that on average, the accelerations at the pelvis measure inclination due to gravity. This can be true during forward walking or when making changes in walking direction. The orientation error was corrected based on the current prediction and expected inclination for the vertical axis. An estimate of the accelerometer output in the frame $\psi_{c s(k-1)}$ was derived using the estimate of the orientation matrix $\left(\widehat{\boldsymbol{R}}_{i}^{c s(k-1), p}\right)$ as

$$
\begin{equation*}
\widehat{\boldsymbol{y}}_{A, i}^{c(k-1)}=\widehat{\boldsymbol{R}}_{i}^{c s(k-1), p} \cdot\left(\boldsymbol{y}_{A, i}^{p}\right) . \tag{6.15}
\end{equation*}
$$

Then, (6.3a) was used to estimate inclination at instant $i$. The difference $\left(\delta \mathbf{y}_{A}^{c s(k-1)}\right)$ between measured $\boldsymbol{y}_{A}^{c s(k-1)}$ and estimated $\hat{\boldsymbol{y}}_{A}^{c s(k-1)}$ was then used to update the orientation error as (Kortier et al., 2014):

$$
\begin{align*}
\delta \boldsymbol{y}_{A}^{c s(k-1)} & =\boldsymbol{y}_{A}^{c s(k-1)}-\widehat{\boldsymbol{y}}_{A}^{c s(k-1)}  \tag{6.16a}\\
& =\widehat{\boldsymbol{R}}^{c s(k-1), p} \cdot\left(\mathbf{I}+\widetilde{\boldsymbol{\theta}}_{\epsilon}\right) \cdot \boldsymbol{y}_{A}^{p}-\widehat{\boldsymbol{R}}^{c s(k-1), p} \cdot \boldsymbol{y}_{A}^{p}+\boldsymbol{e}_{A} \\
& =-\widehat{\boldsymbol{R}}^{c s(k-1), p} \cdot \widetilde{\boldsymbol{y}}_{A}^{p} \cdot \boldsymbol{\theta}_{\epsilon}+\boldsymbol{e}_{A} . \tag{6.16b}
\end{align*}
$$

The measurement can be predicted from the state at instance $i$ using

$$
\begin{align*}
& \hat{\mathbf{z}}_{d V}=\boldsymbol{H}_{d V} \cdot \hat{\boldsymbol{x}}+\boldsymbol{e}_{d V}  \tag{6.16c}\\
& \mathbf{z}_{d V}=\delta \boldsymbol{y}_{A}^{c s(k-1)} \tag{6.16d}
\end{align*}
$$

$$
\text { where } \boldsymbol{H}_{d V}=\left[\begin{array}{lll}
-\widehat{\boldsymbol{R}}^{c s(k-1), p} \cdot & \widetilde{\boldsymbol{y}}_{A}^{p} & \mathbf{0}_{3} \tag{6.16e}
\end{array}\right] \text {. }
$$

In the above equations, $\mathbf{H}$ transforms the state vector to a measurement prediction $(\hat{\boldsymbol{z}})$, and $\boldsymbol{z}$ in (6.16d) denotes the actual measurement (Welch and Bishop, 2006). $\boldsymbol{e}_{d V}$ is the noise associated with this measurement.

When $\mathbf{H}$ is known from (6.16e), the Kalman gain can be estimated and applied to the KF using (Welch and Bishop, 2006):

$$
\begin{align*}
\boldsymbol{K}_{i} & =\boldsymbol{P}_{i}^{-} \cdot \boldsymbol{H}^{T}\left(\boldsymbol{H} \cdot \boldsymbol{P}_{i}^{-} \cdot \boldsymbol{H}^{T}+\boldsymbol{R}\right)^{-1}  \tag{6.17a}\\
\widehat{\boldsymbol{x}}_{i} & =\widehat{\boldsymbol{x}}_{i}^{-}+\boldsymbol{K}_{i} \cdot\left(\boldsymbol{z}_{i}-\boldsymbol{H} \cdot \widehat{\boldsymbol{x}}_{i}^{-}\right)  \tag{6.17b}\\
\boldsymbol{P}_{i} & =\left(\mathbf{I}-\boldsymbol{K}_{i} \cdot \boldsymbol{H}\right) \cdot \boldsymbol{P}_{i}^{-} \tag{6.17c}
\end{align*}
$$

The state matrix and the error covariance matrix were updated with (6.17b) and $(6.17 \mathrm{c})$ respectively.

## Update States

The orientation estimate and gyroscope bias were then updated. Singular value decomposition was used to maintain orthonormality of $\boldsymbol{R}_{i}^{c s(k-1), \text { seg }}$. The error state vector was reset for the next iteration using

$$
\begin{align*}
& \widehat{\boldsymbol{R}}_{i}^{c s(k-1), \text { seg }}=\widehat{\boldsymbol{R}}_{i}^{c s(k-1), \text { seg,- }} \cdot\left(\mathbf{I}-\widetilde{\boldsymbol{\theta}}_{\epsilon, i}\right)  \tag{6.18}\\
& \text { and } \widehat{\boldsymbol{b}}_{i}=\widehat{\boldsymbol{b}}_{i}^{-}+\boldsymbol{b}_{\epsilon, i} . \tag{6.19}
\end{align*}
$$

## Initialization

The initial orientation error $\hat{\boldsymbol{\theta}}_{\epsilon \text {,init }}$ was assumed to be zero, and the initial gyroscope bias error $\hat{\boldsymbol{b}}_{\epsilon, \text { init }}$ was estimated from gyroscope output while standing still. At the start of each step $k$, the $\boldsymbol{R}^{c s(k-1), s e g}$ is known from the previous step. This is described in Section 6.2.5 (Current Step Frame). However, an estimate of $\boldsymbol{R}_{\text {init }}^{c s(k-1) \text {,seg }}$ is needed for the first step ever made. For this, the EEKF is run once for a few steps with an arbitrary initial heading estimate. The change in position between the start and end of these steps was the X axis, and the Z axis was taken to be along the vertical. After estimating the

Y axis using cross product and updating the X axis using (6.3c), the initial $\boldsymbol{R}_{\text {init }}^{c s(k-1), \text { seg }}$ was estimated using (6.3e).

## Estimating Ground Reaction Forces

The accelerations measured at the pelvis IMU were transformed to the $\psi_{c s(k-1)}$ using the estimated $\widehat{\boldsymbol{R}}_{i}^{c s(k-1), p}$ for each step $k$. As these are assumed to be the same as the accelerations at the CoM, the GRF was estimated as the product of acceleration and body mass:

$$
\begin{equation*}
\boldsymbol{G R F} \boldsymbol{F}_{i}^{c s(k-1)}=\operatorname{mass} \cdot \widehat{\boldsymbol{R}}_{i}^{c s(k-1), p} \cdot \boldsymbol{y}_{A, i}^{p} . \tag{6.20}
\end{equation*}
$$

## Current Step Frame

The GRF has been expressed in the $\psi_{c s(k-1)}$, and has to be transformed to $\psi_{c s(k)}$ for the current step $k$. For this, the change in orientation of the feet as well as their positions need to be known. An Extended Kalman filter (EKF) (Weenk et al., 2015) was used to track the foot positions. The states of this EKF were the velocity and position of each foot. Strapdown inertial navigation was used to track these states, and ZV and ZH updates were used to improve these estimations. As we are only interested in the change in position for a given step, the state vector was reset to zero before the next step.

In order to define the $\psi_{c s}$ for each step, we use the information about foot movement. For example, in Fig. 6.1, the right foot changes direction while making the step $k$. The following equations were used to derive the $\psi_{c s}$ and subsequently express the GRF in the $\psi_{c s}$ frame:

$$
\begin{align*}
& \boldsymbol{M}=\left[\begin{array}{lll}
1 & 1 & 0
\end{array}\right] \cdot \mathbf{I}_{3 \times 3}  \tag{6.21a}\\
& \delta \boldsymbol{p o s}=\boldsymbol{M} \cdot\left(\boldsymbol{p o s}_{\text {end }}-\boldsymbol{p o s}_{\text {start }}\right)  \tag{6.21b}\\
& a x_{X}=\frac{\delta \boldsymbol{p o s}}{\|\delta \boldsymbol{p o s}\|}  \tag{6.21c}\\
& a x_{Z}=\left[\begin{array}{lll}
0 & 0 & 1
\end{array}\right]^{T}  \tag{6.21d}\\
& a x_{Z}=a x_{X} \times a x_{Y} \tag{6.21e}
\end{align*}
$$

$$
\begin{gather*}
\boldsymbol{R}_{k}^{c s(k), c s(k-1)}=\left[\begin{array}{lll}
a x_{X} & a x_{Y} & a x_{Z}
\end{array}\right]  \tag{6.21f}\\
\text { Finally, } \boldsymbol{G} \boldsymbol{R} \boldsymbol{F}^{c s(k)}=\boldsymbol{R}_{k}^{c s(k), c s(k-1)} \cdot\left(\boldsymbol{G} \boldsymbol{R} \boldsymbol{F}^{c s(k-1)}\right)_{k} \tag{6.21g}
\end{gather*}
$$

The change in position in the horizontal XY plane (6.21a, 6.21b) between the start and end of this step, shown by the dotted line in Fig. 6.1, was the X axis of the new $\psi_{c s}$ and was estimated from (6.21c). The vertical Z axis was defined as (6.21d). The Y axis of the pelvis was estimated using right hand thumb rule, as seen in (6.3d). The Z axis was then updated using (6.21e). The $\boldsymbol{R}_{k}^{c s(k), c s(k-1)}$ is given in (6.21f), which gives us the transformation to the new $\psi_{c s}$ for the step $k$. This was redefined for every new step being made, and then we transformed the $\boldsymbol{G} \boldsymbol{R} \boldsymbol{F}^{c s(k-1)}$ to the new $\psi_{c s(k)}$ using (6.21g).

## Estimating Noise values

The process and measurement noise were estimated from sensor specifications and static measurements. The measurement noise $\boldsymbol{e}_{d V}$ was fine-tuned manually by minimizing the root mean square of error between the $\boldsymbol{G} \boldsymbol{R} \boldsymbol{F}^{c s(k-1)}$ from ( 6.21 g ) and the reference GRF. The $\boldsymbol{e}_{d V}$ turned out to vary slightly for different trials across participants, and an average value is reported here. The resulting noise values are tabulated in Table 6.2.

## Filtering Estimated Ground Reaction Forces

The estimated 3D GRF was found to have certain sharp peaks around foot contact instances, possibly due to foot impact. Different methods to selectively remove these peaks were tested. This resulted in an adaptive peak removal algorithm. In this method, first, the peaks were identified by finding the local minima or maxima around the foot contact. Then, a Savitsky Golay smoothing filter (Orfanidis, 2010) of order 3 was used to smooth the signal around this peak and suppress it. Following this, a power spectral density analysis showed that each axis had different noise levels at different frequency bands. Therefore, a zero phase band pass Butterworth filter of order 4 and bandwidth of $0.1-5 \mathrm{~Hz}$ and $0.1-3 \mathrm{~Hz}$ was used for the X and Y axis respectively, in order to account for high frequency noise as well as any offset errors. However, the Z axis was filtered using a zero phase Butterworth low pass filter of order 4.

TABLE 6.2 Standard Deviations of the Gaussian Noises used.

| $\boldsymbol{e}_{G}$ | $\boldsymbol{e}_{b}$ | $\boldsymbol{e}_{d V}$ |
| :---: | :---: | :---: |
| $\mathrm{rad} / \mathrm{s}$ | $\mathrm{rad} / \mathrm{s}$ | $\mathrm{rad} / \mathrm{s}$ |
| $1 \cdot 10^{-2}$ | $1 \cdot 10^{-4}$ | $1 \cdot 10^{2}$ |

### 6.2.6. Measurement System

Three Xsens ${ }^{\text {TM }}$ MTw IMUs were used (Fig. 6.4). The MT Manager (version 4.8) software was used to read the data from the IMU wirelessly, sampled at 100 Hz .

The reference system seen in Fig. 6.4 was the ForceShoes ${ }^{\mathrm{TM}}$ which consists of 6 DoF Force and Moment sensor, and an IMU under each toe and heel of both feet (Veltink et al., 2005). It has been validated against force plates (AMTI®) for measurement of contact forces (Schepers et al., 2009). Although portable, it is bulky and not comfortable for every-day use (Liedtke et al., 2007). However, it is a good wearable reference system for this study. The data were sent wirelessly to a PC, sampled at 100 Hz . It was then low pass filtered twice at 10 Hz using a second order Butterworth filter to ensure zero-phase lag. The measured GRF on each foot was summed to obtain the total GRF, which reflected the accelerations at the CoM (Schepers et al., 2009). The GRF was then transformed to the $\psi_{c s}$ as defined in Section 6.2.5 (Current Step Frame).

### 6.2.7. Participants

Eight healthy participants were recruited for the study. The average and standard deviation of the height, weight, and age was $1.78 \pm 0.1 \mathrm{~m}, 76.4 \pm$ 12.5 kg , and $26.7 \pm 3.8$ years respectively. Six participants were male. Leg length was measured from the greater trochanter to the ground (Hof, 1996) and was $0.94 \pm 0.06 \mathrm{~m}$. All participants signed an informed consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethical Committee of the faculty.

### 6.2.8 Experimental Protocol

The participants began by standing still for a few seconds, following which they were asked to bend the trunk forward thrice. This was used to calibrate the sensor to segment orientation for the pelvis sensor as seen in (6.3b).


Figure 6.4 Three Xsens ${ }^{\text {TM }}$ IMUs (in orange) were used as part of the Portable Gait Lab. One was placed at the back of the pelvis using a strap and mounted on the sacrum at the midway point between the line connecting the left and right posterior superior iliac spine. The other two IMUs were placed on top of each foot on the midfoot region. The reference ForceShoes ${ }^{\mathrm{TM}}$ is seen in the right image which consists of 6 DoF Force and Moment sensors that measure ambulatory ground reaction forces.

The participants were then asked to perform variable gait starting with their feet placed parallel. Once the researcher gave the start sign, the participant walked along a given path. The time taken between start and stop of the walking was measured using a stopwatch. The following walking tasks were performed one after the other, with each task repeated four times:

- Normal Walk (NW): The participant was asked to walk at his preferred walking speed for 10 m .
- $\quad L$ Walk ( $L W$ ): The participant was asked to walk for 15 m and then turn $90^{\circ}$ to the right and walk for another 10 m .
- Slow Walk (SW): The participant was asked to walk at a slower pace. They were guided by the use of a metronome beating at 50 beats per minute. Each beat corresponded to a heel strike. This frequency was used so that the participants walked slower than $0.6 \mathrm{~m} / \mathrm{s}$.
- Walk and Turn (WT): The participant was asked to walk for 10 m and then turn and walk back to start position.
- Slalom Walk (SlW): The participant was asked to walk in a slalom pattern. In order to guide them, two pylons were placed on the floor. These were placed slightly away and on either sides of an imaginary line from start to end.
- Asymmetric Walk (AW): In this task, the participant was asked to walk in an asymmetric manner. The instruction given was to induce a stiff left knee and abduct the hip as much as possible on the right side.


### 6.2.9. Analysis of Results

First, an example of the estimations of GRF in 3D using the EEKF $\left(\boldsymbol{G R F} \boldsymbol{F}_{K F}\right)$ and that of the ForceShoes ${ }^{\text {TM }}\left(\boldsymbol{G R F}_{F S}\right)$ is shown in the current step frame $\psi_{c s}$. There were some noisy peaks in the $\boldsymbol{G R} \boldsymbol{F}_{K F}$, which were removed, and an example of the post processed results are displayed. Then, the root mean square of the differences between the post-processed instantaneous $\boldsymbol{G R} \boldsymbol{F}_{K F}$ and $\boldsymbol{G R} \boldsymbol{F}_{F S}$ were studied across different walking tasks. Following this, Pearson's correlations and its significance were analysed. The difference in the angle of estimated GRF vectors from the reference in the horizontal plane was also measured. All analyses were done in MATLAB® ${ }^{\circledR}$ 2018b (MathWorks, Natick, MA, USA).

### 6.3. RESULTS

Some trials were excluded from the analysis due to issues with the reference system. However, each participant had at least three walking trials per task. The average walking speed measured for the included trials of NW task was $1.01 \pm 0.12 \mathrm{~m} / \mathrm{s}$, LW was $1.14 \pm 0.14 \mathrm{~m} / \mathrm{s}$, SW was $0.47 \pm 0.07 \mathrm{~m} / \mathrm{s}$, WT was 0.98 $\pm 0.19 \mathrm{~m} / \mathrm{s}$, during SlW was $0.89 \pm 0.11 \mathrm{~m} / \mathrm{s}$, and during AW was $0.52 \pm 0.17 \mathrm{~m} / \mathrm{s}$.

An example of the estimated $\boldsymbol{G R} \boldsymbol{F}_{K F}$ in the current step frame $\psi_{c s}$ is seen in Fig. 6.5, along with the reference $\boldsymbol{G R F} \boldsymbol{F}_{F S}$. The figure is a five second snapshot of the walking trajectory. It shows peaks in $\boldsymbol{G R F}_{K F}$ specifically around foot contact. They were removed using the method described in Section 6.2.5 (Filtering Estimated Ground Reaction Forces) and this results in Fig. 6.6. Note that Fig. 6.6 shows the complete LW task, including the starting and stopping of the task, and also turning.

In Table 6.3, we compare the post-processed instantaneous $\boldsymbol{G R F}_{K F}$ and reference $\boldsymbol{G R F}_{F S}$, for all walking tasks. The table shows the Root Mean Square (RMS) of differences as a percentage of body weight, correlations (CORR), and also differences in 2D GRF vector angle in the XY plane $\left(\theta_{d}\right)$ between the $\boldsymbol{G R F}_{K F}$ and $\boldsymbol{G R} \boldsymbol{F}_{F S}$. The average RMS and CORR across all participants
are displayed along with their standard deviations. The range of the GRF for the respective axes is also provided in the table. The CORR was found to be significant for all walking tasks.

### 6.4. DISCUSSION

This study is the first to estimate 3D GRF over a complete gait using a pelvis IMU for different gait patterns. It has to be noted that the foot IMUs were not used to estimate the 3D GRF during gait, rather they were used to estimate the current step frames per step. Using a changing frame has two advantages. First, it provides a user centric expression of the kinetics convenient for real time gait assessment. Secondly, they could also be compared with similar estimations made by the reference ForceShoes ${ }^{\mathrm{TM}}$. Nevertheless, it is possible to estimate the changing reference frame using only the pelvis IMU. For this, first, gait events should be detected using the measurements of the pelvis IMU (Pacini Panebianco et al., 2018). Then, during each gait cycle, the change in CoM positions can be estimated using strapdown integration with arbitrary initial and final values (Floor-Westerdijk et al., 2012; Zok et al., 2004). The change in CoM positions would be the X axis, and the vertical would define the Z axis of this new changing reference frame mentioned in Section 6.2.1.

Estimations of the shear GRF are the most challenging using the single IMU approach (Ancillao et al., 2018; Shahabpoor and Pavic, 2018). This is due to the large contribution of gravity, and the assumption that CoM lies at the centre of the pelvis. The EEKF was tuned to be able to resolve the accelerations measured at the pelvis into 3D components of the GRF within the current step frame $\psi_{c s}$. Assuming that the CoM accelerations along the vertical measured inclination due to gravity seemed to be a sufficient measurement update. However, the resulting GRF was found to have high frequency noise in the three axes. Additionally, there were peaks seen during foot impact, as shown in Fig. 6.5. These peaks during foot contact could be due to impact impulse, or soft tissue artefacts, or that the CoM accelerations deviate further from the measured pelvis accelerations. These peaks were more conspicuous in the Y or the medio-lateral axis.

Chapter 6

Figure 6.5 Snapshot of the estimated 3D GRF displayed in current step frame $\psi_{C S}$ for the L Walk. Each row corresponds to one of the 3D components of GRF. The blue line is the $\boldsymbol{G} \boldsymbol{R} \boldsymbol{F}_{K F}$ from the three IMU setup and dotted red line shows the reference $\boldsymbol{G} \boldsymbol{R} \boldsymbol{F}_{F S}$. Dotted horizontal yellow and brown lines denote the left and right foot contact, respectively. Peaks in the estimated GRF around the foot contact instances are seen which are very prominent in the Y axis. The forces were normalised to the body weight of the participant. Each row in the figure corresponds to an axis in $\psi_{C S}$.

Table 6.3 Comparing the Estimated and Reference GRF values: Root Mean Square of the Differences (RMS), Correlations (CORR), and Difference in 2D GRF Vector Angle in the XY Plane $\left(\theta_{d}\right)$.

|  | $\begin{gathered} \boldsymbol{R M S}_{X} \\ (\min , \max ) \\ \text { \% BW } \end{gathered}$ | $\begin{gathered} \boldsymbol{R M S}_{Y} \\ (\min , \max ) \\ \text { \% BW } \end{gathered}$ | $\begin{gathered} \boldsymbol{R M S}_{Z} \\ (\min , \max ) \\ \text { \% BW } \end{gathered}$ | $\mathrm{CORR}_{X}$ | $\mathrm{CORR}_{Y}$ | $\mathrm{CORR}_{Z}$ | $\theta_{d}(\mathrm{deg})$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NW | $\begin{gathered} 4.8 \pm 0.7 \\ (-32.3,28.5) \\ \hline \end{gathered}$ | $\begin{gathered} 4.8 \pm 0.5 \\ (-12.7,15.2) \\ \hline \end{gathered}$ | $\begin{gathered} 6.5 \pm 1.2 \\ (72.1,133.4) \\ \hline \end{gathered}$ | $0.89 \pm 0.1^{*}$ | $0.55 \pm 0.1^{*}$ | $0.80 \pm 0.1^{*}$ | $40.8 \pm 6.1$ |
| LW | $\begin{gathered} 7.3 \pm 1.5 \\ (-38.9,33.5) \end{gathered}$ | $\begin{gathered} 6.6 \pm 0.8 \\ (-24.1,19.5) \end{gathered}$ | $\begin{gathered} 7.2 \pm 1.7 \\ (66.1,136.6) \\ \hline \end{gathered}$ | $0.84 \pm 0 .{ }^{*}$ | $0.45 \pm 0.1^{*}$ | $0.89 \pm 0.1^{*}$ | $39.6 \pm 9$ |
| SW | $\begin{gathered} 5.1 \pm 1.1 \\ (-25.8,23.3) \end{gathered}$ | $\begin{gathered} 4.2 \pm 0.8 \\ (-13.2,15.4) \\ \hline \end{gathered}$ | $\begin{gathered} 4.6 \pm 1.7 \\ (84.7,124.2) \\ \hline \end{gathered}$ | $0.72 \pm 0.2$ * | $0.51 \pm 0.2^{*}$ | $0.55 \pm 0.2$ * | $48.8 \pm 13.6$ |
| WT | $\begin{gathered} 5.6 \pm 1.4 \\ (-36.2,30.4) \end{gathered}$ | $\begin{gathered} 5.5 \pm 0.8 \\ (-15.8,18.3) \end{gathered}$ | $\begin{gathered} 5.3 \pm 1.2 \\ (71.3,135.5) \end{gathered}$ | $0.81 \pm 0.1^{*}$ | $0.37 \pm 0.2^{*}$ | $0.85 \pm 0.1^{*}$ | $51.2 \pm 10$ |
| SIW | $\begin{gathered} 7.4 \pm 2.3 \\ (-34.2,32.1) \end{gathered}$ | $\begin{gathered} 7.4 \pm 1.4 \\ (-28.4,28.4) \\ \hline \end{gathered}$ | $\begin{gathered} 6.8 \pm 1.7 \\ (72.4,135.3) \end{gathered}$ | $0.70 \pm 0.1^{*}$ | $0.48 \pm 0.1^{*}$ | $0.82 \pm 0.1^{*}$ | $56.4 \pm 10.6$ |
| AW | $\begin{gathered} 6.5 \pm 1.7 \\ (-31.2,23.2) \\ \hline \end{gathered}$ | $\begin{gathered} 5.9 \pm 1.0 \\ (-19.3,18.4) \\ \hline \end{gathered}$ | $\begin{gathered} 5.7 \pm 1.2 \\ (76.8,143.4) \end{gathered}$ | $0.56 \pm 0.3^{*}$ | $0.30 \pm 0.3^{*}$ | $0.75 \pm 0.2^{*}$ | $63.8 \pm 20.8$ |

* $p<0.01$. NW: Normal Walk, LW: LWalk, SW: Slow Walk, WT: Walk and Turn, SIW: Slalom Walk, AW: Asymmetrical Walk. (min, max) corresponds to the minimum and maximum values measured by the reference system.

Therefore, to improve the estimations, adaptive peak removal and filtering methods were applied. Fig. 6.6 shows the post processed output of the $\boldsymbol{G R} \boldsymbol{F}_{K F}$ and the reference $\boldsymbol{G R F}_{F S}$ for the LW task. Here, the participant was asked to make a right turn, and the moment this occurs is denoted by a shaded rectangle. We see that after the turn, the X and Y axis measure the anterioposterior and medio-lateral GRF respectively, similar to that before the turn. As the frame used here is defined by the direction of steps being made, the profiles of $F_{x}$ and $F_{y}$ remain unchanged after the turn. However, if a fixed global frame denoted as $\psi_{g}$ in Fig. 6.1 was used, the axes would have been interchanged. Thus, the $\psi_{c s(k)}$ represents the biomechanics of the body irrespective of the change in walking direction. Fig. 6.1 also shows that the error is relatively larger for the $F_{y}$, and more so during the right turn.

Table 6.3 shows that the RMS between the $\boldsymbol{G R F F}_{K F}$ and the reference $\boldsymbol{G R} \boldsymbol{F}_{F S}$ is quite low, less than $7.4 \pm 2.3 \%$ of body weight in the worst case. On average, the normalized root mean square error expressed as percent of range of the reference measurement (NRMSE) was $12.1 \pm 3.3 \%$ for the horizontal plane, which is better than previous studies (Gurchiek et al., 2017). It is similar to findings of Leporace and colleagues (Leporace et al., 2015) who found an average NRMSE of $9.3 \pm 6.4 \%$ in the horizontal plane. They employed a shank IMU and single multilayer perceptron to obtain the 3D GRF. However, comparing only the vertical, we found that the average NRMSE across different walking tasks was $10.2 \pm 1.2 \%$ as compared to $4.2 \pm 1.1 \%$ found by Shahabpoor and colleagues (Shahabpoor and Pavic, 2018). The reference study was able to obtain a better estimation of the vertical GRF for each gait cycle using a dynamic time warping method. On the other hand, in spite of a larger error margin, the current study estimated the instantaneous GRF during the complete gait, including starting and stopping of walking.

Table 6.3 also allows comparison with the actual range of the GRF measured using the reference system. This shows that the errors in Y axis are relatively larger compared to that of the other axes. We find that the correlations were highest for the X and Z axis, except for Z axis of SW task. The AW task shows least correlations as compared to the other walking tasks. This task was meant to simulate impaired gait and is not a standardized test. Though, the participants were given instructions to walk asymmetrically, each of them chose a unique pattern. However, the results show that the algorithm can
be used to measure 3D GRF in a simulated asymmetric gait. Additionally, $\theta_{d}$ shows quite some differences in the XY plane, which could be attributed to the low correlations in the Y axis.

The errors seen in Table 6.3 could be caused by differences in transforming the $\boldsymbol{G R} \boldsymbol{F}_{K F}$ and the reference $\boldsymbol{G R} \boldsymbol{F}_{F S}$ to their respective $\psi_{c s(k)}$ frames. One source of difference is that the IMUs used in this study were placed on top of the mid-foot, whereas the ForceShoes ${ }^{\text {TM }}$ had IMUs under the toe region. Also, the reference system used the forces measured by the ForceShoes ${ }^{\text {TM }}$ to determine foot contact. In the IMU only setup, some approximations were required for the true instances of foot contact.

Each step was first expressed in the previous step frame before transforming it to the $\psi_{c s}$. Alternatively, they could have been estimated in the global frame $\psi_{g}$, and then transformed to the $\psi_{c s}$. However, as the rotation between the $\psi_{c s}$ of each subsequent step is known, the GRF can be expressed in the current step frame of any specific step $m$ of choice. This may be used to visualize changes in shear forces between subsequent steps.

## Limitations and Future Work

The GRF estimated in this study is the sum of the GRF acting under both feet. If required, a smooth transition assumption could be used to resolve the 3D GRF into forces acting under each foot (Karatsidis et al., 2016). In this study, the IMU was placed at the pelvis, which is less susceptible to orientation or placement errors (Tan et al., 2019), when compared to the trunk. Furthermore, the errors associated with the assumption that the CoM lies within the centroid of the pelvis might be larger when we consider people with an unconventional or asymmetrical body posture. Modelling deviations between the true CoM and the placement of the IMU would help improve the results (Floor-Westerdijk et al., 2012). The participant was asked to bend forward to calibrate a sensor to segment orientation for the pelvis sensor. However, this could be avoided by exploring simpler calibration methods based on the user's daily life functional movements, such as squatting or sit to stand. The algorithm needs to be run with an arbitrary initialization before it can converge to the optimal solution. In actual practice, this means that the participant has to make a few physical steps before output is produced.

As Xsens ${ }^{\mathrm{TM}}$ IMUs were used, well defined error specifications were available to initialise the EEKF. Further, the three IMUs were synchronized well. Any mismatch would have caused errors in the estimation of the current step frames, which would be reflected in the estimated GRF. Therefore, good communication protocols are required. Furthermore, identifying foot contact using IMU signals (Skog et al., 2010) might be susceptible to errors. As we are interested at instances where the foot is completely still, we opted to use the midpoint of the foot contact. However, gait event detection can be further improved using other techniques (Pacini Panebianco et al., 2018).

The setup has to be further validated in other variable walking instances such as walking on an incline or stair climbing. The AW task performed in this study may not be similar to gait patterns exhibited by gait impaired populations. The same argument holds for rapid walking or running scenarios. Therefore, a similar experiment shown in this study for gait impaired populations and other gait variations must be performed as a follow up. Finally, the measurements were done when no external loads were acting on the body. Modelling an external load is not trivial, and its contribution to the GRF has to be measured with additional sensors.

As a next step, the 3D components of GRF can be used to estimate the interfoot distances during gait (Chapter V, Equations (5.6) and (5.7)) following a Centroidal Moment Pivot assumption. This can reduce drift when using a three IMU setup to track the feet and CoM over time, and also during variable gait. Thus, the findings of this article can be useful to estimate relative foot positions. This will be described in Chapter IX.

### 6.5. CONCLUSIONS

We show how to monitor 3D GRF in an ambulatory manner using a pelvis IMU. Foot IMUs were used to express the measured GRF with respect to the moving and turning body. The steps made for this study are useful for developing a minimized and portable gait lab.

# Portable Gait Lab: Estimating 3D Ground Reaction Forces Using Only a Pelvis IMU 

"One child, one teacher, one book, one pen can change the world." Malala Yousafzai, I am Malala

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#### Abstract

As an alternative to force plates, an Inertial Measurement Unit (IMU) at the pelvis can offer an ambulatory method for measuring total Centre of Mass (CoM) accelerations and, thereby, the Ground Reaction Forces (GRF) during gait. The challenge here is to estimate the 3D components of the GRF. We employ a calibration procedure and an error state extended Kalman filter based on Chapter VI to estimate the instantaneous 3D GRF for different over-ground walking patterns. The GRF were then expressed in a body-centric reference frame defined using only the information from the pelvis IMU, to enable an ambulatory setup not related to a fixed global frame. The results were validated with Forceshoes ${ }^{\mathrm{TM}}$, and the average error in estimating instantaneous shear GRF was $5.2 \pm 0.5 \%$ of body weight across different variable over-ground walking tasks. The study shows that a single pelvis IMU can measure 3D GRF in a minimal and ambulatory manner during over-ground gait.


### 7.1. INTRODUCTION

Measuring kinetics of gait such as 3D Ground Reaction Forces (GRF) includes estimating the vertical and shear forces acting on the body during gait. The total GRF acting on the body, and its derived parameters related to the Centre of Mass (CoM) such as dynamic balance and stability measures (van Meulen et al., 2016c), can be helpful in understanding gait quality (Bruijn and van Dieën, 2018). Therefore, measuring GRF is useful in studying healthy gait, as well as sports biomechanics (Komaris et al., 2019; Wouda et al., 2018) and recovery in gait impaired populations (van Meulen et al., 2016c).

Unfortunately, the reliable estimation of GRF requires expensive measurement setups such as force plates. These may be installed under the floor or incorporated into treadmills. In either case, they either measure limited strides or restrict the movement space of the participant. It is therefore useful to explore wearable setups that allow freedom of movement, while providing reliable estimates of the GRF during gait or variable walking. Wearable alternatives (Chen et al., 2016) to these restricted laboratory setups include systems such as Forceshoes ${ }^{\mathrm{TM}}$ (Schepers et al., 2009) and pressure insoles (Chapter IV), although each of them are associated with their respective drawbacks. Forceshoes ${ }^{\mathrm{TM}}$ are bulky (Liedtke et al., 2007), and pressure insoles require additional analytical or machine-learning-based models to extract the 3D GRF (Chapter IV) (Forner Cordero et al., 2004).

Assuming a simple inverted pendulum gait model, GRF can be considered equal and opposite to the weight plus mass times linear accelerations at the $\mathrm{CoM}\left(\mathrm{CoM}_{\text {acc }}\right)$ (Hof et al., 2005), given no additional external forces are present. Therefore, if we can measure the $\mathrm{CoM}_{\mathrm{acc}}$, we can estimate the GRF. Note that here, the GRF are the sum of all forces acting on the body, which is the sum of reactive forces at both feet, provided no additional contact with the environment. As Inertial Measurement Units (IMUs) measure accelerations of the segment they are attached to, the GRF acting on the body can be estimated either using a biomechanical model (Chapter VI) (Karatsidis et al., 2016) or machine learning techniques (Ancillao et al., 2018; Komaris et al., 2019; Revi et al., 2020). Ancillao and colleagues (Ancillao et al., 2018) summarize several of these methods and find that they either estimate only the vertical GRF using
a minimal setup or estimate the shear forces using machine learning methods or an array of several IMUs. The drawback of using machine learning methods includes the need for a representative training dataset. A minimal set of IMUs, combined with biomechanical models of gait is, therefore, a preferred setup for ambulatory sensing of 3D GRF.

In the previous chapter (Chapter VI), we estimated the instantaneous 3D GRF during over-ground gait using a pelvis IMU expressed in a body-centric frame. We first identified the pelvis segment frame $\left(\psi_{p}\right)$ using a bowing calibration method (Bonnet et al., 2009). Assuming that the CoM is encompassed within the pelvis, an Error Extended Kalman Filter (EEKF) was designed to track the change in orientation of the $\mathrm{CoM}_{\mathrm{acc}}$ during each step. IMUs placed on either foot were used to detect gait events and, additionally, provide the bodycentric frame of reference. The heading for the reference frame was estimated using the movement of the feet, thereby avoiding the use of magnetometers. This avoids the handling of distortions induced due to measurement of magnetic field (Fan et al., 2018). The body-centric frame provides a first person perspective, irrespective of the measurement setup, and thereby a functional representation of the gait, unlike a fixed global frame (Rebula et al., 2013). The average error across all walking tasks was $6 \pm 1 \%$ Body Weight (BW). In Chapter VI, although 3D GRF were estimated using the pelvis IMU, the estimation of the body-centric frame $\left(\psi_{c s}\right)$ required the use of foot IMUs. An ideal next step would be to estimate a body-centric frame using the pelvis IMU instead of the foot IMUs, in order to enable a minimal wearable setup.

Therefore, in this study, our goal is to use a pelvis IMU to measure 3D GRF during over-ground gait and express it in a body-centric frame also defined using the pelvis IMU. Ergo, we first estimate 3D GRF using methods from Chapter VI, and additionally, detect gait events, and a body-centric reference frame using information from the pelvis IMU. Different methods can be employed to estimate the heading for a body-centric frame using a pelvis IMU. For instance, the heading of the frame could be defined along the average pelvis acceleration over a few steps. However, validating this approach with reference setups is non-trivial. Change in CoM position could be used to define the heading, but it requires deriving the position from pelvis accelerations while correcting for drift, thereby introducing additional complexities. In this study, the heading of the body-centric frame was estimated using the
direction of the high frequency CoM velocity $\left(\mathrm{CoM}_{\text {vel }}\right)$. This approach was easier to validate with reference setups and less complex compared to the other approaches. The estimations of 3D GRF were then validated using reference setups and results from Chapter VI and literature.

### 7.2. MATERIALS AND METHODS

In this section, we first show the estimation of gait events using a pelvis IMU in Section 7.2.1, following which, we define the body-centric reference frame in Section 7.2.2. Then, in Section 7.2 .3 we summarize the method used to estimate the GRF from the pelvis IMU. In Section 7.2.4, we describe the measurement setup and then the experimental protocol in Section 7.2.5. Finally, Section 7.2 .6 summarizes the analysis that will be performed on the data.

### 7.2.1 Initial Contact Detection

Studies have investigated heuristic approaches to detect gait events using only a pelvis IMU (González et al., 2010; Hyo-Ki Lee et al., 2009; Pacini Panebianco et al., 2018; Sabatini et al., 2005). We employ a simple approach using the accelerations measured in the pelvis frame $\left(\psi_{p}\right)$. The $\psi_{p}$ frame was estimated from a forward bowing calibration method (Chapter VI). A second order zero phase Butterworth filter of cut off 2 Hz was used to low pass filter the sensor accelerations, which were transformed to $\psi_{p}$. The magnitude of the resulting signal was de-trended, and the peaks in the signal, which had a prominent height of at least $0.2 \mathrm{~m} / \mathrm{s}^{2}$, were considered to be Initial Contact (IC) moments. Subsequently, we defined a step as the instance between two ICs.

### 7.2.2 Reference Frames Used

Here, we describe the definition of the body-centric frame. This frame is referred to in this study as the IC frame $\psi_{i c}$. The $\psi_{i c}$ frame is similar to the current step frame $\psi_{c s}$ (Chapter VI), but relies only on information from the pelvis IMU. Fig. 7.1 graphically defines the IC frame $\psi_{i c}$. The heading of the $\psi_{i c}$ frame was defined using the direction of $\mathrm{CoM}_{\text {vel }}$ estimated from the pelvis IMU during a step. The X axis of this frame is positive in the forward direction, and the Z axis lies along the vertical. The $\psi_{i c}$ was redefined per step, and the 3D GRF were transformed to this frame.

## Chapter 7



Figure 7.1 Graphical interpretation of the reference frames. The left foot is light blue, and the centre of mass (CoM) trajectory is the thin grey line. Instead of a fixed global frame $\psi_{g}$, an initial contact frame $\psi_{i c(k)}$, which depends on the direction of the CoM velocity vector in step $k$, is employed.

The steps required to estimate the $\psi_{i c}$ are shown in Fig. 7.2. Table 7.1 lists the different notations employed in this study. The pelvis IMU measures accelerations $\left(\boldsymbol{y}_{A}^{S}\right)$ and angular velocities $\left(\mathbf{y}_{G}^{S}\right)$ in the sensor frame $\psi_{s}$. As mentioned earlier, the data were transformed to the pelvis frame $\psi_{p}$, which was defined using the bowing calibration method (Chapter VI). Then, during step $k$, an EEKF was designed to track the change in orientation $\left(\mathbf{R}_{i}^{i c(k-1), p}\right)$ of the pelvis with respect to a predefined frame $\psi_{i c(k-1)}$ for a given sample $i$. This EEKF is described in detail in Chapter VI. The states tracked by the filter were orientation error $\boldsymbol{\theta}_{\epsilon}$ and gyroscope bias error $\mathbf{b}_{\epsilon}$. The change in orientation was first tracked with respect to a previous step $k-1$, and then, using the change in orientation in step $k$, the current IC frame $\psi_{i c(k)}$ was estimated. The orientation estimated by integrating the angular velocity was corrected by inclination information derived from the accelerometer. The $\mathbf{R}_{i}^{i c(k-1), p}$ was estimated using (Weenk et al., 2015):

$$
\begin{equation*}
\hat{\mathbf{R}}_{i}^{i c(k-1), p}=\hat{\mathbf{R}}_{i}^{i c(k-1), p,-}\left(\mathbf{I}-\tilde{\boldsymbol{\theta}}_{\epsilon}\right) \tag{7.1}
\end{equation*}
$$

We assumed the initial orientation error $\hat{\boldsymbol{\theta}}_{\epsilon \text {,init }}$ to be zero. The initial gyroscope bias error $\hat{\mathbf{b}}_{\epsilon \text {,init }}$ was measured from gyroscope data when the participants were standing still. Note that $\mathbf{R}^{i c(k-1), p}$ is known at the beginning of each step $k$, as it would have been estimated using the EEKF in the previous step. However, an estimate of $\mathbf{R}_{\text {init }}^{i c(k-1), p}$ is needed for the first step ever made.

For this, the EEKF is run once for a few steps with an arbitrary initial heading estimate. After this, the change in orientation was used to estimate $\mathbf{R}_{\text {init }}^{i c(k-1), p}$ using methods in Chapter VI.


Figure 7.2 Overview of the method used to estimated 3D Ground Reaction Forces (GRF): the error extended Kalman filter (Chapter VI) tracks the orientation error $\boldsymbol{\theta}_{\epsilon}$ and gyroscope bias error $\mathbf{b}_{\epsilon}$, to estimate the $\mathbf{R}_{i}^{i c(k-1), p}$ for each step. Then, $\mathbf{R}_{\text {step }}^{i c(k), i c(k-1)}$ was estimated using the direction of CoM velocity.

Table 7.1 Notations used, shown for an arbitrary vector $\boldsymbol{a}$.

| Notation | Definition |
| :--- | :--- |
| $\boldsymbol{a}_{k}$ | $\boldsymbol{a}$ at k-th instant |
| $\boldsymbol{a}^{S}$ | $\boldsymbol{a}$ expressed in frame $\psi_{S}$ |
| $\dot{\boldsymbol{a}}$ | derivative of $\boldsymbol{a}$ |
| $\hat{\boldsymbol{a}}$ | a posteriori estimate of $\boldsymbol{a}$ |
| $\boldsymbol{a}^{-}$ | a priori estimate of $\boldsymbol{a}$ |
| $\tilde{\boldsymbol{a}}$ | skew symmetric operator on $\boldsymbol{a}$ |
| $\boldsymbol{e}_{\boldsymbol{a}}$ | Gaussian white noise associated with $\boldsymbol{a}$ |

In the following equations, we describe how the $\psi_{i c}$ frame is defined for each step:

$$
\begin{align*}
& \boldsymbol{y}_{A, i}^{i c(k-1)}=\widehat{\mathbf{R}}_{i}^{i c(k-1), p} \cdot \boldsymbol{y}_{A, i}^{p}  \tag{7.2}\\
& X=\frac{\mathbf{C o M}_{v e l, m}}{\left\|\mathbf{C o M}_{v e l, m}\right\|}  \tag{7.3}\\
& Z=\left[\begin{array}{lll}
0 & 0 & 1
\end{array}\right]^{T}  \tag{7.4}\\
& \mathbf{R}_{k}^{i c(k), i c(k-1)}=\left[\begin{array}{lll}
X & Z \times X & Z
\end{array}\right] \tag{7.5}
\end{align*}
$$

Pelvis accelerations in each step are first expressed in $\psi_{i c(k-1)}(7.2)$ as $\boldsymbol{y}_{A}^{i c(k-1)}$ and must be transformed to $\psi_{i c(k)}$. Using arbitrary initial and final conditions, $\boldsymbol{y}_{A}^{i c(k-1)}$ was high-pass filtered using a second order zero phase Butterworth filter with a cut off of 2 Hz to obtain the high frequency $\mathrm{CoM}_{\text {vel }}$. Then, during step $k$, the time instance $m$ was selected when the magnitude of $\mathrm{CoM}_{\text {vel }}$ vector was highest in the XY plane. At this time, instance $m$, the direction of the velocity vector in the XY plane, was defined using (7.3) below. This was the heading or X axis for $\psi_{i c(k)}$. After assuming that the Z axis lies along the vertical in (7.4), the $\mathbf{R}_{k}^{i c(k), i c(k-1)}$ was determined in (7.5). This was redefined for each step, resulting in a $\psi_{i c(s t e p)}$ per step. Note that, in this study, a step is the instance between subsequent ICs.

### 7.2.3 Estimating Ground Reaction Forces

The accelerations $\boldsymbol{y}_{A}^{i c(k-1)}$ in frame $\psi_{i c(k-1)}$ from (7.2) were transformed to the frame $\psi_{i c(k)}$ using $\mathbf{R}_{k}^{i c(k), i c(k-1)}$ per step $k$ as:

$$
\begin{align*}
& \boldsymbol{y}_{A, i}^{i c(k)}=\mathbf{R}_{k}^{i c(k), i c(k-1)} \cdot \boldsymbol{y}_{A, i}^{i c(k-1)}  \tag{7.6}\\
& \mathbf{G R F}_{A, i}^{i c(k)}=\operatorname{mass} \cdot \boldsymbol{y}_{A, i}^{i c(k)} . \tag{7.7}
\end{align*}
$$

As we assume the pelvis accelerations to be similar to $\mathrm{CoM}_{\mathrm{acc}}$, the GRF ( $\mathbf{G R F}_{\mathrm{IM}}$ ) were estimated using Newton's second law (7.7). During preliminary analysis, we identified sharp peaks around the IC instances, possibly due to impact in the estimated 3D GRF. An adaptive peak removal algorithm was employed to remove these peaks (Chapter VI). The peaks around an IC were first


Figure 7.3 The image on the left shows the placement of the Xsens ${ }^{\mathrm{TM}} \mathrm{MTw}$ Inertial Measurement Unit (IMU) at the lower back of the participant. The sensor frame $\psi_{s}$ of the IMU is also shown. The right image is a simplified overview of the experimental protocol. The participants stand still for a few seconds, following which they bow thrice, and then perform the walking task. After this, they bow again and stand still for a few seconds before the measurement is stopped. The bowing movement is used to determine the pelvis frame $\psi_{p}$ seen in the figure.
identified by detecting the local maxima and minima. Then, the signal in this region around the peak was smoothened using a Savitsky Golay smoothing filter (Orfanidis, 2010) of order 3. Following this, a second order zero phase Butterworth band pass filter with a cut off range of $0.1-5 \mathrm{~Hz}$ and $0.1-3 \mathrm{~Hz}$ was used to filter the X and Y axis, respectively. For the Z axis, a second order zero phase Butterworth low pass filter with a cut off of 10 Hz was employed.

### 7.2.4 Measurement System

Fig. 7.3 shows the sensor setup; a single Xsens ${ }^{\mathrm{TM}}$ MTw IMU was placed at the lower back on the pelvis. The data from the IMU were read using an MT Manager (version 4.8) software (Xsens ${ }^{\mathrm{TM}}$, Enschede, Netherlands) at 100 Hz . We employed two reference systems in this study. The ForceShoes ${ }^{\mathrm{TM}}$ (Xsens ${ }^{\mathrm{TM}}$, Enschede, Netherlands), consisting of two 6DoF Force and Moment sensors per foot, was used for validating the estimation of GRF. IC instances were determined when the magnitude of GRF on each foot exceeded 30 N . The GRF on both feet were summed to obtain the total reference GRF $\left(\mathbf{G R F}_{\mathrm{FS}}\right)$, which is equal and opposite to the body weight plus mass times $\mathrm{CoM}_{\text {acc }}$ (Schepers et al., 2009).

The frame $\psi_{i c}$ for the IMU-based system was defined using (7.2) - (7.5). Similarly, we need to determine the frame $\psi_{i c}$ for the reference datasets. For this purpose, we measured the kinematics of CoM using a VICON© (Oxford

Metrics PLC., Oxford, UK) motion capture system. Markers were placed on the right anterior superior iliac spine, right posterior iliac spine, left anterior superior iliac spine, and left posterior iliac spine. We assumed that the position of the CoM was at the centroid of the pelvis, demarcated by the four pelvis markers. Velocities and accelerations of the CoM were obtained using differentiation and subsequent low pass filtering with a second order zero phase Butterworth filter of cut off 10 Hz . Then, gravitational acceleration was added to the Z axis of the accelerations to obtain the $\mathrm{CoM}_{\text {acc }}$. A second order zero phase Butterworth high-pass filter with cut off of 2 Hz was used to obtain the $\mathrm{CoM}_{\text {vel }}$. The direction of the velocity vector in the XY plane was used to transform the reference $\mathbf{G R F}_{\mathrm{FS}}$ to the frame $\psi_{\text {ic }}$ using the steps defined in Section 7.2.2. Thus, we estimate the acceleration from the VICON® position data, and then integrate it after including gravitational acceleration to obtain the high frequency $\mathrm{CoM}_{\text {vel }}$, in order to make sure that our reference $\psi_{i c}$ frame was estimated in a similar manner as the IMU-based system.

The data from VICON© and ForceShoes ${ }^{\text {TM }}$ were sampled at 100 Hz . The data from Xsens ${ }^{\text {TM }}$ IMU, ForceShoes ${ }^{\text {TM }}$, and VICON© were synchronized. The participants raised their right foot before each task, and this movement was used for the synchronization of the three systems.

### 7.2.5 Participants and Experimental Protocol

Three healthy male participants were recruited for the study. The average height, weight, and age was $1.8 \pm 0.04 \mathrm{~m}, 74.3 \pm 7.6 \mathrm{~kg}$, and $25.6 \pm 3.3$ years, respectively. Before the experiment, each participant signed an informed consent. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethical Committee of the research faculty under protocol number RP 2019-108.

The experimental protocol is shown in Fig. 7.3. The participants began by standing still for a few seconds, following which they were asked to bend the trunk forward thrice. This movement is used for the calibration. Once the researcher gave the start sign, the participant performed each of the following walking tasks four times:

- Normal Walk (NW): the participants walked at their preferred walking speed for 5 m .
- $L$ Walk ( $L W$ ): the participants walked for 3 m and then turned $90^{\circ}$ to the right, and walked for 2 m .
- Walk and Turn (WT): the participants walked for 5 m , and then turned and walked back to start position.
- Walk and Turn Twice (WT2): the participants walked for 5 m , turned and walked back to start position, and then turned again and walked for 5 m .
- Slalom Walk (SlW): the participants walked in a snake-like slalom pattern. A pylon was placed at 2 m and another at 4 m to help them with this pattern.


### 7.2.6 Analysis of Results

First, we validated the estimation of IC instances using the information from the pelvis IMU. Then, we evaluated the differences in heading $\left(\theta_{d}\right)$ between the $\psi_{i c}$ frames defined using the pelvis IMU, and that of the reference setup. This was estimated by measuring the angle between the heading vectors used to define the $\psi_{i c}$ frames. Following this, we test the accuracy of our method in estimating 3D GRF using different analyses. This includes measuring the Root Mean Square (RMS) of the differences and Pearson's correlations (CORR) between the estimated 3D GRF ( $\mathbf{G R F}_{\text {IM }}$ ) from the pelvis IMU and the reference $\mathbf{G R F}_{\mathrm{FS}}$ for the different walking tasks. A Bland-Altman analysis was also performed. MATLAB® 2018b (MathWorks, Natick, MA, USA) was used for all analyses.

### 7.3. RESULTS

Some trials had to be excluded from the analysis due to technical issues with the reference system. However, it was made sure that each participant had at least three walking trials per task.

Fig. 7.4 compares the $\mathbf{G R F}_{\text {IM }}$ and $\mathbf{G R F}_{\text {FS }}$ for a participant performing a WT trial. Table 7.2 summarizes the results of the analysis and compares the method against reference setups for each walking task. First, the average mean error in estimating IC instances per task is summarized in the column IC. Based on preliminary comparison with reference values, the estimated IC instances were adjusted for a uniform offset of 0.08 s for all trials.


Figure 7.4 Estimated ( $\mathbf{G R F}_{\mathrm{IM}}$ ) and reference GRF ( $\mathbf{G R F}_{\mathrm{FS}}$ ) compared for a Walk and Turn (WT) task shown as \% BW. The participant makes a $180^{\circ}$ around 25 s highlighted with the shaded region. The $\mathbf{G R F}_{\mathrm{IM}}$ is shown in blue and $\mathbf{G R F}_{\mathrm{FS}}$ is shown in red. The difference between them for each axis is shown in black, with the reading on the right Y axis.

Using our simplified approach, the average median error in estimating IC was found to be $2 \pm 4.4 \mathrm{~ms}$ across all walking tasks. Table 7.2 also shows the average heading error $\theta_{d}$ for the $\psi_{i c}$ frames, excluding the first and last steps made. We see that the NW task has the highest errors with respect to estimation of IC, and therefore, the $\theta_{d}$, as the $\psi_{i c}$ frames are identified between ICs. Then, Table 7.2 summarizes the errors in estimating the 3D GRF over the complete gait, including quiet standing, gait initiation, turning events, and termination. The RMS values shown in the table are an average of all trials of all participants for each walking task. The maximum RMS across all axes was found to be 5.7, $6,6.8,7.2$, and $5.8 \%$ BW for the NW, LW, WT, WT2, and SIW walking tasks, respectively. The average RMS of the magnitude of the GRF was $5 \pm 0.4 \%$ BW across all walking tasks. The WT2 task showed a slightly larger error across the XY plane, probably because it had more changes in heading. The RMS errors Normalized (NRMSE) against the range of the reference GRF values were found to be $16.3 \pm 1.7 \%$ across all walking tasks. We found an average CORR of $0.5 \pm 0.2$ for the shear GRF, and a higher correlation of $0.8 \pm 0.03$ in estimating vertical GRF. We estimated the RMS and correlation between the measurements for the complete gait cycle.

Fig. 7.5 shows the Bland-Altman plot comparing the magnitude of the estimated shear GRF (GRF in the XY plane) from GRF $_{\mathrm{IM}}$ with the reference

GRF $_{\mathrm{FS}}$. The values for magnitude of shear GRF were not normally distributed. Therefore, the mean difference is shown along with the Interquartile Ranges (IQR) in the figure. The mean difference between the systems is on average $0.24 \%$ BW across all tasks. We see a concentration of differences for mean shear GRF values close to $0 \% \mathrm{BW}$. The difference between the systems becomes more random as the mean magnitude of shear GRF increases. Fig. 7.6 depicts the Bland-Altman comparison for the estimation of vertical GRF. Here, the average of the mean difference across all walking tasks was found to be $-2.7 \%$ BW. In this figure, we find a concentration of the difference spread across the vertical GRF close to $100 \%$ BW. For other values of vertical GRF, the difference is spread randomly. Note that $0 \%$ BW and $100 \%$ BW are the GRF values during no-motion for the shear GRF and vertical GRF, respectively. Hence, they show larger concentrations of the difference between systems.

### 7.4. DISCUSSION

The methods used in this study to estimate 3D GRF are similar to Chapter VI. Here, we additionally describe how to estimate gait events, and the bodycentric initial contact frame using the pelvis IMU, thereby avoiding the need for foot IMUs. This enables development of a minimal sensing system for 3D GRF during gait. The method has been applied to a limited set of participants, but a range of variable walking tasks, and shows the estimation of 3D GRF during the complete gait trial, including gait initiation, walking, and termination.

A number of assumptions have been made in this study. We assume an inverted pendulum model of gait, where the CoM is the swinging bob. We also assumed that the CoM moves within the pelvis, and that the accelerations can be measured with a pelvis IMU. The GRF opposes gravity and accelerates the CoM. Our methods are restricted to situations when only the feet are in contact with the environment. Our methods estimate the total GRF acting on the body, and therefore, we do not measure how the weight shifts from one foot to another. The only gait events estimated were the IC instances. There are several methods in literature for estimating ICs using one pelvis IMU (Pacini Panebianco et al., 2018). Our average median error in estimating IC was found to be similar to the results found using the method of Lee and colleagues (HyoKi Lee et al., 2009; Pacini Panebianco et al., 2018), which was 2 ms .

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Table 7.2 Differences between IMU-based GRF $_{\text {IM }}$ and reference ForceShoes ${ }^{\text {TM }}$-based GRF $_{\text {FS }}$ : Initial Contact (IC) estimation, heading differences $\left(\theta_{d}\right)$, Root Mean Square of the differences (RMS), and Pearson's correlations (CORR).

| --- | IC (ms) | $\theta_{d}$ (deg) | $\mathrm{RMS}_{\mathrm{x}}$ (\%) | $\mathrm{RMS}_{\mathrm{Y}}$ (\%) | $\mathrm{RMS}_{\mathrm{z}}$ (\%) | $\mathrm{CORR}_{\mathrm{x}}$ | $\mathrm{CORR}_{\mathrm{Y}}$ | $\mathrm{CORR}_{\mathrm{z}}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NW | 20 | $18.33 \pm 8.57$ | $4.47 \pm 1.42$ | $4.38 \pm 1.17$ | $5.14 \pm 0.89$ | $0.68 \pm 0.24$ * | $0.29 \pm 0.21$ * | $0.73 \pm 0.11$ * |
| LW | 0.21 | $16.89 \pm 9.52$ | $5.42 \pm 1.35$ | $4.86 \pm 1.04$ | $5.02 \pm 0.85$ | $0.66 \pm 0.14$ * | $0.40 \pm 0.14$ * | $0.81 \pm 0.06$ * |
| WT | 1.35 | $13.11 \pm 9.60$ | $5.55 \pm 1.50$ | $4.72 \pm 2.16$ | $5.46 \pm 1.46$ | $0.64 \pm 0.25$ * | $0.46 \pm 0.34$ * | $0.79 \pm 0.05$ * |
| WT2 | 2.12 | $12.97 \pm 6.96$ | $6.92 \pm 1.89$ | $5.02 \pm 1.33$ | $5.54 \pm 0.84$ | $0.61 \pm 0.19$ * | $0.50 \pm 0.16$ * | $0.82 \pm 0.04$ * |
| SIW | -0.49 | $7.83 \pm 6.47$ | $5.50 \pm 0.94$ | $5.00 \pm 0.57$ | $4.38 \pm 1.13$ | $0.56 \pm 0.08$ * | $0.43 \pm 0.05$ * | $0.81 \pm 0.04$ * |

All values are an average of the three participants that were tested. The RMS is expressed in \% BW. NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SIW: Slalom Walk. *All correlations were found to be significant ( $p<0.01$ ).


Figure 7.5 Bland-Altman plots: The magnitude of the shear GRF is compared between the reference $\mathbf{G R F}_{\mathrm{FS}}$ and estimated $\mathbf{G R F}_{\mathrm{IM}}$. The mean shear GRF of the two systems are plotted along the X axis, and the difference between them is shown along the Y axis. All data are in \% BW. The mean of the differences is shown by a thick black line. The data were not normally distributed, and the Interquartile Ranges (IQR) are shown by dotted black lines. The values of mean and the IQR are also shown in the graph. NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SIW: Slalom Walk.


Figure 7.6 Bland-Altman plots: The magnitude of the vertical GRF is compared between the reference $\mathbf{G R F}_{\mathrm{FS}}$ and estimated $\mathbf{G R F}_{\mathrm{IM}}$. The mean vertical GRF of the two systems are plotted along the X axis, and the difference between them is shown along the Y axis. All data are in \% BW. The mean of the differences is shown by a thick black line. The data were not normally distributed, and the Interquartile Ranges (IQR) are shown by dotted black lines. The values of mean and the IQR are also shown in the graph. NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SlW: Slalom Walk.

Although we found one walking trial where our IMU-based method estimated an additional IC instance, our method is much simpler to that of Lee and colleagues (Hyo-Ki Lee et al., 2009). Our largest error was found for the NW task, which was 20 ms . Nonetheless, the robustness of IC detection may be improved with alternatives in literature (Pacini Panebianco et al., 2018). Our algorithm does not differentiate between left and right ICs, as that information was not required in this study. Differentiating left and right gait events from pelvis IMU data is challenging, but possible (Pacini Panebianco et al., 2018). The estimation of the heading for the $\psi_{i c}$ frame may be further improved with this knowledge, especially when measuring asymmetrical gait such as hemiparesis after stroke. During asymmetrical gait, it might be necessary to distinguish turning from asymmetrical inclination of the body towards the less affected side, while defining the heading for the for the $\psi_{i c}$ frame. In Table 7.2, we find larger errors in the heading $\left(\theta_{d}\right)$ for the NW task. This could be influenced by the larger mismatch in IC instances, which in turn, has an influence on the selection of time window for the steps. The $\psi_{i c}$ frame is a reference frame attached to the body, thereby tracking its kinetics irrespective of the change in direction. The use of such a reference frame avoids the need to correct for drift with respect to a fixed global frame. Our magnetometer free approach is insensitive to magnetic disturbances, which is an additional advantage.

Ancillao and colleagues (Ancillao et al., 2018) mentioned that the most challenging task when using IMUs to estimate GRF is determining the shear GRF; the anterio-posterior and medio-lateral components. As we assume that the CoM is located within the pelvis, its accelerations are estimated using the pelvis IMU. The estimation of $\mathrm{CoM}_{\text {acc }}$ from the pelvis IMU in the anterio-posterior, medio-lateral, and vertical axes by the EEKF serves as the largest influence of errors. The estimation of $\mathrm{CoM}_{\text {acc }}$ could be improved using additional biomechanical models (Floor-Westerdijk et al., 2012). Nevertheless, our results show that it is possible to estimate GRF using a single pelvis IMU. For instance, in Fig. 7.4 we see overlap between $\mathbf{G R F}_{\mathrm{IM}}$ and $\mathbf{G R F}_{\mathrm{FS}}$ for the complete gait cycle. Table 7.2 summarizes the errors in estimating the 3D GRF for the complete walking tasks, from start to stop. The WT2 task showed a slightly larger error across the XY plane, probably because it had more changes in heading. The average NRMSE of $16.3 \pm 1.7 \%$ for all walking
tasks is slightly larger than our previous study (Chapter VI), where we found an average NRMSE of $12.1 \pm 3.3 \%$, and also that of Leporace and colleagues (Leporace et al., 2015) who found an average of $9.3 \pm 6.4 \%$ in the horizontal plane. The $\mathbf{G R F}_{\mathrm{IM}}$ correlated strongly with the reference in the vertical axis due to the large influence of gravity and correlated weakly in the Y axis because of larger errors in this axis. We found all CORR to be significant ( $p<0.01$ ). Our average CORR for the vertical GRF is close to the results of Jiang and colleagues (Jiang et al., 2020), in which an array of IMU sensors were used to estimate only the vertical GRF with an average RMS of $2 \%$ BW and high correlations of 1. Nevertheless, our method offers an estimation of 3D GRF albeit with slightly larger errors.

The low number of participants and the low variability in age and gender are limitations. Our calibration method requires a bowing movement, which might be difficult for participants with back issues. Nevertheless, this paper presents a new method to estimate the 3D GRF as a function of time in a body-centric frame employing a single pelvis IMU, and thus offers a proof of principle of this new method. Finally, using simple models (Karatsidis et al., 2016; Ren et al., 2008), and knowledge of distinct left and right gait events (Pacini Panebianco et al., 2018), the 3D GRF may also be separated into GRF acting on either foot.

### 7.5. CONCLUSIONS

The study shows the feasibility of using a single pelvis IMU to track the 3D GRF during over-ground gait and expressing it in a body-centric initial contact reference frame. The shear GRF were estimated with a root mean square error of $5.2 \pm 0.5 \%$ BW over the complete gait cycle including initiation and termination of gait. Though these margins are comparable with the literature, further validation studies in which more participants, including those with gait impairment, are required. Furthermore, more variable walking must be studied.

# Portable Gait Lab: Instantaneous centre of mass velocity using three IMUs 

"Sometimes all it takes is a tiny shift of perspective to see something familiar in a totally new light."<br>Dan Brown, The Lost Symbol

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#### Abstract

Estimating instantaneous 3D Centre of Mass (CoM) velocity using wearables can improve ambulatory gait monitoring. Inertial Measurement Units (IMUs) are commonly used to estimate CoM velocity, although, studies have either measured only the magnitude, or use machine learning methods. Here, we propose a three IMU setup, where the CoM velocity is obtained by a complementary filter method. This method fuses high frequency information achieved using strapdown integration of accelerations measured at the pelvis with low frequency information of CoM velocity obtained from foot velocities. This method is applied in variable gait which includes turns. The root mean square of the error between the IMU estimated CoM velocity against a reference VICON® measurement was $0.1 \pm 0.02 \mathrm{~m} / \mathrm{s}$ across all walking tasks. This method provides a drift free ambulatory estimation of CoM velocity using minimal IMUs.


### 8.1. INTRODUCTION

Estimation of the Centre of Mass (CoM) velocity has several practical applications, including measuring gait parameters, and balance measures such as Extrapolated CoM (XCoM) (van Meulen et al., 2016c). Inertial Measurement units (IMUs) offer solutions for ambulatory estimation of CoM velocity (Mannini and Sabatini, 2014; Sabatini and Mannini, 2016). However, so far, studies have either measured the magnitude of CoM velocity (Mannini and Sabatini, 2014), or used machine learning techniques (Sabatini and Mannini, 2016) which require additional training.

Here, we propose a setup of three IMUs for estimating the CoM velocity; one IMU at the pelvis, and one on each foot. Information about CoM velocity is extracted from the movement of the pelvis and feet, and are fused using a complementary filter method (Sabatini and Mannini, 2016; Schepers et al., 2009), resulting in drift free instantaneous estimation of 3D CoM velocity. The following sections describe the methods used to obtain the instantaneous 3D CoM velocity in a special current step frame ( $\psi_{c s}$ ) (Chapter VI), and describes the performance of the method in variable over ground gait.

### 8.2. METHODS

First, Section 8.2.1 provides a brief overview of reference frames used in this study as already described in Chapter VI. Cyclical changes in CoM velocity was obtained by integrating pelvis accelerations and high pass filtering the output (Mannini and Sabatini, 2014; Sabatini and Mannini, 2016). Furthermore, average movement of the feet encode information about the CoM velocity. These two sources of CoM velocity can be fused using a complementary filter method. Here we assume that gait is modelled as an inverted pendulum, with the pelvis IMU accelerations measuring the CoM accelerations. Section 8.2 .2 shows the method used for strapdown integration of CoM accelerations. Following this, Section 8.2.3 explains the estimations of an average CoM velocity from foot velocities, and the fusion of the two information sources. Section 8.2.4 describes the measurement system used and the participants involved, and Section 8.2.5 describes the experimental protocol used to validate this study.


Figure 8.1 Graphical interpretation of the frames. The left foot is light blue, and the CoM trajectory is the thin grey line. Instead of a fixed global frame $\psi_{g}$, a current step frame of reference $\psi_{c s(k)}$ is used for step $k$ which changes for each step. The frame is defined using the movement of the feet. Segment frames used are $\psi_{f l}$ and $\psi_{f r}$ for foot frames, and for the pelvis frame.

### 8.2.1. Using a Current Step Frame $\psi_{c s}$

In this study, instead of a fixed global frame, a changing reference frame was employed. The body-centric current step frame, $\psi_{c s}$, was defined using the change in foot positions per step (Chapter VI). A graphical depiction is shown in Fig. 8.1. Fig. 8.2 summarizes the estimation of $\mathbf{R}_{k}^{c s(k), c s(k-1)}$ for the pelvis IMU. The steps are explained in detail in Chapter VI. To transform from sensor frame to current step frame makes, first a calibration to segment frame is performed (Bonnet et al., 2009). Then, an Error Extended Kalman Filter (EEKF) was employed to track the changes in orientation during the step. At the end of the step, using the change in swing foot position in the horizontal floor plane as the heading, and Z axis along the vertical, a $\psi_{c s(k)}$ of the current step $k$ was defined.

### 8.2.2. CoM velocity using strapdown integration

As seen in Fig. 8.2, gravity was removed from CoM accelerations in $\psi_{c s(k)}$ $\left(a c c^{c s(k)}\right)$, and then strapdown integrated using the Direct and Reverse Integration method (DRI) (Zok et al., 2004) to obtain velocity $V C O M_{\text {sdi }}$. The velocities at the beginning and end of trial were set to 0 , as required by the DRI method. $V C O M_{s d i}$ is a time varying velocity estimate with drift that accumulates over time. Therefore, a high pass 2nd order zero phase Butterworth filter was applied to obtain the $V C O M_{h f}$.


Figure 8.2 Estimating instantaneous CoM velocity $\left(V C O M_{e s t}\right)$ : First, the $\psi_{C S}$ is estimated from foot movement (Chapter VI), and all data is expressed in this frame. Pelvis accelerations (acc ${ }^{C S(k)}$ ) are integrated after removing gravity, and high pass filtered to obtain $V C O M_{h f}$. This is fused with a low pass filtered $\left(V C O M_{l f .}\right)$ average velocity of the feet using a complementary filter method.

### 8.2.3. CoM velocity from foot velocities

A low frequency estimate of the CoM velocity can be approximated from averaging the foot velocities. Drift free foot velocity estimates were obtained using an extended Kalman Filter and zero velocity constraints (Weenk et al., 2015). As seen in Fig. 8.2, the velocities of both feet ( $v e l_{f l}$ and $v e l_{f r}$ ) were averaged. A low pass 2nd order zero phase Butterworth filter was applied to obtain the $V C O M_{l f}$.

In order to employ a complementary filter (Schepers et al., 2009), the cut off frequencies used for the high pass filter of $V C O M_{h f}$ and low pass filter of $V C O M_{l f}$ were the same. After a preliminary analysis, the optimal values were found to be $0.5,0.2$, and 1.4 Hz for $\mathrm{X}, \mathrm{Y}$, and Z axes respectively. The $V C O M_{h f}$ and $V C O M_{l f}$ were then fused to obtain the instantaneous $V C O M_{\text {est }}$.

### 8.2.4. Measurement System and Participants

Three IMUs were used: One Xsens ${ }^{\text {TM }}$ IMU was mounted on the sacrum using a strap, and one was placed on each foot on the midfoot region (Chapter VI).

A MT Manager was used to read the data from the IMU wirelessly, which was sampled at 100 Hz . A VICON© (Oxford Metrics PLC.) motion capture system was used as the reference. Markers were placed on the following locations on both the left and right limbs: anterior superior iliac spine, posterior iliac spine, the second and fifth metatarsal, and heel. The VICON© was sampled at 100 Hz .

The CoM position obtained from VICON© $\left(P C O M_{r e f}\right)$ was assumed to lie at the centroid of the pelvis markers. The $P C O M_{r e f}$ was differentiated and low pass filtered with a 2nd order zero phase Butterworth filter with cut off 10 Hz to obtain the $V C O M_{r e f}$. These were transformed to the $\psi_{c s(k)}$, determined independently using the foot position data of the VICON©.

Walking data was collected from trials by three healthy males. The mean height, weight, and age was $1.74 \pm 3 \mathrm{~m}, 79.3 \pm 9 \mathrm{~kg}$, and $25 \pm 3.5$ years respectively. Leg length was $94 \pm 3 \mathrm{~cm}$ (Hof, 1996). All participants signed an informed consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethical Committee of the faculty.

### 8.2.5. Experimental Protocol

The participants began by standing still for a few seconds, following which they were asked to bend the trunk forward thrice. Once the researcher gave the start sign, the participant walked along a given path. The following walking tasks were each repeated four times:

- Normal Walk (NW): The participant was asked to walk at their preferred walking speed for 5 m .
- $\quad L$ Walk (LW): The participant was asked to walk for 3 m and then turn right at $90^{\circ}$ and walk for another 2 m .
- Walk and Turn (WT): The participant was asked to walk for 5 m and then turn and walk back to start position.
- Walk and Turn Twice (WT2): The participant performed WT and then asked to turn and walk for 5 m .
- Slalom Walk (SlW): The participant was asked to walk in a slalom pattern. Two pylons, at 2 m and 4 m from start respectively, were placed on the floor to guide them.
- Asymmetric Walk (AW): The participant was asked to walk in an asymmetric manner. The instruction given was to induce a stiff left knee and abduct the hip as much as possible, and also have a shorter step on the right side.


### 8.3. RESULTS

Fig. 8.3 shows an example of $V C O M_{h f}$ and $V C O M_{l f}$ for the WT2 task. Following this, Fig. 8.4 shows an example of the estimated instantaneous $V C O M_{\text {est }}$ (blue line) compared with the reference $V C O M_{r e f}$ (red line). Here, we also depict the strapdown integrated $V C O M_{s d i}$ (thin black line), which is seen to clearly drift. Table 8.1 compares the average root mean square of the error between the $V C O M_{\text {est }}$ and $V C O M_{r e f}$ across all participants for different walking tasks as both absolute, and percentage error normalized to the range of $V C O M_{r e f}$.


Figure 8.3 Comparing the high frequency $V C O M_{h f}$ in blue and low frequency $V C O M_{l f}$ in red for a WT2 task performed by a participant where they make two $180^{\circ}$ turns. The complete gait including the initiation, termination, and turning (shaded as red regions) is shown. Each subplot corresponds to an axis of the $\psi_{c s(k)}$.


Figure 8.4 Comparing the estimated $V C O M_{e s t}$ (blue line) and $V C O M_{s d i}$ (thin black line) and $V C O M_{r e f}$ (red line) for the WT2 task performed by a participant where they make two $180^{\circ}$ turns. The complete gait including the initiation, termination, and turning (shaded as red regions) is shown. Each subplot corresponds to an axis of the $\psi_{c s(k)}$.

Table 8.1 Absolute and percentage root mean square error between $V C O M_{\text {est }}$ and $V C O M_{r e f}$.

|  | $\boldsymbol{R M S}_{\boldsymbol{X}}$ |  | $\boldsymbol{R M S} \boldsymbol{S}_{\boldsymbol{Y}}$ |  | $\boldsymbol{R M S}_{\boldsymbol{Z}}$ |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\mathrm{m} / \mathbf{s}$ | $\%$ | $\mathbf{m} / \mathbf{s}$ | $\%$ | $\mathbf{m} / \mathbf{s}$ | $\%$ |
| NW | $0.1 \pm 0.03$ | $12.2 \pm 3.1$ | $0.1 \pm 0.02$ | $13.9 \pm 4.2$ | $0.1 \pm 0.01$ | $11.6 \pm 5.3$ |
| LW | $0.1 \pm 0.01$ | $9.0 \pm 1.4$ | $0.2 \pm 0.05$ | $15.0 \pm 2.6$ | $0.1 \pm 0.01$ | $12.0 \pm 2.8$ |
| WT | $0.1 \pm 0.04$ | $10.1 \pm 2.6$ | $0.2 \pm 0.02$ | $14.4 \pm 2.3$ | $0.1 \pm 0.01$ | $12.3 \pm 3.0$ |
| WT2 | $0.2 \pm 0.04$ | $11.5 \pm 1.8$ | $0.2 \pm 0.07$ | $11.9 \pm 2.0$ | $0.1 \pm 0.02$ | $12.1 \pm 2.8$ |
| SIW | $0.1 \pm 0.02$ | $12.8 \pm 3.5$ | $0.2 \pm 0.01$ | $18.6 \pm 1.3$ | $0.1 \pm 0.01$ | $18.9 \pm 6.1$ |
| AW | $0.1 \pm 0.02$ | $12.2 \pm 6.7$ | $0.1 \pm 0.02$ | $13.4 \pm 3.3$ | $0.1 \pm 0.02$ | $15.7 \pm 2.2$ |

NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SlW: Slalom Walk, AW: Asymmetrical Walk.

### 8.4. DISCUSSION

The current method shows the feasibility of estimating 3D CoM velocity during variable gait. Although, the complementary method is similar to Sabatini and colleagues (Sabatini and Mannini, 2016), they used machine learning
to estimate the average CoM velocity. Our approach discards the need for a training step by including the foot IMUs. Note that the use of foot IMUs is two-fold: for defining the $\psi_{c s(k)}$ as well as obtaining a low frequency CoM velocity information. Fig. 8.3 shows the complementary information present in the $V C O M_{h f}$ and $V C O M_{l f .} V C O M_{l f}$ derived from the foot velocities encodes the trend and $V C O M_{h f}$ has information regarding a drift free change in this trend. In Fig. 8.3 and 8.4, the kinematics are expressed in $\psi_{c s}$, and hence, the velocities remain positive in the X axis even as the participant makes two $180^{\circ}$ turns, during the shaded regions. Note that in Fig. 8.4, the drift in the vertical $V C O M_{s d i}$ is quite limited compared to the other axes, but exists, as evident during the last few steps. Further, the $V C O M_{r e f}$ shows more drastic jumps during the turns, as compared to $V C O M_{e s t}$, more clearly seen in the Y axis due to transformation to the $\psi_{c s}$. As we account for the $\mathbf{R}_{k}^{c s(k), c s(k-1)}$ per step $k$, we can represent the kinematics in a fixed global frame, or the frame of any other required step.

Table 8.1 shows that the errors are on average $13.1 \pm 2.2 \%$ of the range of CoM velocity across all axes and walking tasks. The errors seem to be largest for the SlW task, as the gait was always changing direction. The error margins are quite low overall, about less than $19 \%$ of the range in the worst case. The algorithm has lower errors for variable walking when compared to the results of Sabatini and colleagues (Sabatini and Mannini, 2016). The applicability of the method however, would be dependent on the application, and proposed error margins. Note that the cut offs used in the complementary filter was optimized across all participants. The errors found could be further lowered if this was optimized per participant. A drawback of this method is that it employs a DRI method for integration, which requires knowledge of the final state of the velocities.

A three IMU setup can provide a minimal sensing setup for drift free estimates of CoM velocity. This can further improve estimates of the position of CoM, and XCoM.

# Portable Gait Lab: Tracking Relative Distances of Feet and CoM using three IMUs 

"Step with care and great tact.<br>And remember that life's<br>A Great Balancing Act."<br>Dr. Seuss, Oh, The Places You'll Go

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#### Abstract

Ambulatory estimation of gait and balance parameters requires knowledge of relative feet and Centre of Mass (CoM) positions. Inertial Measurement Units (IMUs) placed on each foot, and on the pelvis are useful in tracking these segments over time but cannot track the relative distances between these segments. Further, drift due to strapdown inertial navigation results in erroneous relative estimates of feet and CoM positions after a few steps. In this study, we track the relative distances using the assumptions of the Centroidal Moment Pivot (CMP) point. A Kalman filter approach was used to fuse information from different sources: strapdown inertial navigation, commonly used constraints such as zero velocity updates, and relative segment distances from the CMP assumption; to eventually track relative feet and CoM positions. These estimates were expressed in a reference frame defined by the heading of each step. The validity of this approach was tested on variable gait. The step lengths and step widths were estimated with an average absolute error of $4.6 \pm 1.5 \mathrm{~cm}$ and $3.8 \pm 1.5 \mathrm{~cm}$ respectively when compared against the reference VICON®. Additionally, we validated the relative distances of the feet and the CoM, and further, show that the approach proves useful in identifying asymmetric gait patterns. We conclude that a three IMU approach is feasible as a portable gait lab for ambulatory measurement of foot and CoM positions in daily life.


### 9.1. INTRODUCTION

Gait kinematics and kinetics are necessary for assessing spatiotemporal as well as qualitative metrics such as Base of Support (BoS), and Margin of Stability (MoS), that are useful in assessing dynamic balance (van Meulen et al., 2016b). Ambulatory assessment of these parameters helps us understand gait biomechanics outside the restricted laboratory environment, providing potential applications in daily life monitoring.

A minimal approach using only Inertial Measurement Units (IMUs) has great benefits in being portable. They are suitable for measuring kinematics of any rigid body segment they are attached to using strapdown inertial navigation. However, this introduces errors in the position estimates. Further, IMUs do not track relative distances from nearby body segments. This results in erroneous estimates of relative distances of segments over time. There are different solutions to solve this issue of drift between two segments. For instance, Xsens ${ }^{\text {TM }}$ offers a full body suit of IMUs that employ a biomechanical chain (Roetenberg et al., 2009) to track movement of associated body segments. This requires setting up a lot of IMUs and initializing a few biomechanical parameters. Alternatively, specially designed systems such as the ForceShoes ${ }^{\mathrm{TM}}$ (Weenk et al., 2015), and SWING (Bertuletti et al., 2019) use time of flight information from ultrasound or infrared respectively, to measure the relative distance between the feet. Unfortunately, the ForceShoes ${ }^{\text {TM }}$ is quite thick and heavy, and not suited for daily wear (van Meulen et al., 2016b). Also, additional sensors require extra calibration and synchronisation steps for reliable monitoring.

A minimal three IMU setup, where one IMU is placed on each foot and one on the pelvis is an ideal setup for ambulatory monitoring. However, this may be insufficient for measuring relative foot and pelvis positions, owing to the issue of drift described earlier. Some studies solve this by using mathematical constraints that prevents drift between the feet (Niu et al., 2019; Skog et al., 2012). However, these may not reflect the true foot positions during continuous tracking, or in cases of an asymmetric gait. Other studies use biomechanical constraints related to the pattern of gait. Bancroft and colleagues (Bancroft et al., 2008) use information about stride length, and a difference in vector
between foot positions to reduce the drift. Zhao and colleagues (Zhao et al., 2018) use a derivation of step length from information about limb sway for this purpose. In both cases, approximations have been made regarding a general pattern of gait cycle. Sy and colleagues (Sy et al., 2020) show that using an extended set of biomechanical constraints can help estimate kinematics from a reduced sensor setup, but they assume a fixed pelvis, and do not comment on relative segment distances.

The Centroidal Moment Pivot (CMP) point could serve as a realistic biomechanical principle that relates the movement of the CoM with the stance foot. Assuming an inverted pendulum model of gait, for normal, levelground human walking, the moments around the CoM can be assumed to be zero (Popovic et al., 2005; Schepers et al., 2009). This implies that the whole body Ground Reaction Force (GRF) and a vector connecting the virtual CMP point and CoM are parallel. This gives us a relation between the virtual CMP point and CoM, and that of the GRF as described in Chapter V. For an IMU based approach, the virtual CMP point can be assumed to be the same as foot position. Additionally, estimations of the shear GRF and the height of the CoM are required (Chapter V). Using the pelvis IMU, we already estimated the 3D GRF in Chapter VI, and the height of the CoM can be tracked by adapting existing methods in literature (Floor-Westerdijk et al., 2012; Zok et al., 2004).

The goal of this study is to track the relative positions of the feet and CoM using only three IMUs and a Kalman Filter (KF) approach. For this, first, the foot trajectories were estimated from the foot IMUs using strapdown integration, improved by zero velocity and zero height updates (Weenk et al., 2015). Then, the 3D instantaneous estimates of GRF, CoM velocity (as described in Chapter VIII), and height (Zok et al., 2004) were estimated from the pelvis IMU. 3D GRF and CoM height were used to solve the CMP equation, and derive relative positions between the feet and CoM. These positions were used to reduce the drift between the feet and CoM. The proposed algorithm was tested for variable gait patterns. The resulting kinematics were expressed in a body-centric frame of reference or current step frame (Chapter VI), and compared with reference systems.

### 9.2. METHODS

Here, the methods used to track the kinematics of feet and CoM are further explained. First, in Section 9.2.1, we briefly explain the reference frames used in this study. Next, Section 9.2.2 describes the IMU models used. In Section 9.2.3, the design of the KF for the tracking is described. Section 9.2.4 describes the measurement systems used, and Sections 9.2 .5 and 9.2 .6 describe the participant group, and the experimental protocol used to obtain measurements and validate this study respectively. Finally, Section 9.2.7 explains how the results were analysed.

### 9.2.1. Reference Frames used

A changing reference frame as explained in Chapter VI was used to express the kinematics in this study. This allows us to provide a body-centric frame of expression, as opposed to an arbitrary global frame used commonly. A detailed description of the different frames used and the transformations between them are given in our earlier Chapter VI. Here, we summarize them briefly.

The changing reference frame was based on the direction of steps being made and will be referred to as the current step frame, denoted as $\psi_{c s}$. In Fig. 6.1 (Chapter VI), an example of $\psi_{c s}$ for the step $k$ made by the right leg is shown. The frame was defined with the X axis along the heading of the step (bold dotted line in Fig. 6.1) and Z along the vertical.

As the IMU measures in its sensor frames, $\psi_{s}$, it has to be transformed to the $\psi_{c s}$ per step. First, a sensor to segment calibration was performed to the respective segment (seg) frames $\psi_{\text {seg }}$ (Chapter VI). The segments included the pelvis $(p)$, left foot ( $f l$ ), and the right foot ( $f r$ ). Then, the change in orientation of the segments during a step $k$ was first expressed in the current step frame $\psi_{c s(k-1)}$ of the previous step $k-1$. The change in orientation was estimated using an error extended Kalman filter. At the end of the step $k$, using the change in position of the swing foot the $\psi_{c s(k)}$ was estimated. This procedure was iterated for each step.

In short, four frames of reference were used in this study: sensor frame $\left(\psi_{s}\right)$, segment frames (pelvis $\psi_{p}$, right foot $\psi_{f r}$ and left foot $\psi_{f l}$ ), a current step frame defined by the previous step $\left(\psi_{c s(k-1)}\right)$, and the current step $k\left(\psi_{c s(k)}\right)$.

### 9.2.2. Inertial Measurement Unit Model

Similar to (6.1) and (6.2) in Chapter VI, the 3D accelerometer and 3D rate gyroscope present in the IMU provides the acceleration and angular velocities in the sensor frame $\psi_{s}$ respectively, and can be modelled as

$$
\begin{array}{r}
\boldsymbol{y}_{A}^{s}=\boldsymbol{a}^{s}-\mathbf{g}^{s}+\boldsymbol{e}_{A} \\
\text { and } \boldsymbol{y}_{G}^{S}=\boldsymbol{\omega}^{s}+\boldsymbol{b}^{s}+\boldsymbol{e}_{G} \tag{9.2}
\end{array}
$$

where $\boldsymbol{y}_{A}^{s}$, and $\boldsymbol{y}_{G}^{s}$ denote the accelerometer and gyroscope signals respectively from the IMU. They are measured in the $\psi_{s}$ reference frame denoted by the superscript $s . \boldsymbol{a}$ is the linear acceleration of the sensor, $\mathbf{g}$ is gravity, and $\boldsymbol{e}_{A}$ is Gaussian white noise. Also, $\boldsymbol{\omega}$ is the angular velocity, $\boldsymbol{b}$ is a slowly varying offset, and $\boldsymbol{e}_{G}$ is the Gaussian noise. Both (9.1) and (9.2) are discrete time equations and are expressed for a given time instance $i$.

### 9.2.3. Fusion filter to track relative feet and CoM positions

Fig. 9.1 shows a brief overview of the steps involved. There are a few working assumptions we need to consider. We assumed an inverted pendulum model of gait where all mass is concentrated at the CoM that is located within the pelvis (Floor-Westerdijk et al., 2012; Schepers et al., 2009). Thus, the GRF accelerates the CoM and opposes gravity. These assumptions should hold as long as the participant walks normally and doesn't fall or negotiate large obstacles. Additionally, the feet are the only contact with the external world, and no additional load is carried by the body. Given these assumptions, the accelerations measured by the IMU at the pelvis is similar to the accelerations at the CoM. Thereby, the pelvis segment ( $p$ ) will be hereto referred as the CoM (c).

The method of Skog and colleagues (Skog et al., 2010) was used to estimate the foot contact instances for each foot. As the IMUs were synchronized in time, double stance instances can be estimated. Though, distinct gait events


Figure 9.1 Overview of Sensor fusion filter design. For each step the process model and measurement models are fused using a Kalman Filter. Biomechanical constraints applied as measurement updates include Zero Velocity (ZV), Zero Height (ZH), CoM Velocity (CV), CoM Height (CH), and Centroidal Moment Pivot (CMP).
can be estimated from foot IMUs (Pacini Panebianco et al., 2018), for sake of simplicity, a step was defined to take place between halfway of a double stance until halfway of the subsequent double stance.

Table 9.1 Notations used, shown for an arbitrary vector $\boldsymbol{a}$.

| Notation | Definition |
| :--- | :--- |
| $\boldsymbol{a}_{k}$ | $\boldsymbol{a}$ at k-th instant |
| $\boldsymbol{a}^{s}$ | $\boldsymbol{a}$ expressed in frame $\psi_{S}$ |
| $\dot{\boldsymbol{a}}$ | derivative of $\boldsymbol{a}$ |
| $\hat{\boldsymbol{a}}$ | a posteriori estimate of $\boldsymbol{a}$ |
| $\boldsymbol{a}^{-}$ | a priori estimate of $\boldsymbol{a}$ |
| $\boldsymbol{e}_{\boldsymbol{a}}$ | Gaussian white noise associated with $\boldsymbol{a}$ |

A Kalman filter (KF) was used to track the velocity and position of the three segments: both feet and CoM, in the current step frame $\psi_{c s}$. The filter notations used are tabulated in Table 9.1. The state vector of the KF was denoted as $\boldsymbol{x}=\left(\begin{array}{llllll}\boldsymbol{p}^{f r} & \boldsymbol{p}^{f l} & \boldsymbol{p}^{C} & \boldsymbol{v}^{f r} & \boldsymbol{v}^{f l} & \boldsymbol{v}^{C}\end{array}\right)^{T}$
and its covariance matrix was $\boldsymbol{P}$. The states shown in (9.3) include the 3D position $\boldsymbol{p}$, and 3D velocity $\boldsymbol{v}$ of each segment, with the superscript denoting the corresponding segment.

The following text expands on the overview shown in Fig. 9.1. It describes the a-priori estimate determined using strapdown integration of the accelerations measured at each segment. Then, the special biomechanical constraints applied to each segment are shown. The implementation of the CMP assumptions to reduce the drift between the three segments is also described.

## Strapdown Inertial Navigation

This is the prediction step of the KF. The accelerations of each segment was expressed in the $\psi_{c s(k)}$ as:

$$
\begin{align*}
\widehat{\boldsymbol{a}}_{i}^{c s(k)} & =\boldsymbol{R}_{k}^{c s(k), c s(k-1)} \cdot\left(\boldsymbol{R}_{i}^{c s(k-1), s e g} \cdot \widehat{\boldsymbol{a}}_{i}^{s e g}\right)  \tag{9.4}\\
& =\boldsymbol{R}_{k}^{c s(k), c s(k-1)} \cdot\left(\boldsymbol{R}_{i}^{c s(k-1), s e g} \cdot\left(\boldsymbol{y}_{A, i}^{s e g}+\mathbf{g}^{s e g}\right)\right) \\
& =\boldsymbol{R}_{k}^{c s(k), c s(k-1)} \cdot\left(\boldsymbol{R}_{i}^{c s(k-1), s e g} \cdot \boldsymbol{y}_{A, i}^{s e g}+\mathbf{g}^{c s(k-1)}\right)
\end{align*}
$$

where $\boldsymbol{R}^{a, b}$ denotes the rotation from frame $\psi_{b}$ to $\psi_{a} . \mathbf{R}_{k}^{c s(k), c s(k-1)}$, and $\mathbf{R}_{k}^{c s(k-1), s e g}$ were estimated using the methods described in Sections 6.2 (Chapter VI) and 9.2.1. Here, $i$ denotes the samples during the current step $k$. The velocity $\left(\hat{\boldsymbol{v}}_{i}^{c s}\right)$ and position $\left(\hat{\boldsymbol{p}}_{i}^{c s}\right)$ can be estimated using (Weenk et al., 2015)

$$
\begin{align*}
\widehat{\boldsymbol{v}}_{i}^{c s} & =\widehat{\boldsymbol{v}}_{i-1}^{c s}+T \cdot \widehat{\boldsymbol{a}}_{i}^{c s}  \tag{9.5}\\
\text { and } \widehat{\boldsymbol{p}}_{i}^{c s} & =\widehat{\boldsymbol{p}}_{i-1}^{c s}+T \cdot \widehat{\boldsymbol{v}}_{i}^{c s}+\frac{T^{2}}{2} \cdot \widehat{\boldsymbol{a}}_{i}^{c s}
\end{align*}
$$

where $T$ is the time step. The Kalman filter prediction equation can be written as (Welch and Bishop, 2006)

$$
\begin{equation*}
\widehat{\boldsymbol{x}}_{i}^{-}=\boldsymbol{F} \cdot \widehat{\boldsymbol{x}}_{i-1}+\boldsymbol{u}_{i-1} \tag{9.7}
\end{equation*}
$$

$$
\text { where } \boldsymbol{F}=\left(\begin{array}{ll}
\mathbf{I}_{3} & T  \tag{9.8}\\
\mathbf{0}_{3} & \mathbf{I}_{3}
\end{array}\right) \text { and } \boldsymbol{u}=\left(\begin{array}{c}
T^{2} \\
2 \\
T \cdot \widehat{\boldsymbol{a}}_{i}^{c s} \\
T \cdot \widehat{\boldsymbol{a}}_{i}^{c s}
\end{array}\right)
$$

and the covariance matrix was predicted using

$$
\begin{equation*}
\widehat{\boldsymbol{P}}_{i}^{-}=\boldsymbol{F} \cdot \widehat{\boldsymbol{P}}_{i-1}^{-} \cdot \boldsymbol{F}^{T}+\boldsymbol{Q} \tag{9.9}
\end{equation*}
$$

where, $\boldsymbol{Q}$ is the process noise covariance matrix.

## Measurement Update

The measurement updates used to reduce drift in the estimation of position and velocity of the feet and CoM are as follows. A summary of when these updates are applied is shown in Fig. 9.1.

- Zero Velocity Update (ZV): As shown in Fig. 9.1, this is applied when the foot is in contact with the ground (Skog et al., 2010), as the velocity of the feet are assumed to be zero. Therefore, we have a measurement update $z_{z v}$ applied to the foot velocity such that

$$
\begin{align*}
& \boldsymbol{z}_{z v}=\mathbf{0}_{3 \times 1}  \tag{9.10a}\\
& \hat{\mathbf{z}}_{z v}=\boldsymbol{H}_{z v} \cdot \hat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{z v}  \tag{9.10b}\\
& \text { with, } \boldsymbol{H}_{z v}^{f r}=\left(\begin{array}{lll}
\mathbf{0}_{3 \times 9} & \mathbf{I}_{3 \times 3} & \mathbf{0}_{3 \times 6}
\end{array}\right)  \tag{9.10c}\\
& \text { and } \boldsymbol{H}_{z v}^{f l}=\left(\begin{array}{lll}
\mathbf{0}_{3 \times 12} & \mathbf{I}_{3 \times 3} & \mathbf{0}_{3 \times 3}
\end{array}\right) \tag{9.10d}
\end{align*}
$$

In the above equations, $\boldsymbol{z}$ denotes the measurement, and $\boldsymbol{H}$ transforms the state vector to a measurement prediction $(\hat{\boldsymbol{z}})$ (Welch and Bishop, 2006). $\boldsymbol{e}_{z v}$ denotes the error associated with this measurement. The subscript $z v$ corresponds to the update ZV . The same notations are used in the following equations.

- Zero Height Update (ZH): Again, during foot contact instances, and assuming gait over a flat surface, we can model the information regarding the height of the foot from the floor as

$$
\begin{align*}
& \mathbf{z}_{z h}=\boldsymbol{p}_{z, i n i t}^{f}  \tag{9.11a}\\
& \hat{\mathbf{z}}_{z h}=\boldsymbol{H}_{z h} \cdot \widehat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{z h}  \tag{9.11b}\\
& \text { with } \boldsymbol{H}_{z h}^{f r}=\left(\begin{array}{lllllll}
0 & 0 & 1 & 0 & 0 & 0 & \mathbf{0}_{1 \times 15}
\end{array}\right)  \tag{9.11c}\\
& \text { and } \boldsymbol{H}_{z h}^{f l}=\left(\begin{array}{lllllll}
0 & 0 & 0 & 0 & 0 & 1 & \mathbf{0}_{1 \times 12}
\end{array}\right) \tag{9.11d}
\end{align*}
$$

The measurement matrix $\boldsymbol{H}_{z h}$ has only one row as it was applied only to the Z axis of each foot. Here, $\boldsymbol{p}_{Z, \text { init }}^{f}$ is the initial height and the superscript $f$ denotes either the left ( $f l$ ) or right foot ( $f r$ ). This update was only applied to the feet.

- CoM Velocity (CV): The ZV update ensures that the velocity of the feet do not drift due to integration errors. However, the CoM is constantly moving. Therefore, using the methods described in Chapter VIII, an estimate of the CoM velocity was derived by fusing two complementary sources of information. A high frequency information $\left(\boldsymbol{v}_{h f}^{C}\right)$ was derived from an optimally filtered direct and reverse strapdown integration (Zok et al., 2004) of the CoM accelerations using a cut off of 0.6 Hz . Then, low frequency information $\left(\boldsymbol{v}_{l f}^{C}\right)$ of the CoM velocity was derived from low pass filtering the average of the foot velocities using the same cut off used for $\boldsymbol{v}_{h f}^{C}$. The two sources were fused to get estimates of the instantaneous 3D CoM velocity:

$$
\begin{equation*}
\boldsymbol{v}^{C}=\boldsymbol{v}_{l f}^{C}+\boldsymbol{v}_{h f}^{C} . \tag{9.12}
\end{equation*}
$$

- CoM Height $(\mathrm{CH})$ : The height of the $\operatorname{CoM}\left(\boldsymbol{p}_{Z}^{C}\right)$ was also estimated using a complementary filter method (Schepers et al., 2009). An optimally filtered direct and reverse strapdown integration (Zok et al., 2004) of vertical CoM velocity was used to obtain the changes in CoM height during gait using a cut off of 0.3 Hz to obtain the $\boldsymbol{p}_{Z, h f}^{C}$. Then, as the participant does not crouch or jump while walking, the height of the CoM should oscillate around an offset. Assuming an average walking CoM height as $98 \%$ of the height during quiet standing $\left(\boldsymbol{p}_{Z, \text { init }}^{C}\right)$ showed
least errors when validating this method. The average height and the $\boldsymbol{p}_{Z, h f}^{C}$ were fused to get an estimate of CoM height $\boldsymbol{p}_{Z}^{C}$ during walking:

$$
\begin{equation*}
\boldsymbol{p}_{Z}^{C}=0.98 \cdot \boldsymbol{p}_{Z, \text { init }}^{C}+\boldsymbol{p}_{Z, h f}^{C} \tag{9.13}
\end{equation*}
$$

- Centroidal Moment Pivot Update (CMP): The CMP update was used to restrict the feet and CoM from drifting apart or towards each other. Fig. 9.1 summarizes the steps involved; the CMP update was used to first estimate the horizontal position of stance foot with respect to the movement of the CoM. After correcting discrete changes at the start of each swing phase, the CoM trajectory was updated for the corrected foot positions. The biomechanical constraint derived from the CMP point (Popovic et al., 2005) is written as

$$
\begin{equation*}
\boldsymbol{c m}_{a x}^{f}=\boldsymbol{p}_{a x}^{C}-\left(\boldsymbol{p}_{Z}^{C} \cdot \frac{F_{a x}}{F_{Z}}\right) \tag{9.14}
\end{equation*}
$$

Here, $\boldsymbol{c m} \boldsymbol{p}_{a x}^{f}$ is the virtual CMP point under the stance foot $f$. $a x$ denotes either X or Y axes, and $F$ is the 3D GRF in a specific axis. When the 3D components of GRF are known, the distance between the $\operatorname{CoM}\left(\boldsymbol{p}_{a x}^{C}\right)$ and the CMP point under the stance foot can be estimated using the methods described in Chapter V. The 3D components of GRF estimated from the CoM accelerations were used to estimate the ratio $\frac{F_{a x}}{F_{Z}}$. The $\boldsymbol{p}_{Z}^{C}$ or height of the CoM was already estimated using the update CH in (9.13). Note that there are a few assumptions regarding (9.14). First, we assumed that the virtual CMP position $\left(\boldsymbol{c m p}_{a x}^{f}\right)$ coincides with the stance foot positions ( $\boldsymbol{p}_{a x}^{f}$ ) tracked by the IMU. Secondly, we assumed that the moment of inertia around the trunk is negligible while walking. Thus, during single stance phase, (9.14) provides the relation between CoM and the stance foot $\left(\boldsymbol{p}_{a x}^{f}\right)$. This can be used as measurement updates $\boldsymbol{z}_{c m r}^{f r}$ and $\boldsymbol{z}_{c m l}^{f l}$ for either foot as follows:

During left swing:

$$
\begin{align*}
\mathbf{z}_{c m r}^{f r} & =\boldsymbol{c m p}_{a x}^{f r}  \tag{9.15a}\\
\hat{\mathbf{z}}_{c m r}^{f r} & =\boldsymbol{H}_{c m r}^{f r} \cdot \hat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{c m r}^{f r} \tag{9.15b}
\end{align*}
$$

$$
\begin{equation*}
\text { with } \boldsymbol{H}_{c m r}^{f r}=\left(\mathbf{I}_{2 \times 2} \mathbf{0}_{2 \times 16}\right) \text {. } \tag{9.15c}
\end{equation*}
$$

During right swing:

$$
\begin{align*}
& \mathbf{z}_{c m l}^{f l}=\boldsymbol{c m} \boldsymbol{p}_{a x}^{f l}  \tag{9.15d}\\
& \hat{\mathbf{z}}_{c m l}^{f l}=\boldsymbol{H}_{c m l}^{f l} \cdot \hat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{c m l}^{f l}  \tag{9.15e}\\
& \text { with } \boldsymbol{H}_{c m l}^{f l}=\left(\begin{array}{ll}
\mathbf{0}_{2 \times 3} & \mathbf{I}_{2 \times 2} \\
\mathbf{0}_{2 \times 13}
\end{array}\right) . \tag{9.15f}
\end{align*}
$$

The measurement matrices $\boldsymbol{H}_{c m r}^{f r}$ and $\boldsymbol{H}_{c m l}^{f l}$ were applied only to the X and Y axes of the foot positions in the state vector. This update corrects the drift in relative positions between the CoM and stance foot during swing phase. However, this may cause a discrete jump in relative foot distances at the start of the swing phase. To have a smooth change in relative foot distances between subsequent steps, knowledge of the relative foot distances at the end of the preceding step was used to update the relative foot distances at the beginning of the subsequent swing phase.

Start of left swing:

$$
\begin{align*}
& \mathbf{z}_{r d r}^{f r}=\boldsymbol{p}_{a x, e d}^{f r}  \tag{9.16a}\\
& \hat{\mathbf{z}}_{r d r}^{f r}=\boldsymbol{H}_{r d r}^{f r} \cdot \hat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{r d r}^{f r}  \tag{9.16b}\\
& \text { with, } \boldsymbol{H}_{r d r}^{f r}=\left(\mathbf{I}_{2 \times 2} \mathbf{0}_{2 \times 16}\right) \tag{9.16c}
\end{align*}
$$

Start of right swing:

$$
\begin{align*}
& \mathbf{z}_{r d l}^{f l}=\boldsymbol{p}_{a x, e d}^{f l}  \tag{9.16d}\\
& \hat{\mathbf{z}}_{r d l}^{f l}=\boldsymbol{H}_{r d l}^{f l} \cdot \hat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{r d l}^{f l}  \tag{9.16e}\\
& \text { with } \boldsymbol{H}_{r d l}^{f l}=\left(\begin{array}{ll}
\mathbf{0}_{2 \times 3} & \mathbf{I}_{2 \times 2} \\
\mathbf{0}_{2 \times 13}
\end{array}\right) . \tag{9.16f}
\end{align*}
$$

In (9.16a) and (9.16d), $\boldsymbol{p}_{a x, e d}^{f r}$ and $\boldsymbol{p}_{a x, e d}^{f l}$ are the respective foot positions at the end of the preceding step in the axis $a x$. As in (9.15), the measurement matrices $\boldsymbol{H}_{r d r}^{f r}$ and $\boldsymbol{H}_{r d l}^{f l}$ were applied only to the X and Y axes of the foot positions. This correction of relative foot distances requires a final update of the CoM position following the assumptions of CMP point. (9.14) was adapted to obtain the CoM from foot estimates as

$$
\begin{equation*}
\boldsymbol{p}_{a x}^{C}=\boldsymbol{c} \boldsymbol{m} \boldsymbol{p}_{a x}^{f}+\left(\boldsymbol{p}_{Z}^{C} \cdot \frac{F_{a x}}{F_{Z}}\right) . \tag{9.17}
\end{equation*}
$$

During left swing, cmp $\boldsymbol{p}_{a x}^{f}$ represents the right foot, and vice-versa for the right swing. During these instances, the CoM position was improved using the following measurement update:

$$
\begin{align*}
& \mathbf{z}_{c m c}^{C}=\boldsymbol{p}_{a x}^{C}  \tag{9.18a}\\
& \hat{\mathbf{z}}_{c m c}^{C}=\boldsymbol{H}_{c m}^{C} \cdot \hat{\boldsymbol{x}}^{-}+\boldsymbol{e}_{c m}^{C}  \tag{9.18b}\\
& \text { with } \boldsymbol{H}_{c m c}^{C}=\left(\mathbf{0}_{2 \times 6} \mathbf{I}_{2 \times 2} \mathbf{0}_{2 \times 10}\right) \tag{9.18c}
\end{align*}
$$

$\boldsymbol{p}_{a x}^{C}$ was derived from (9.17). The measurement matrix $\boldsymbol{H}_{c m}^{C}$ was applied to the X and Y axes of the CoM positions.

The measurement updates were applied to the KF using the standard equations:

$$
\begin{align*}
& \boldsymbol{K}_{i}=\boldsymbol{P}_{i}^{-} \cdot \boldsymbol{H}^{T}\left(\boldsymbol{H} \cdot \boldsymbol{P}_{i}^{-} \cdot \boldsymbol{H}^{T}+\boldsymbol{R}\right)^{-1}  \tag{9.19}\\
& \widehat{\boldsymbol{x}}_{i}=\widehat{\boldsymbol{x}}_{i}^{-}+\boldsymbol{K}_{i} \cdot\left(\mathbf{z}_{i}-\boldsymbol{H} \cdot \widehat{\boldsymbol{x}}_{i}^{-}\right)  \tag{9.20}\\
& \boldsymbol{P}_{i}=\left(\mathbf{I}-\boldsymbol{K}_{i} \cdot \boldsymbol{H}\right) \cdot \boldsymbol{P}_{i}^{-} \tag{9.21}
\end{align*}
$$

The Kalman gain was estimated using (9.19), the state matrix was updated with (9.20), and the error covariance matrix was updated using (9.21).

## Reinitialising for step $\mathbf{k + 1}$

After the state vector has been updated using the prediction and measurement updates, the trajectory of the segments is known for the current step $k$. The $\psi_{c s(k)}$ was adjusted using methods described in Section 9.2.1 using the improved estimates of the foot positions. For the next step $k+1$, accelerations are transformed to the current step frame $\psi_{c s(k+1)}$ using (9.4), and the steps described in Sections 9.2.3 were reiterated.

## Initialisation and Noise

Before applying the KF, the states for each segment and their covariance noises have to be initialised. The right foot was assumed to be the origin. The initial locations of the CoM, and the left foot were measured from VICON®. All initial velocities $\boldsymbol{v}_{s e g}$ were set to zero, and the initial noise was set to arbitrary values. The process and measurement noises shown in Table 9.2 were estimated from sensor specifications, and then fine-tuned by optimizing the error between estimated and reference values.

Table 9.2 Standard Deviations of the Gaussian Noises Used.

| $\boldsymbol{e}_{G}$ | $\boldsymbol{e}_{A}$ | $\boldsymbol{e}_{z v}$ | $\boldsymbol{e}_{z h}$ | $\boldsymbol{e}_{c m l}^{f l}$ and $\boldsymbol{e}_{c m r}^{f r}$ | $\boldsymbol{e}_{r d l}^{f l}$ and $\boldsymbol{e}_{r d r}^{f r}$ | $\boldsymbol{e}_{c m}^{c}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\mathrm{rad} / \mathrm{s}$ | $\mathrm{m} / \mathrm{s}^{2}$ | $\mathrm{~m} / \mathrm{s}$ | m | m | m | m |
| $1 \cdot 10^{-2}$ | $1 \cdot 10^{3}$ | $7 \cdot 10^{-2}$ | $5 \cdot 10^{-2}$ | $1 \cdot 10^{2}$ | $\left[5 \cdot 10^{-2}\right.$ | $\left.9 \cdot 10^{-3}\right] \mathbf{I}_{2 \times 2}$ |

### 9.2.4. Measurement System

Three Xsens ${ }^{\text {TM }}$ MTw IMUs formed the minimal setup as can be visualized in Chapter VI (Fig. 6.4): one IMU was mounted on the pelvis, and one on each foot. The pelvis IMU was placed below the midway point between the line connecting the left and right posterior superior iliac spine. The foot IMUs were placed on the midfoot region. The MT Manager (version 4.8) software was used to read the data from the IMU wirelessly, which was sampled at 100 Hz .

Two reference systems were used. The ForceShoes ${ }^{T M}$ was used as wearable reference for the estimation of forces required in (9.14). The ForceShoes ${ }^{\mathrm{TM}}$ consists of a 6DoF Force and Moment sensor, and an IMU under each toe and heel of both feet (Veltink et al., 2005). It has been validated against force plates (AMTI®) for measurement of contact forces (Schepers et al., 2009). A VICON®
motion capture system (Oxford Metrics PLC.) was used as the reference system for validating the velocities and positions estimated using the state vector. Markers were placed on the following locations on both the left and right limbs: anterior superior iliac spine, posterior iliac spine, the second and fifth metatarsal, and heel. One marker was also placed on each IMU. The data from VICON© and ForceShoes ${ }^{\text {TM }}$ were sampled at 100 Hz . The data was then low pass filtered at 10 Hz with a zero-phase second order Butterworth filter.

Foot contact was estimated when the magnitude of forces measured by the ForceShoes ${ }^{\text {TM }}$ was below a set threshold of 30 N on each foot. Foot positions were derived from the marker on the IMU. The CoM position obtained from VICON© was assumed to lie at the centroid of the four pelvis markers. The feet and CoM positions were differentiated, and low pass filtered with a second order zero phase Butterworth filter of cut off 10 Hz to obtain the respective velocities. The measurements by both reference systems were transformed to the $\psi_{c s}$ frame that was determined using the VICON® foot positions.

To synchronize the two reference systems with that of the Xsens ${ }^{\text {TM }}$ MTw IMUs, the participants were asked to raise their right leg before starting the experimental protocol. The magnitude of angular velocities measured with the Xsens ${ }^{\mathrm{TM}}$, as well as the IMUs in the ForceShoes ${ }^{\mathrm{TM}}$ were used to synchronize these systems. The change in right foot position was used to synchronize the VICON® with the other two systems. A manual check was performed in order to verify if all the signals were properly synchronized.

### 9.2.5. Participants

Six healthy participants were recruited for the study. The average and standard deviation of the height, weight, and age was $1.7 \pm 0.1 \mathrm{~m}, 74.1 \pm 10 \mathrm{~kg}$, and $25.6 \pm 2.8$ years respectively. Leg length was measured from the greater trochanter to the ground (Hof, 1996) and was $0.9 \pm 0.04 \mathrm{~m}$. All participants signed an informed consent before the experiment. The study was conducted in accordance with the Declaration of Helsinki, and the protocol was approved by the Ethical Committee of the faculty. The inclusion criteria included participants with no history of impaired gait or leg injury. One participant was female, and all of their shoe sizes were 40 (European Size Chart).

### 9.2.6. Experimental Protocol

The ForceShoes ${ }^{\mathrm{TM}}$ was calibrated using the MT Manager software, and the VICON© was calibrated using standard procedures. Fig. 9.2 summarizes the experimental protocol. The participants began by standing still for a few seconds with their feet placed parallel and were asked to bend the trunk forward. This was used to calibrate the pelvis segment frame in Section 9.2.1 (Chapter VI). The participants were then asked to perform a set of walking tasks, each repeated four times:

- Normal Walk (NW): The participant was asked to walk at their preferred walking speed for 5 m .
- $\quad L$ Walk ( $L W$ ): The participant was asked to walk for 3 m and then turn right at $90^{\circ}$ and walk for another 2 m .
- Walk and Turn (WT): The participant was asked to walk for 5 m and then turn and walk back to start position.
- Walk and Turn Twice (WT2): The participant performed WT and then asked to turn and walk for 5 m .
- Slalom Walk (SlW): The participant was asked to walk in a slalom pattern. Two pylons, at 2 m and 4 m from start respectively, were placed on the floor to guide them.
- Asymmetric Walk (AW): The participant was asked to walk in an asymmetric manner. The instruction given was to induce a stiff left knee and abduct the hip as much as possible, and also have a shorter step on the right side.


### 9.2.7. Analysis of Results

In the following text, the minimal IMU sensing setup, along with the algorithms explained in Section 9.2 .3 will be referred to as Portable Gait Lab (PGL). A zero-phase Butterworth low pass filter of order 4 and cut off 3 Hz was used to filter noise from the estimated kinematics.

The estimated forces and kinematics were compared against the reference systems, ForceShoes ${ }^{\mathrm{TM}}$ and VICON® respectively. First, the errors in estimating the ratio of forces $\left(\frac{F_{a x}}{F_{Z}}\right)$ in (9.14) from the pelvis IMU was studied. The errors were expressed as the Root Mean Square (RMS) of the differences normalised by the range of the reference values in both $\mathrm{X}\left(r R a t_{X}\right)$ and $\mathrm{Y}\left(r R a t_{Y}\right)$ axis.


Figure 9.2 An overview of experimental protocol. The participants stand still for a few seconds, following which they bow thrice, and then perform the walking task. After this, they bow again and stand still for a few seconds before the measurement is stopped. The bowing movement is used to determine the pelvis frame $\psi_{p}$.

Then, the RMS of the differences in estimating CoM height $\left(R C o M_{Z}\right)$ was studied. The error margins $r$ Rat $_{X}, r$ Rat $_{Y}$, and $R \mathrm{CoM}_{Z}$ are required to understand the errors associated with (9.14), and eventually, the relative distance estimates.

The RMS of the errors $\left(\right.$ Right $_{X}$, Right $_{Y}$, Left $_{X}$, Left $_{Y}, \operatorname{CoM}_{X}$, and $\operatorname{CoM}_{Y}$ ) in estimating the horizontal positions of feet and CoM were then analysed for each step. The vertical foot clearance comparison has been neglected in this study, as it is not novel (Benoussaad et al., 2015). Then, the average 2D horizontal Euclidean Distance ( $E D$ ) between the feet at the end of each step for all walking tasks was measured and compared against the VICON© reference. Following this, spatial gait parameters, such as the Step Lengths (SL), and Step Widths (SW) were estimated (Huxham et al., 2006). A metric CoM Width (CW) was derived by estimating the average 2D Euclidean distance between the stance foot and CoM trajectory for each step. This provided an average relative distance between either foot and CoM. Correlation and Bland-Altman plots were used to compare the $S L, S W$, and $C W$ derived from the PGL with the reference VICON©. Finally, the feasibility of the PGL in differentiating between symmetrical and asymmetrical walking was studied by comparing the differences between left and right steps in two walking tasks, the NW and AW.

### 9.3. RESULTS

A few trials were removed from analysis due to issues with the reference setups. Further, it was made sure that each participant had at least three

Table 9.3 RMS of the Differences in estimating $r$ Rat $_{X}$, and $r$ Rat $_{Y}$ and CoM height $R \operatorname{CoM}_{Z}$.

|  | rRat $_{X}(\%)$ | rRat $_{Y}(\%)$ | RCoM $_{Z}(\mathrm{~mm})$ |
| :--- | :---: | :---: | :---: |
| NW | $15.0 \pm 3.74$ | $16.1 \pm 3.15$ | $6.1 \pm 0.9^{*}$ |
| LW | $15.2 \pm 2.53$ | $13.5 \pm 3.55$ | $5.6 \pm 1.0^{*}$ |
| WT | $17.8 \pm 2.65$ | $15.1 \pm 4.69$ | $5.3 \pm 1.0^{*}$ |
| WT2 | $19.1 \pm 2.7$ | $15.5 \pm 3.46$ | $7.0 \pm 3.1^{*}$ |
| SIW | $17.7 \pm 3.6$ | $17.4 \pm 6.84$ | $6.3 \pm 1.0^{*}$ |
| AW | $13.0 \pm 2.6$ | $19.3 \pm 3.13$ | $11.7 \pm 4.5^{*}$ |

NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SlW: Slalom Walk, AW: Asymmetrical Walk. * denotes significant $(p<0.05)$ correlations.
walking trials per walking task. First, an example of the CoM height estimated using the complementary filter approach in (9.13) is shown in Fig. 9.3. Table 9.3 shows the errors $\left(r R a t_{X}\right.$, and $\left.r R a t_{Y}\right)$ in estimating the ratio of forces and that of CoM height $\left(R C o M_{Z}\right)$ in (9.14) for the different walking tasks. The CoM height estimations were significantly ( $p<0.05$ ) correlated with an average of $83 \pm$ $8.2 \%$ across all tasks, suggesting good agreement with the reference values.


Figure 9.3 Trajectory of CoM Height for a participant performing a WT task estimated from the pelvis IMU seen as solid blue line. The dotted red line is the VICON® reference. The participant performed a $180^{\circ}$ turn around 25 s .





Figure 9.4 Step-wise comparison of foot and CoM positions by the Portable Gait Lab (PGL) system and VICON® reference in the $\psi_{\text {cs }}$ frame. The participant performs a WT task, with the turning step highlighted with a light red shaded background. The circles denote the PGL values, and the lines denote the reference values. In either case, positions of the right foot, left foot, and CoM are shown using crimson, black, and bluish green colours respectively. The step numbers are mentioned within each plot. Each subplot is a top-down view of a step expressed in the current step frame $\psi_{c S}$; with the X and Y axes of the plots corresponding to the X and Y axes of the $\psi_{c s}$.

(w) $\boldsymbol{L}$ - $\mathrm{so}_{\mathrm{d}}$

Fig. 9.4 shows a graphical step-wise comparison of the feet and CoM positions estimated by the PGL with the reference VICON© for the same trial as shown in Fig. 9.3. As each step is represented in its own $\psi_{c s}$ frame, they all progress to the right, even during turns. In the first subplot, the left foot moves first. Then, the participant can be seen to make consecutive steps, until step 6, where they prepare for the $180^{\circ}$ turn. The turning step is highlighted with a shaded light red background. Although the PGL shows deviations during the turn when compared to the reference, it converges to the reference values two steps after.

Table 9.4 Average RMS of the errors in horizontal positions of the feet and CoM, and the differences $(E D)$ in relative foot distances at the end of each step.

| -- | Right $_{X}$ <br> $(\mathrm{~cm})$ | Right $_{Y}$ <br> $(\mathrm{~cm})$ | Left $_{X}$ <br> $(\mathrm{~cm})$ | Left $_{Y}$ <br> $(\mathrm{~cm})$ | CoM $_{X}$ <br> $(\mathrm{~cm})$ | $\operatorname{CoM}_{Y}$ <br> $(\mathrm{~cm})$ | $E D$ <br> $(\mathrm{~cm})$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| NW | $12.7 \pm 3.3$ | $4.1 \pm 1.3$ | $11.2 \pm 1.5$ | $3.6 \pm 0.7$ | $8.3 \pm 2.2$ | $5.3 \pm 1.4$ | $9.3 \pm 3.4$ |
| LW | $12.7 \pm 5.2$ | $4.8 \pm 0.6$ | $11.6 \pm 3.2$ | $4.6 \pm 1.1$ | $8.8 \pm 3.1$ | $5.7 \pm 0.8$ | $9.4 \pm 4.5$ |
| WT | $12 \pm 3.3$ | $5.3 \pm 2.1$ | $11.3 \pm 2.3$ | $4.7 \pm 1.3$ | $7.8 \pm 2.3$ | $6.3 \pm 1.0$ | $8.9 \pm 2.5$ |
| WT2 | $12.1 \pm 3.6$ | $5.4 \pm 0.9$ | $11.4 \pm 1.6$ | $4.6 \pm 0.9$ | $8.1 \pm 1.9$ | $7.1 \pm 0.9$ | $9.3 \pm 2.3$ |
| SlW | $11.7 \pm 3.9$ | $5.7 \pm 0.7$ | $11.5 \pm 2.3$ | $5.0 \pm 0.9$ | $7.6 \pm 2.4$ | $7.5 \pm 1.2$ | $9.2 \pm 1.1$ |
| AW | $9.2 \pm 3.0$ | $4.9 \pm 1.4$ | $9.3 \pm 1.6$ | $4.1 \pm 0.9$ | $6.8 \pm 1.9$ | $5.5 \pm 1.3$ | $5.5 \pm 2.0$ |

NW: Normal Walk, LW: L Walk, WT: Walk and Turn, WT2: Walk and Turn Twice, SlW: Slalom Walk, AW: Asymmetrical Walk.

Table 9.4 displays the errors $\left(\right.$ Right $_{X}$, Right $_{Y}$, Left $_{X}$, Left $_{Y}, \operatorname{CoM}_{X}$, and $\operatorname{CoM}_{Y}$ ) in estimating the horizontal feet and CoM positions for each step. These are an average across all steps in a walking task excluding the turning steps. Turning steps were those that made a $60^{\circ}$ or larger change in direction when compared to the preceding step. Table 9.4 also summarizes the difference in relative distance between the feet $(E D)$ at the end of each step. Across all walking tasks, this was found to be $8.8 \pm 1.0 \mathrm{~cm}$ on average.

The estimates of $S L, S W$, and $C W$ for all tasks except AW are compared against the reference using Fig. 9.5, 9.6, and 9.7 respectively. Some steps had particularly large $S L$ or $C W$ values measured by the VICON® than the average, thereby skewing the distribution as outliers. They were removed based on the interquartile range of the distribution of the VICON© estimates for each parameter ( $S L, S W$, and $C W$ ). Further, in Fig. 9.5, 9.6,


Figure 9.5 Comparing step lengths for all walking tasks except AW using correlation (left) and Bland-Altman (right) plots. The red circles are turning steps. In the correlation plot, the dotted grey line is the linear fit for the straight steps, and solid red line is the linear fit for the turning steps. For the Bland-Altman plot, the solid lines denote the median difference between the two systems, with * denoting significant ( $p<0.05$ ) difference between the mean of the two systems. The dotted lines denote the $95 \%$ limits of agreement. The legend shows the correlation between the Portable Gait Lab (PGL) and the reference with * denoting significance ( $p<0.05$ ). The average RMS of the errors is also shown.


Figure 9.6 Comparing step widths for all walking tasks except AW using correlation (left) and Bland-Altman (right) plots. The red circles are turning steps. In the correlation plot, the dotted grey line is the linear fit for the straight steps, and solid red line is the linear fit for the turning steps. For the Bland-Altman plot, the solid lines denote the median difference between the two systems, with * denoting significant ( $p<0.05$ ) difference between the mean of the two systems. The dotted lines denote the $95 \%$ limits of agreement. The legend shows the correlation between the Portable Gait Lab (PGL) and the reference with * denoting significance ( $p<0.05$ ). The average RMS of the errors is also shown.


Figure 9.7 Comparing CoM widths for all walking tasks except AW using correlation (left) and Bland-Altman (right) plots. The red circles are turning steps. In the correlation plot, the dotted grey line is the linear fit for the straight steps, and solid red line is the linear fit for the turning steps. For the Bland-Altman plot, the solid lines denote the median difference between the two systems, with * denoting significant ( $p<0.05$ ) difference between the mean of the two systems. The dotted lines denote the $95 \%$ limits of agreement. The legend shows the correlation between the Portable Gait Lab (PGL) and the reference with * denoting significance ( $p<0.05$ ). The average RMS of the errors is also shown.
and 9.7, the right subplot shows the Bland-Altman plot. The Limits of Agreement (LoA) for $S L$ were found to be [-25.5; 15.9] cm and [-24.7; 37] cm for the straight and turning steps respectively. For $S W$, an LoA of $[-16 ; 11.6]$ cm and $[-40.3 ; 11.3] \mathrm{cm}$, and for $C W$ a value of $[-9.5 ; 1.6] \mathrm{cm}$ and $[-17.2 ; 6.1]$ cm was found.

Finally, the feasibility of PGL in differentiating symmetric from asymmetric gait is shown in Fig. 9.8 and 9.9. Both figures compare the distribution of $S L$ on the left and right side. From Fig. 9.9, we see that both, the reference and PGL, find significant differences in $S L$ between the right and left side for the AW task.

### 9.4. DISCUSSION

This study shows the feasibility of relying on simply a three IMU setup for estimating relative distances of the feet and CoM. Estimating kinetics and kinematics using the principles in this study allows us to use the three IMU setup as a portable gait lab.


Figure 9.8 Comparing distributions of right and left step lengths for the NW task. The left subplot shows the distributions measured by the reference system, and the right subplot shows that of the Portable Gait Lab. Outliers are shown as red pluses.


Figure 9.9 Comparing distributions of right and left step lengths for the AW task. The left subplot shows the distributions measured by the reference system, and the right subplot shows that of the Portable Gait Lab. Outliers are shown as red pluses. Significant difference is denoted by * $p<0.05$ ).

There are several biomechanical assumptions considered for this study. In order to apply (9.14), 3D GRF and height of CoM have to be estimated instantaneously. In Chapter VI, we have discussed the feasibility of using the PGL in estimating 3D GRF while assuming that the CoM resides within the centroid of the pelvis. Here, the errors associated with the ratios (rRat ${ }_{X}$, and
$r$ Rat $_{Y}$ ) as seen in Table 9.3 was $19.3 \pm 3.1 \%$ of the range of the reference values in the worst case. The RMS error in estimating the vertical CoM position using alternative approaches in literature was on average $3.5 \pm 1.3 \mathrm{~mm}$ (FloorWesterdijk et al., 2012) and did not exceed 20 mm in another study (Paiman et al., 2016). In our study, it was on average $7 \pm 2.4 \mathrm{~mm}$ across all walking tasks. Additionally, the other studies only compared the differences in a detrended position for an average stride (Floor-Westerdijk et al., 2012), or considered treadmill gait (Paiman et al., 2016). We state the average error in estimating the instantaneous CoM height over the complete gait including initiation, turning, and stopping. Knowledge of the force ratios and CoM height allows us to use the CMP constraint using (9.14) and (9.17). As the CMP measurement updates were applied only during specific instances of gait, the errors in estimating ratio of forces and CoM height influences the relative positions during these instances.

Fig. 9.4 shows the step-wise comparison of the tracking by the PGL for a participant performing the WT task. Each step is shown in its respective current step frame $\psi_{c s}$ with the feet and CoM moving from left to right. In some steps, for instance step 3, the trajectory of the stance (right) foot position measured by PGL is slightly different from the VICON©. This could be the rolling of the foot during stance phase, which is measured by VICON©. As the PGL tracks the foot as a fixed point, this rolling is not modelled during stance phase. Thus, we observe a steady medio-lateral position of the stance foot for the PGL estimates. Furthermore, although the virtual CMP point follows the trajectory of the Center of Pressure (CoP) (Popovic et al., 2005), in (9.14) we assumed that it follows the trajectory of the stance foot tracked by the PGL. These two issues could induce a systematic difference in estimations of foot positions or spatial parameters of gait. The PGL could be further improved with a model for CoP movement (Chapter IV) or the rolling of the stance foot. Further, we see more discrepancies during the turning steps than other steps. These issues could be because the movement of the CoM deviates further from the centroid of the pelvis when making turns. Additional biomechanical constraints should be explored to improve estimation of kinematics during turning. Measuring the influence of the rotational inertia of the upper body could improve the assumptions of CMP. Nevertheless, the estimated positions
converge to the reference values when the participant continues to make additional steps.

Table 9.4 shows that the algorithm has comparable performances across different walking tasks in estimating the absolute position of the feet and CoM. As these errors are an average across all steps in a trial, they indicate the usefulness of PGL in restricting drift between the segments with time. Although marginal, the differences in the orientation of $\psi_{c s}$ defined separately by the PGL and VICON© could influence these errors. The error margins can be put into perspective when comparing it against the average stride length, which was found to be $1.1 \pm 0.2 \mathrm{~m}$ by VICON© for all tasks except AW. The mean absolute error in estimating stride lengths across all walking tasks was found to be $5.9 \pm 1.5 \mathrm{~cm}$ in our study as compared to $-1.5 \pm 4.6 \mathrm{~cm}$ as found by Kitagawa and Ogihara (Kitagawa and Ogihara, 2016). Note that the errors in estimating positions for the AW task are similar to the others, even though this task comprised of an asymmetrical gait with shorter steps on the right. In our validation study (Chapter V) on the assumptions of CMP point, we found that there was an average error of $6.7 \pm 0.6 \mathrm{~cm}$ between the virtual CMP position and true foot position as measured by VICON©. These influence the errors in the relative distances ( $E D$ ) between either feet as seen in Table 9.4. Sy and colleagues (Sy et al., 2020) used a set of biomechanical constraints to track the lower limb using a similar three IMU approach with an average error of $5.2 \pm 1.4 \mathrm{~cm}$. This was $13.5 \pm 0.7 \mathrm{~cm}$ for our study. However, in the reference study (Sy et al., 2020), they assume a fixed pelvis, and measure all segments with respect to it. On the other hand, we track the relative distances between the feet and CoM for variable as well as asymmetric gait. The error margins include all steps in the walking task, thereby showing robustness against drift in relative distances, which becomes larger with time. It may be of interest to include the constraints explored in Sy and colleagues (Sy et al., 2020) where they also estimate joint kinematics. Combining other biomechanical model of gait (Paiman et al., 2016; Sy et al., 2020) with the current study can result in a system that provides complete linear and joint kinematics of the lower limb using a minimal IMU setup.

We have also validated the PGL for estimating spatial parameters: $S L, S W$, and $C W$ for variable gait. These parameters are dependent on good estimations
of relative distances of both feet and CoM. In healthy participants and patients with hemi paresis, the $S L$ variability is close to 2 cm and 3.4 cm respectively, and the $S W$ variability is close to 2 cm and 1.8 cm respectively (Balasubramanian et al., 2009). Using an ultrasound sensor to measure relative distances, Weenk and colleagues (Weenk et al., 2015) estimated the SL and SW with an average absolute error of $1.7 \pm 2 \mathrm{~cm}$ and $1.5 \pm 1.5 \mathrm{~cm}$ respectively. In our study, using only three IMUs, we found it to be $4.6 \pm 1.5 \mathrm{~cm}$ and $3.8 \pm 1.5 \mathrm{~cm}$ respectively. These errors include variable walking and are slightly larger than clinical variability. Analysing straight line walking tasks such as the 10 metre walk will reduce the impact of variable walking when using the PGL for clinical studies. Furthermore, although the estimates were significantly correlated with the reference system (Fig. 9.5, 9.6, and 9.7), the correlations were found to be moderate for estimations of $S L$, and $C W$, and weak for the $S W$. This suggests that there is merit in using the PGL to study average spatial parameters over a number of trials, although caution must be taken when comparing individual steps.

Fig. 9.5, 9.6, and 9.7 do not include the spatiotemporal parameters for AW task, as the steps were asymmetric on either side. The spread of the spatiotemporal parameters for straight steps in the correlation subplot in all three figures lies along the identity line. The bias seen in the Bland-Altman plots could be due to systematic differences owing to the several assumptions considered and discussed in this study.

Finally, Fig. 9.8 and 9.9 show that the algorithm can distinguish between normal and asymmetric walking patterns, as identified by significant differences in step lengths for the AW task. This indicates that the PGL may be adequately sensitive for differences of clinical importance such as gait asymmetry due to stroke or other conditions.

## Limitations and Future Work

The PGL requires reliable estimations of the CoM height and velocity, feet velocities, and 3D GRF before it can track the relative distances. Therefore, a number of assumptions were used regarding the biomechanics of gait. For instance, in (9.13), we found the average height of CoM during walking by optimizing the errors between the PGL estimate and reference values.

Further, we used an inverted pendulum model of walking where the CoM is encompassed within the pelvis segment (Floor-Westerdijk et al., 2012). There may be larger errors if the CoM deviates further from the centroid of the pelvis, or if the participant crouches or jumps. Errors may also be larger for participants with an asymmetric body posture due to an impairment or paralysis.

Applying the PGL requires knowledge of initial relative distances of the feet and CoM, which could be input using a tape or other sources. Further, the algorithms require a few steps to calibrate and define the different reference frames, and to initialise the heading of the feet. This could mean that there are some restrictions to be considered when designing a real time application system. The current design of the sensor fusion filter tracks 18 parameters for each iteration that includes the position and velocity of each foot and CoM, and might result in a heavy computational load. However, this should not pose a problem if the processing is performed offline, on a desktop, or a cloud service. Further, it is important that the three IMUs are synchronized well, as the movements are related to each other.

The PGL has not been tested on other aspects of variable gait such as shuffling of the feet, ascending or descending stairs, walking backwards, etc. Although, we have shown that the errors are close to margins of variability, they can be improved, and a follow up study with measurements from a free daily life environment must be designed. The error margins found in the current PGL could be acceptable to derive an overview of gait patterns, track people in daily life, and also to derive balance and stability measures using the relative foot distances. For instance, the BoS and MoS (van Meulen et al., 2016b) can be derived using this approach. However, employing the PGL to study individual steps must be considered within the provided error margins.

Here, the AW task was used to validate the feasibility of using PGL in asymmetric gait. Nevertheless, a validation study using participants with impaired and/or asymmetric gait is required, as it might be difficult to detect distinct gait events in impaired gait. Issues with lower limb motor control may result in shuffling patterns, such as freezing of gait as seen in patients
with Parkinson's disease. This will influence the estimation of gait events, and therefore the application of CMP updates.

### 9.5. CONCLUSIONS

The feasibility of using a minimal three IMU based setup in measuring relative distances between the feet and CoM is shown for over ground variable gait. The average absolute errors in estimating step lengths and step widths were $4.6 \pm 1.5 \mathrm{~cm}$ and $3.8 \pm 1.5 \mathrm{~cm}$ respectively. The approach is sensitive in differentiating symmetric and asymmetric gait. Further validation in free walking conditions and participants with impaired gait patterns must be done.

# Centroidal Moment Pivot for ambulatory estimation of relative feet and CoM movement post stroke: Portable Gait Lab 

"Change is one thing. Acceptance is another."
Arundhati Roy, The God of Small Things

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#### Abstract

Measuring gait and balance recovery is necessary post stroke. In Chapter IX, we developed a minimal system using only three Inertial Measurement Units (IMUs) called Portable Gait Lab (PGL). The PGL used the Centroidal moment Pivot (CMP) assumption to estimate relative foot and Centre of Mass (CoM) positions, and thereby estimate gait parameters in healthy participants. In this study, we validate the feasibility of the PGL using the CMP assumption to track foot and CoM trajectory during gait in four persons with chronic stroke. Spatiotemporal gait and balance measures were estimated from the estimated foot and CoM trajectories and compared with the reference ForceShoes ${ }^{\mathrm{TM}}$. Each participant made at least 20 steps, and the PGL was able to track foot and CoM trajectories with a root mean square of the differences with the reference of 2.9 $\pm 0.2 \mathrm{~cm}$ and $4.6 \pm 3.6 \mathrm{~cm}$. The distances between either foot at the end of the walking task, and step lengths were estimated by PGL with an average error with the reference of $1.98 \pm 2.2 \mathrm{~cm}$ and $7.8 \pm 0.1 \mathrm{~cm}$ respectively across participants. We show that our approach was able to estimate spatiotemporal and balance parameters related to gait quality in a clinically useful manner. We recommend conducting further studies to study the feasibility of using the PGL for variable gait patterns measured post stroke.


### 10.1. INTRODUCTION

Clinical gait analysis is required for diagnosis of disease, assessment of its severity, or monitoring progress after onset (Baker, 2006). In spite of several clinical assessment instruments (Baker, 2006; Hart-Hughes et al., 2014), biomechanics can be useful in understanding objective changes in gait, and balance mechanisms, and thereby developing tailored therapies post stroke (van Meulen et al., 2016b).

Spatiotemporal gait characteristics, and joint biomechanics are often measured during clinical gait analysis (Muro-de-la-Herran et al., 2014; Punt et al., 2017b). Bilateral temporal control of gait, step lengths, and stride time are useful indicators of gait quality (Buurke et al., 2019; Punt et al., 2017b). Dynamic stability can be defined as the ability to maintain balance during locomotion (Chang et al., 2010). Margin of stability (MoS), defined as the movement of the Centre of Mass (CoM) and the Extrapolated CoM (XCoM) with respect to the Base of Support (BoS) during gait, is a potential indicator of dynamic stability (Hof et al., 2005; Punt et al., 2017b; van Meulen et al., 2016b). A decreased MoS can be related to lower walking speed or a reduced balance control ability (Bruijn and van Dieën, 2018; Lugade et al., 2011; van Meulen et al., 2016b).

Currently, accurate measurement of these parameters require optical motion capture systems or force plates (Bruijn et al., 2013). These require a large installation space, and have low ecological validity (Colyer et al., 2018). Portable sensing systems are therefore necessary to enable ambulatory sensing (Fong and Chan, 2010; Kobsar et al., 2020; Rueterbories et al., 2010; Wong et al., 2015).

Inertial Measurement Units (IMUs) are ideal miniature sensors for wearable gait analysis (Caldas et al., 2017; Kobsar et al., 2020). In order to estimate spatial gait parameters, the accelerations and angular velocities measured by the IMUs strapdown integration to derive kinematics of interest (Kok et al., 2017; Woodman, 2007). Estimating spatial parameters that require knowledge about relative feet movement is even more challenging when using IMUs. This is mainly due to the issue of drift caused by integration (Woodman, 2007), and that the IMUs cannot measure relative positions directly.

We developed a Portable Gait Lab (PGL) system that estimates relative movement of the feet and CoM using a minimal set of IMUs in Chapter IX. The PGL uses three IMUs; one on each feet, and one on the pelvis, to track the relative movement of the feet and CoM using the assumptions of the Centroidal Moment Pivot (CMP) point described in Chapter V. The CMP assumes that for an inverted pendulum model of gait, the net moments around the CoM are zero (Popovic et al., 2005) . Solving this provides a relation between movement of the CoM and the CMP point. The latter can be assumed to coincide with foot trajectories estimated by the foot IMUs based on our analysis in Chapter V. We validated the PGL for estimation of 3D Ground Reaction Forces (GRF), CoM velocity, and relative foot movement with gold standards such as force sensors, and optical motion capture systems in healthy gait (Chapter VI - IX). We also showed the feasibility of PGL in estimating the asymmetry in step length when healthy participants were asked to mimic asymmetric gait. However, the PGL has not been validated for use in persons with stroke.

The aim of this study was to test the feasibility of tracking relative movement of the feet and CoM and estimating spatiotemporal gait and balance measures using the assumptions of the CMP in a minimal IMU only setup for gait in persons with chronic stroke.

### 10.2. METHODS

### 10.2.1. Participants

The dataset used in this study was approved by the METC Twente, The Netherlands (P12-27), registered in the Netherlands Trial Registry (NTR3636) and used in the INTERACTION project (van Meulen et al., 2016b, 2016c). The patients included were between 35-75 years and had hemiparesis due to haemorrhagic or single unilateral ischemic stroke which occurred at least six months earlier (van Meulen et al., 2016b). Patients excluded were those unable to perform given instructions, understand questionnaires, had a medical history of more than one stroke or other that might influence gait (van Meulen et al., 2016b). In this preliminary study, we processed the data from four participants. The patient demographics are shown in Table 10.1. All participants provided their consent for the study prior participation.


Figure 10.1 Measurement setups used: The participants wore the (a) $\mathrm{Xsens}^{\mathrm{TM}}$ full body suit consisting of 17 IMU sensors placed at different locations on the body (Roetenberg et al., 2009; Xsens, 2020). In (b), we see the Forceshoes ${ }^{\text {TM }}$, which consists of a 6DOF force and moment sensors, and an IMU under the heel and toe for each foot (Schepers et al., 2009). The shoes included ultrasound sensors which are not shown here (Weenk et al., 2015). The pelvis IMU, and the IMUs under the toe of each Forceshoes ${ }^{\mathrm{TM}}$ in panel (b) was used in the Portable Gait Lab system

Table 10.1 Demographic details of the study participants

| ID | Gender | Age <br> (years) | Post <br> Stroke <br> (months) | Dominant <br> Side | Affected <br> Side | Weight <br> $(\mathrm{kg})$ | Height <br> $(\mathrm{m})$ | BBS | 10MWT <br> $(\mathrm{m} / \mathrm{s})$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| P01 | M | 70 | 89 | R | L | 94 | 1.74 | 52 | 0.76 |
| P02 | F | 67 | 40 | R | L | 80 | 1.62 | 43 | 0.54 |
| P03 | M | 65 | 16 | R | L | 92 | 1.86 | 52 | 0.94 |
| P04 | F | 71 | 17 | R | R | 67 | 1.53 | 56 | 0.83 |
| Mean <br> $\mathbf{\pm}$ SD) |  | 68.3 | 40.5 |  |  | 84 | 1.7 | 50.8 | 0.8 |

### 10.2.2. Measurement setup and Experimental protocol

Fig. 10.1a shows the full body Xsens ${ }^{\text {TM }}$ suit (Xsens Technologies B.V., Enschede, The Netherlands) worn by participant. The raw data, sampled at 120 Hz , was processed using a Xsens MVN studio (Xsens Technologies B.V., Enschede,

The Netherlands) software which contains a biomechanical model of the participant.

Each participant also wore the Forceshoes ${ }^{\text {TM }}$ (Xsens Technologies B.V., Enschede, The Netherlands) as seen in Fig. 10.1b. The Forceshoes ${ }^{\text {TM }}$ have been validated for estimations of gait kinematics (Schepers et al., 2009; Weenk et al., 2015). Therefore, it is used as the reference for 3D foot kinematics, and the CoM kinematics in the horizontal ground plane. Information regarding the CoM height was supplemented by the Xsens ${ }^{\mathrm{TM}}$ suit. All data from the Forceshoes ${ }^{\mathrm{TM}}$ were sampled at 50 Hz and sent wirelessly to a PC running a MT Manager software (Xsens Technologies B.V., Enschede, The Netherlands). All data were then resampled to 100 Hz . Data from the Forceshoes ${ }^{\mathrm{TM}}$ and $\mathrm{Xsens}^{\mathrm{TM}}$ suit were synchronized using IMU data from the first foot movement.

The three IMUs of the PGL are seen in Fig. 10.1b. This includes the foot IMUs (from the ForceShoes ${ }^{\mathrm{TM}}$ ) and the pelvis IMU (part of the Xsens ${ }^{\mathrm{TM}}$ suit). The raw acceleration and angular velocities measured from three IMUs were processed using the PGL system based on the methods described in Chapter VI - IX.

All participants performed a timed 10 m walk task (10MWT) at a self-selected comfortable pace without the use of any walking aid (van Meulen et al., 2016b). Clinical gait assessment was performed using the Berg Balance Scale (BBS).

### 10.2.3. Data Analysis

## Portable Gait Lab system

The PGL assumes an inverted pendulum model of gait where the CoM is located within the pelvis, and the pelvis IMU measures the CoM accelerations. The PGL assumes that the feet are the only points of contact with the environment and no additional load is carried by the participant. The kinematics of the CoM, affected foot, and less affected foot (superscripts $C, A F$, and $L A$ respectively) that were tracked include the 3D position and velocity ( $[\boldsymbol{p} \boldsymbol{v}]$ ). For each step $k$, the kinematics were expressed in the current step frame $\left(\psi_{c s(k)}\right)$ described in our previous study (Chapter VI). The anterio-posterior $(A P)$, medio-lateral (ML), and vertical $(V)$ axes of the $\psi_{c s(k)}$ are denoted as subscripts in the equations used in this chapter. The PGL employs strapdown
integration in order to estimate kinematics from the IMU data, and the equations were applied in the context of Kalman filters (Chapter VI - IX). Additionally, biomechanical constraints were used to reduce the drift in estimating kinematics of the feet and CoM, and their relative distances. The constraints are as follows:

- Zero Velocity constraint: This assumed that during gait, the velocity of the stance foot was zero.
- Zero Height constraint: This assumed walking on a flat surface and therefore the height of the stance foot was the same as that at the start of the walking.
- Inclination constraint: This assumed that on average the pelvis IMU measures inclination due to gravity. This was used to estimate the 3D GRF using the pelvis IMU as shown in Chapter VI.
- CoM Velocity constraint: The CoM velocity was estimated by fusing two complementary sources as described in Chapter VIII:

$$
\begin{align*}
& \boldsymbol{v}_{h f}^{C}=\operatorname{HPF}\left(\int \boldsymbol{a}^{C} d t\right)  \tag{10.1}\\
& \boldsymbol{v}_{l f}^{C}=L P F\left(0.6 * \boldsymbol{v}^{L A}+0.4 * \boldsymbol{v}^{A F}\right)  \tag{10.2}\\
& \boldsymbol{v}^{C}=\boldsymbol{v}_{l f}^{C}+\boldsymbol{v}_{h f}^{C} \tag{10.3}
\end{align*}
$$

The first source was strapdown integration of the accelerations ( $\boldsymbol{a}^{C}$ ) measured at the CoM that was high pass filtered as seen in (10.1). The lost low frequency information was supplemented by averaging the foot velocities during gait. As persons with stroke have an asymmetrical gait, assigning a $40 \%$ weight to the velocity of the affected foot improved the estimation of CoM velocity. The averaged foot velocities were then low pass filtered as seen in (10.2). Both, the high and low pass filters had the same cut off frequencies [1.7 0.5 0.5] Hz for the AP, ML, and V axes respectively. In (10.3), the $\boldsymbol{v}_{h f}^{C}$ and $\boldsymbol{v}_{l f}^{C}$ were fused using a complementary filter to obtain the instantaneous CoM velocity estimate. In the equations, the subscripts lf and $h f$ refer to low and high frequency information respectively.

- CoM Height constraint: The height of the CoM was also estimated by fusing two sources using the approaches in Chapter IX:

$$
\begin{align*}
& \boldsymbol{p}_{V, h f}^{C}=H P F\left(\int \boldsymbol{v}_{V}^{C} d t\right)  \tag{10.4}\\
& \boldsymbol{p}_{V, l f}^{C}=L P F\left(0.99 * \boldsymbol{p}_{V, i n i t}^{C}\right)  \tag{10.5}\\
& \boldsymbol{p}_{V}^{C}=\boldsymbol{p}_{V, l f}^{C}+\boldsymbol{p}_{V, h f}^{C} \tag{10.6}
\end{align*}
$$

In (10.4), the CoM height was derived by strapdown integration of the CoM velocity, and subsequent high pass filtering. It was assumed that during gait the average CoM height was $99 \%$ of of the height during initial stance $\left(\boldsymbol{p}_{V, i n i t}^{C}\right)$ resulting in (10.5). Both filters had the same cut off of 0.8 Hz , and both sources are fused in (10.6).

- Centroidal Moment Pivot (CMP) constraint: During normal gait, the moments around the CoM can be assumed to be close to zero (Popovic et al., 2005). Using this, the relative distance between the stance foot and CoM can be constrained as:

$$
\begin{equation*}
p_{a x}^{f o o t}=p_{a x}^{C}-\left(p_{V}^{C} \cdot \frac{F_{a x}}{F_{V}}\right) \tag{10.7}
\end{equation*}
$$

where foot refers to either the affected or less affected stance foot. The constraint was only applied to the stance foot when the contralateral foot was in swing. The subscript $a x$ refers to either the AP or ML axis, and $F$ denotes the GRF for a particular axis. The constraint reduced the drift between the stance foot and CoM during the swing phase of the contralateral foot. However, there might be a sudden change in foot position during the start of the swing phase. To remedy this, the foot position at the beginning of a current step $k$ was constrained to be the same as at the end of the preceding step $k-1$. This constraint was used after the end of the previous contralateral swing and at the beginning of the subsequent swing phase:

$$
\begin{equation*}
p_{\operatorname{start}(k)}^{f o o t}=p_{\text {end }(k-1)}^{\text {foot }} \tag{10.8}
\end{equation*}
$$

Finally, the CoM was constrained by using the CMP equation in (10.7) and the information regarding the updated foot positions using methods in Chapter IX.

## Measurement noise associated with the biomechanical constraints

The Kalman filter estimates an optimal value of ([ $\boldsymbol{p} \boldsymbol{v}]$ ) while accounting for the Gaussian measurement noise associated with each constraint (Welch and Bishop, 2006). The standard deviation (SD) of the Gaussian noises for the zero velocity, zero height, inclination, CoM velocity, and CoM height constraints were similar to Chapter IX. The SD of the noise for the constraint in (10.7) was [3 $\left.10^{-1} 1 \cdot 10^{-1}\right] \mathrm{m}$ for the AP and ML directions. Then, we optimized the SD of the noise for (10.8) per participant by using two parameters that can be easily measured in the clinic. This included the total walking distance ( dist $_{\text {total }}$ ), and the relative foot distances $\left(R F P_{\text {total }}\right)$ at the end of gait. For each participant, we identified the SD of the noise for (10.8) that minimized $\|\Delta \boldsymbol{y}\|$, where $\Delta \boldsymbol{y}=\boldsymbol{y}_{P G L}-\mathbf{y}_{R E F}$.

$$
\begin{align*}
& \text { where } \boldsymbol{y}=\left[\text { dist }_{\text {total }} ; R F P_{\text {total }}\right]  \tag{10.9}\\
& \text { and } R F P=\left\|\boldsymbol{p}_{\text {end }}^{A F}-\boldsymbol{p}_{\text {end }}^{L A}\right\| . \tag{10.10}
\end{align*}
$$

The participant specific values are tabulated in Table 10.2. Using a similar approach, the SD of the Gaussian noise for constraining the CoM using (10.7) was found to be $\left[3 \cdot 10^{-1}\right] \mathrm{m}$.

Table 10.2 Participant specific standard deviation of the Gaussian noise for (10.8).

| ID | Foot | Anterio-posterior <br> $(\mathrm{m})$ | Medio-lateral <br> $(\mathrm{m})$ |
| :--- | :--- | :---: | :---: |
| $\mathbf{P 0 1}$ | Affected | $1 \cdot 10^{-1}$ | $1 \cdot 10^{-1}$ |
|  | Less Affected | $1 \cdot 10^{-1}$ | 1 |
| $\mathbf{P 0 2}$ | Affected | $1 \cdot 10^{1}$ | $1 \cdot 10^{1}$ |
|  | Less Affected | 3 | $3 \cdot 10^{2}$ |
| $\mathbf{P 0 3}$ | Affected | $3 \cdot 10^{-1}$ | $3 \cdot 10^{-1}$ |
|  | Less Affected | $3 \cdot 10^{-1}$ | 3 |
| $\mathbf{P 0 4}$ | Affected | $8 \cdot 10^{-1}$ | $3 \cdot 10^{-1}$ |
|  | Less Affected | $8 \cdot 10^{-1}$ | 3 |

## Initialization of parameters

The initial orientation of the feet was estimated from its initial heading and gravitational inclination (Weenk et al., 2015). The initial orientation of the CoM was estimated from an additional Timed Up and Go (TUG) test performed by the participants. Principal component analyses was applied to changes in angular velocity during the sit to stand task to estimate the medio-lateral axis ( $a x_{M L}$ ) of CoM (corresponding to the sagittal axis) as shown in (10.11). The inclination due to gravity $\left(a x_{V}\right)$ was estimated during quiet standing in (10.12). After estimating $a x_{A P}$ using (10.13), $a x_{M L}$ was adjusted using (10.14) to ensure an orthonormal coordinate system. Finally, (10.15) provides the rotation matrix $\left(\boldsymbol{R}_{\text {init }}^{\text {seg,s }}\right)$ that transforms data from sensor $\left(\psi_{s}\right)$ to segment $\left(\psi_{\text {seg }}\right)$ frame.

$$
\begin{align*}
& a x_{M L}=P C A\left(\boldsymbol{y}_{G}^{s}\right)  \tag{10.11}\\
& a x_{V}=\frac{y_{A}^{s}}{\left\|y_{A}^{s}\right\|}  \tag{10.12}\\
& a x_{A P}=a x_{M L} \times a x_{V}  \tag{10.13}\\
& a x_{M L}^{\prime}=a x_{V} \times a x_{A P}  \tag{10.14}\\
& \boldsymbol{R}_{\text {init }}^{\text {seg,s }}=\left[\begin{array}{lll}
a x_{A P} & a x_{M L}^{\prime} & a x_{V}
\end{array}\right] \tag{10.15}
\end{align*}
$$

The initial 3D foot positions and the AP and ML position of CoM were obtained from the reference Forceshoes ${ }^{\mathrm{TM}}$, and the initial CoM height was estimated by the Xsens ${ }^{\text {TM }}$ suit. The initial velocities were all set to zero. Foot contact was estimated using the method of Skog and colleagues (Skog et al., 2010). All filters used were zero phase Butterworth filters with order 4. All equations were a function of time.

### 10.2.4. Analysis of Results

We first assessed the errors in estimating the feet and CoM positions during the complete 10MWT including initiation, steady state, and termination. We report the root mean square of the differences in the AP and ML directions as estimated by the PGL and reference ForceShoes ${ }^{\mathrm{TM}}$ (van Meulen et al., 2016b, 2016c; Weenk et al., 2015).

## Spatiotemporal and balance measures of gait

Then, we assessed the errors in measuring spatiotemporal measures such as stance time, and step length (Huxham et al., 2006). We defined stance phase when the velocity of each foot was less than $0.1 \mathrm{~m} / \mathrm{s}$. Following this, we estimated the MoS in the AP and ML directions. First, the Extrapolated Centre of Mass (XCoM) was estimated (Hof et al., 2005):

$$
\begin{equation*}
X C o M=C o M+\frac{v^{C}}{\omega_{\circ}} \tag{10.16}
\end{equation*}
$$

where $\omega_{\circ}=\sqrt{\mathbf{g} / l_{\circ}}$, in which $\mathbf{g}$ is the acceleration due to gravity, and $l_{\circ}$ is the length of the inverted pendulum that is approximated as the height of the CoM when standing still. Estimation of the MoS requires knowledge of the Base of Support (BoS). A foot model was built that estimated anterior and lateral foot boundaries based on the positions estimated by the PGL, and similarly for the reference ForceShoes ${ }^{\mathrm{TM}}$ (van Meulen et al., 2016c). MoS during double support was estimated just before the contralateral foot entered swing phase. AP and ML MoS was defined as the distance between XCoM and anterior and lateral boundary of the foot respectively (Punt et al., 2017b; van Meulen et al., 2016c). We estimated the AP and ML MoS during three samples just before the contralateral foot-off and report the average values. This corresponds to a window of 30 ms before foot-off for a sampling frequency of 100 Hz .

We report the mean absolute difference, the correlation and Bland-Altman plots between all parameters estimated by the PGL and the reference system for each step. As each participant made at least 20 steps, we use two-sample t-tests to identify if there are differences in these parameters estimated on either foot by the PGL. We compare this with the findings of the reference.

### 10.3. RESULTS

Due to discrepancies in pelvis IMU placement for P03 between the 10MWT and TUG tasks, (10.11) did not provide a reliable initial orientation for the CoM. Therefore, for P03, the initial orientation estimated by the Xsens ${ }^{\mathrm{TM}}$ suit was employed.

In Table 10.3, we summarize the errors between the PGL and reference Forceshoes ${ }^{\mathrm{TM}}$. The Root Mean Square (RMS) error in estimating foot positions in the AP direction are smaller than our previous study in Chapter IX performed on healthy participants. This was probably due to the use of participant specific noise models as shown in Table 10.2. The PGL also reliably estimated the relative foot distance at the end of the walking task with a root mean square of differences of $1.98 \pm 2.20 \mathrm{~cm}$.

In Table 10.4, we summarize the average spatiotemporal and balance parameters estimated across the four participants for the reference and PGL system. In the following figures, we take a closer look at each of the different parameters. In Fig. 10.2, we compare the estimation of stance time for both the affected and less affected foot. The correlation and Bland-Altman plots are shown in Fig. 10.2a and Fig. 10.2b. Table 10.5 summarizes if there are differences in the spatiotemporal and balance measures estimated on either foot and compares them between the PGL and reference. The table shows that both systems find similar differences in stance time on either foot for all participants.

Fig. 10.3 compares the step lengths estimated by the PGL and reference system. We see in Table 10.5 that the step lengths on either foot was not significantly different, as reported by both the reference and PGL. Fig. 10.4 and Fig. 10.5 compare the estimated AP MoS and estimated ML MoS respectively. In Table 10.5 we see that the PGL showed significant differences in AP MoS on either foot for P03, and similarly for ML MoS for P01. However, in both cases, the reference system did not measure such differences between either foot. For other participants, both systems show similar differences for these measures.

### 10.4. DISCUSSION

In this limited study, we show the feasibility of the PGL system using the CMP assumption to estimate foot and CoM trajectories over the complete 10MWT including initiation and termination in persons with chronic stroke. We also show the use of PGL in estimating spatiotemporal and balance parameters of gait. Further, we have tested the use of PGL in one severe (P02) as well as mildly affected persons with stroke.

Table 10.3 Performance of the PGL as compared with the reference.

| Segment | Positions $^{+}$ |  | Step <br> Length* | AP MoS* | ML MoS* |
| :--- | :--- | :--- | :--- | :--- | :--- |
| Mean $\pm$ SD (cm) | AP | ML |  |  |  |
| Affected foot | $4.38 \pm 0.61$ | $3.05 \pm 0.74$ | $7.88 \pm 0.85$ | $5.60 \pm 1.20$ | $5.31 \pm 1.76$ |
| Less Affected foot | $5.01 \pm 1.13$ | $3.04 \pm 0.88$ | $7.69 \pm 1.46$ | $4.88 \pm 0.89$ | $6.43 \pm 2.89$ |
| Centre of Mass | $8.20 \pm 1.36$ | $4.70 \pm 0.65$ |  |  |  |

AP: anterio-posterior. ML: medio -lateral. ${ }^{+}$Root mean square of the differences across participants are reported. *Mean absolute differences across participants are reported.

Table 10.4 Spatiotemporal and balance parameters estimated by the PGL and reference.

| Metric | Units | Foot | Reference | PGL |
| :--- | :--- | :--- | :--- | :--- |
| Stance Time | s | Affected | $0.67 \pm 0.13$ | $0.67 \pm 0.13$ |
|  |  | Less Affected | $0.67 \pm 0.13$ | $0.68 \pm 0.13$ |
| Step Length | m | Affected | $0.43 \pm 0.14$ | $0.47 \pm 0.17$ |
|  |  | Less Affected | $0.47 \pm 0.11$ | $0.43 \pm 0.15$ |
| AP MoS | m | Affected | $0.08 \pm 0.08$ | $0.10 \pm 0.10$ |
|  |  | Less Affected | $0.12 \pm 0.08$ | $0.13 \pm 0.08$ |
| ML MoS | m | Affected | $0.14 \pm 0.04$ | $0.17 \pm 0.08$ |
|  |  | Less Affected | $0.15 \pm 0.04$ | $0.19 \pm 0.07$ |

AP MoS: Anterio-posterior margin of stability, ML MoS: Medio-lateral margin of stability.

Table 10.5 Differences between the spatiotemporal and balance measures of the affected and less affected foot ( $\mathrm{p}<0.05$ ).

| ID | Stance time |  | Step length |  | AP MoS |  | ML MoS |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
|  | Reference | PGL | Reference | PGL | Reference | PGL | Reference | PGL |
| P01 | yes | yes | no | no | yes | yes | no | yes |
| P02 | yes | yes | no | no | yes | yes | yes | yes |
| P03 | no | no | no | no | no | yes | no | no |
| P04 | yes | yes | no | no | yes | yes | yes | yes |

## Chapter 10



Figure 10.2 Correlation (left subplot) and Bland-Altman (right subplot) plots comparing the stance time estimated by the reference and Portable Gait Lab (PGL) on the (a) affected and (b) less affected foot. In both plots, steps made by P01, P02, P03, and P04 are shown by pluses, circles, inverted triangles, and squares respectively. The dotted gray line in the correlation plot shows the identity line. The black line shows the linear fit. The legend shows the Pearsons' correlation, their significance denoted by * $(p<0.05$ ), and the root mean square of the differences. The dotted lines in the Bland-Altman plot show the $95 \%$ limits of agreement, and the solid line shows the average mean of difference between the reference and PGL.


Figure 10.3 Correlation (left subplot) and Bland-Altman (right subplot) plots comparing the step lengths estimated by the reference and Portable Gait Lab (PGL) system on (a) affected and (b) less affected foot. In both plots, steps made by P01, P02, P03, and P04 are shown by pluses, circle, inverted triangle, and squares respectively. We compared the steps during steady gait (Steady) in blue, and the first and last two steps (Other) are shown in red. The dotted gray line in the correlation plot shows the identity line. The blue and red lines shows the linear fit for the Straight and Other steps respectively. The legend shows the Pearsons' correlation for both types of steps, their significance denoted by * $(p<0.05$ ), and the root mean square of the differences. The Bland-Altman plots show the average mean of the differences for Steady state in blue and Other steps in red.


Figure 10.4 Correlation (left subplot) and Bland-Altman (right subplot) plots comparing the anterio-posterior margin of stability (AP MoS) estimated by the reference and Portable Gait Lab (PGL) system on (a) affected and (b) less affected foot. In both plots, steps made by P01, P02, P03, and P04 are shown by pluses, circle, inverted triangle, and squares respectively. We compared the steps during steady gait (Steady) in blue, and the first and last two steps (Other) are shown in red. The dotted gray line in the correlation plot shows the identity line. The blue and red lines shows the linear fit for the Straight and Other steps respectively. The legend shows the Pearsons' correlation for both types of steps, their significance denoted by * $(p<0.05)$, and the root mean square of the differences. The Bland-Altman plots show the average mean of the differences for Steady state in blue and Other steps in red.


Figure 10.5 Correlation (left subplot) and Bland-Altman (right subplot) plots comparing the medio-lateral margin of stability (ML MoS) estimated by the reference and Portable Gait Lab (PGL) system on (a) affected and (b) less affected foot. In both plots, steps made by P01, P02, P03, and P04 are shown by pluses, circle, inverted triangle, and squares respectively. We compared the steps during steady gait (Steady) in blue, and the first and last two steps (Other) are shown in red. The dotted gray line in the correlation plot shows the identity line. The blue and red lines shows the linear fit for the Steady state and Other steps respectively. The legend shows the Pearsons' correlation for both types of steps, their significance denoted by * $p<0.05$ ), and the root mean square of the differences. The Bland-Altman plots show the average mean of the differences for Steady state in blue and Other steps in red.

The results of this study show that the PGL can be an alternative to high-end optical measurement systems given its portability, and ease of setup. This can help clinicians measure at remote locations, as well as more often post stroke, thereby generating an improved picture of lower limb motor recovery post stroke.

### 10.4.1. Clinical testing versus clinical research

Gait analysis can be used to either study changes in lower limb quality post stroke, or be used in clinical research to identify biomarkers of recovery (Baker, 2006). We show here that the PGL is useful in case of the former, although it requires longitudinal studies that test the feasibility of measuring change over time. In case of use in clinical research, the usability of PGL must be tested in larger patient groups with varying levels of severity in order to evaluate if it can distinguish differences that are clinically significant and relevant. Nonetheless, the portability of the PGL allows setting up studies with these goals.

### 10.4.2 Assumptions underlying the PGL

The PGL is expected to fail when trunk rotational moments significantly deviate from zero, for example during turning (Popovic et al., 2005). If the moments around the CoM can be measured, then (10.7) can be updated as

$$
\begin{equation*}
p_{a x}^{f o o t}=p_{a x}^{C}-\left(p_{V}^{C} \cdot \frac{F_{a x}}{F_{V}}\right)-\frac{M_{a x \prime}}{F_{V}} \tag{10.17}
\end{equation*}
$$

where $M$ is the moment around the CoM, and $a x^{\prime}$ is the AP axis when $a x$ is the ML axis and vice-versa. As it reduces the uncertainty with (10.7), this could improve the estimations of relative distance between CoM and stance foot during non-steady state gait. Thus, it is useful to consider additional wearable sensors such as a sternum IMU that can measure trunk rotations.

We estimated the initial orientation of the pelvis from a sit to stand movement. We assumed that the participant moves along the ML axis of their pelvis during these movements. However, this assumption must be tested further as persons with stroke can have an asymmetrical posture during gait or standing. It would also be useful to explore other movements from the extensive library of daily life postures for calibrating the initial orientation of the pelvis. Better calibration of initial orientation improves the performance of PGL.

The PGL employs sensor fusion techniques to optimize the kinematics measured from different sources. Therefore, it has to be noted that the estimation of relative distances is an optimal estimate that depend on a good noise model for the constraints.
10.4.3. Measuring foot trajectories, spatiotemporal and balance parameters We see that the PGL is able to reliably estimate relative foot positions in spite of each participant making at least 20 steps. This shows that the PGL is able to deal with drift associated with strapdown inertial navigation over longer gait. As gait in persons with stroke vary based on their impairment, we introduce a method to tune the noise models for the constraints based on parameters that can be measured easily in the clinic. This improved the performance of the PGL for each participant.

We chose a limited set of spatiotemporal and balance parameters that could be useful to monitor gait recovery after stroke longitudinally, and objectively measure gait quality (Punt et al., 2017b; van Meulen et al., 2016c). However, the PGL has to be tested on more participants in order to make generalizable conclusions. Estimating stance time does not require knowledge of the relative foot distances. Nevertheless, we report it here as it is a useful temporal parameter for gait quality (Buurke et al., 2019).

The average step lengths reported (Table 10.4) were similar to those reported by Punt and colleagues for persons with stroke (Punt et al., 2017b). The error in measuring step lengths (on average $7.8 \pm 0.1 \mathrm{~cm}$ ) were mainly due to the approximations made by the PGL system in estimating relative foot positions during gait. Weenk and colleagues found lower errors in estimating step lengths (Weenk et al., 2015). Nevertheless, the PGL uses only three IMUs, and does not rely on additional sensors such as ultrasound or infrared time of flight sensors to estimate relative foot distances (Bertuletti et al., 2019; Weenk et al., 2015). Using an extended list of biomechanical constraints, similar to our study, Sy and colleagues estimated positions of lower limb segments with an average error of $5.2 \pm 1.3 \mathrm{~cm}$ for healthy participants (Sy et al., 2020), whereas we report an average of $3.5 \pm 1 \mathrm{~cm}$ for persons with stroke.

The average AP MoS measured using the PGL was $11.5 \pm 2.1 \mathrm{~cm}$, with an average error of $5.2 \pm 0.8 \mathrm{~cm}$. This was relatively larger than the error in
measuring ML MoS, which was on average $5.9 \pm 0.8 \mathrm{~cm}$ for an average ML MoS of $18 \pm 1.4 \mathrm{~cm}$. The larger errors in AP MoS could be due to larger discrepancies in the foot model used in the anterior direction, than the lateral direction. The accuracy of the PGL is expected to improve if foot contact and CoP movement can be measured using pressure insoles.

Based on these findings, we show that the PGL estimates the foot and CoM positions, stance times and step lengths well. The discrepancies in measuring MoS can be improved using additional portable sensors such as a sternum IMU, and pressure insoles.

### 10.4.4. Limitations

The possible issues due to the PGL assumptions have been discussed earlier. Another limitation is the use of a limited dataset, and therefore the results cannot be generalized to all persons with stroke. For each participant, we studied only one 10MWT which does not include turns or side steps.

In our previous study in Chapter IX, we showed the feasibility of PGL in measuring variable gait in healthy participants. We recommend setting up similar studies with persons with stroke and comparing the performance of PGL with optical motion capture systems. Furthermore, joint kinematics are quite useful in gait analysis, but we do not estimate them in this study. However, the method by Sy and colleagues can be combined with the PGL in order to measure joint kinematics and provide a comprehensive analysis of gait and balance (Sy et al., 2020).

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# General Discussion 


"Mischief, thou art afoot; Take thou what course thou wilt!"
William Shakespeare, Julius Caesar

### 11.1. THE VISION FOR STROKE REHABILITATION

Considerable progress in stroke recovery has been made in the recent decades owing to advances in stroke research and medical technology (Hachinski et al., 2010). The onset of stroke disrupts Activities of Daily Life (ADL) and stroke rehabilitation is a process that takes place over several months or in some cases years (Langhorne et al., 2011). In spite of the large body of literature, insights from animal models and human trials have not been efficiently integrated into standard stroke practices (Krakauer et al., 2012).

Standardizing stroke rehabilitation, especially for motor recovery, is an important vision on the stroke roadmap (Bernhardt et al., 2016; Kwakkel et al., 2017). A major limitation to standardization and developing new therapies that improve recovery post stroke is not knowing how best to measure recovery (Bernhardt et al., 2016). Biomarkers of neuroimaging such as transcranial magnetic stimulation and neurophysiology of the Corticospinal tract (CST) can be used to stratify persons with stroke, predict motor outcomes, and track motor recovery post stroke (Boyd et al., 2017). Alternatively, objective measurement of movement biomechanics can also be ideal for measuring motor recovery and distinguishing behavioural restitution from compensation (Kwakkel et al., 2019).

Another milestone on the stroke roadmap is improving diagnosis of stroke recovery and upgrading post stroke care (usually at home) by harnessing advances in technology (Kwakkel et al., 2019). Technology also impacts standardization of stroke rehabilitation and accessibility to equal care for people of all means and background (Health Holland, 2020). It can be used to enhance clinical analysis of recovery and home care. For instance, measuring movement biomechanics (to track recovery) using wearables is less intensive, invasive, and expensive when compared to neuroimaging or neurophysiological studies. Wearable solutions can enable clinicians to monitor motor recovery more often in the acute phases post stroke and help stratify patients based on their impairment. Wearables can be used during ADL to understand movement performance at home (Klaassen et al., 2014). Thus, identifying the right metrics to track movement recovery and measuring
them using wearables is needed to understand recovery and setting up patient tailored rehabilitation programs.

The chapters in this thesis contribute to this long-term vision for stroke: standardization of rehabilitation and integration of technology in practice and home care. It became clear during the project that as movements in the upper and lower extremity are different, they must be addressed separately. This approach is also required before we study complex movements that incorporate both the upper and lower extremities. Therefore, in Chapter I, we identified specific research questions for each extremity (upper and lower). In the chapters related to the upper extremity (Chapters II - III), we prioritized questions related to standardization of stroke rehabilitation. These chapters advance our knowledge regarding the relation between movement biomechanics and motor recovery. As for the lower extremity, we prioritized questions related to integration of technology. Thereby, we developed wearable solutions (Chapters IV - X) to measure gait parameters of interest. In this chapter, we address the implications of the earlier chapters towards the long term vision and specify future research directions.

### 11.2. A KINEMATIC PERSPECTIVE OF MOTOR RECOVERY

### 11.2.1. Upper extremity

Our first section (Chapters II and III) focused on reviewing literature to identify and recommend kinematic metrics that reflect movement quality in the upper extremity.

Spontaneous neurological recovery is a dynamic process that cannot be studied at a single time point (Langhorne et al., 2011). If we wish to investigate the time course of movement quality, longitudinal studies of changes in kinematics of upper limb reaching early after stroke are required. Existing reviews on metrics for reaching with the upper paretic limb did not study the correlation between changes in kinematics with motor recovery longitudinally (De Los ReyesGuzmán et al., 2014; Schwarz et al., 2019; Tran et al., 2018). Hence, our review in Chapter II was needed. In spite of the many longitudinal studies starting early post stroke, none of them identified kinematic metrics that distinguished behavioural restitution from compensation. This differentiation is required to
determine whether an intervention can influence motor recovery. Therefore, we strongly recommend setting up studies that target this gap.

Consensus on kinematics and kinetics that are capable of measuring quality of movement and distinguishing behavioural restitution from compensation post stroke must be reached.

Based on consensus from experts, the Stroke Recovery and Rehabilitation Roundtable (SRRR) recommend a set of criteria for setting up studies that can standardize measurement of movement quality (Kwakkel et al., 2019). These criteria include the number of measurement time points post stroke, measurement setup, assays performed etc. Studies setup with these criteria can help identify kinematics and/or kinetics that can be used as biomarkers of behavioural restitution and compensation. Note that we would be better able to gauge the criteria provided, once we have sufficient studies performed using the recommendations of SRRR.

Next, we focused on smoothness of reaching in the upper paretic limb. Studying recovery of smoothness deficits can help understand recovery of abnormal muscle synergies post stroke (Rohrer et al., 2004, 2002). Elucidating the interplay between neural circuits and biomechanics that give rise to muscle synergies can help us understand deficits in neural control mechanisms used in movement of the upper limb (Ting and McKay, 2007). Unfortunately, the definition of smoothness varied across studies, and this may bring to question the results of existing studies on smoothness. We addressed this problem in Chapter III and found that Spectral Arc Length (SPARC) was best suited for measuring smoothness of reach-to-point and reach-to-grasp tasks. The set of inclusion and exclusion criteria, as well as the simulation analyses provided in Chapter III offers a method to assess future proposals for novel smoothness metrics.

The next step was to investigate the time course of smoothness deficits early post stroke, as well as its longitudinal association with abnormal muscle synergies in persons with stroke. In an observational study (not part of this thesis), we studied changes in SPARC in a clinical setting during a reach-
to-grasp task in the first 6 months after stroke in a cohort of 40 patients who suffered a first-ever ischemic stroke (Saes et al., n.d.). The study showed that recovery of smoothness during a multi-joint reaching task reflected by SPARC and the recovery from abnormal muscle synergies reflected by FM-UE are longitudinally associated and follow a similar time course. This suggests that the reduction of smoothness deficits and abnormal muscle synergies may be driven by a common underlying process of spontaneous neurological recovery. This was seen in the first 5 weeks post stroke in persons who were moderately to mildly affected due to a stroke. Therefore, we recommend studying smoothness measured by SPARC in future stroke studies, and in clinical measures on movement quality in the upper limb.

Thus, Chapters II and III make significant steps for future research in the direction of kinematics and its relation to changes in motor recovery. Both chapters focused on the 2D reaching assay. This assay was studied more often in literature (Schwarz et al., 2019) as it reflects the participant's capacity to coordinate planar movements around more than one joint including the shoulder and elbow (Kwakkel et al., 2019). The assay requires the participant to produce smooth and accurate reaching trajectories and to maintain a stable endpoint position at the end of the movement (Kwakkel et al., 2019). Using 2D reaching as a performance assay results in selection bias, as the assay is usually feasible only in persons moderately or mildly affected with stroke. Therefore, additional assays must be considered to study recovery post stroke.

Additional performance (finger individuation, grip strength and precision grip between thumb and index finger) or functional (3D drinking task) assays may be used to measure movement quality (Kwakkel et al., 2019). The 3D drinking task further consists of several sub-tasks including reaching and grasping, transporting glass to mouth, drinking, transporting the glass back to its starting point, and retuning the hand to the starting point (Kwakkel et al., 2019; Murphy et al., 2006). Identifying the quality of each sub-task is required to understand the quality of the complete functional assay (Adans-Dester et al., 2020; Murphy et al., 2006). Further research is required to identify and reach consensus on the metrics that measure quality of the overall tasks, or the sub tasks.

### 11.2.2. Lower Extremity

Movements in the upper and lower extremities are indeed different. Movements in the upper extremity are goal directed, usually related to interaction with the environment, and employ one or both sides. However, movements in the lower extremity are related to transfer of oneself, periodic or non-periodic patterns, or balance correction that use both sides. Therefore, stroke affects the two extremities differently, and measuring movement quality of the lower extremity and distinguishing between recovery and compensation using biomechanics is more complicated. Measures of symmetry and inter-limb coordination are proposed to reflect movement quality (Kwakkel et al., 2019; Shin et al., 2020). However, it is not clear how they relate to motor recovery. In order to measure recovery on each leg, we have to first disentangle their respective contribution towards gait and balance (van Asseldonk, 2008). This requires special tools such as system identification and induced acceleration (van Asseldonk, 2008). Using these tools, we can identify biomechanical metrics that reflect gait quality. These metrics must be assessed longitudinally post stroke in order to state whether they reflect motor recovery. Therefore, our understanding of kinematics and kinetics that can distinguish recovery from compensation in the lower extremity post stroke is currently in a nascent stage.

In spite of this gap, we rather focused on developing wearable solutions that can measure gait parameters in the second section of this thesis. These solutions can arm clinicians with an extended set of tools for measuring movement quality. This increases the number of possible measurement points over time, thereby painting a more detailed picture of motor recovery post stroke.

### 11.2.3. Compensating for less optimal recovery after stroke

Compensation is defined as accomplishing a goal through substitution with a new approach rather than use of normal pre-stroke behavioural repertoire (Bernhardt et al., 2017). After the spontaneous recovery that takes place in the first 5 weeks post stroke, functional improvements in the chronic phase are probably supported by compensation strategies (Cirstea and Levin, 2000; van Kordelaar et al., 2013). Identifying compensation strategies helps clinicians prescribe appropriate therapies that either reduce or optimize these strategies
per patient. Jones summarized the different compensatory strategies used in human and animals during the upper limb movement after stroke (Jones, 2017):

C1. Using trunk displacement to support hand extension.
C2. Excess finger opening before a grasping task.
C3. Excessive grip force during gripping.
C4. Grasping by flexing proximal finger joints, whereas healthy participants usually flex their distal finger joints, and extend their proximal finger joints.
C5. Relying more on the non-paretic hand.
C6. Using trunk rotation to assist hand orientation.
C7. Bringing the palm towards the mouth using trunk and head rotation, with lesser wrist supination.
C8. Compensating precision grip by grasping between fingertip and palm or proximal thumb.

Compensatory strategies $\mathrm{C} 1-\mathrm{C} 4$ were reported in human clinical trials, C5 and C6 were seen in both clinical as well as rodent studies, and the last two were only reported in animal (rodent and monkey) studies (Inset: Compensation strategies). In rodent stroke models, kinematics have been the gold standard for differentiating motor recovery from compensation (Jones, 2017), and this could be extended to clinical stroke models. Marker based video capture systems can measure appearance of pathological synergies (van Kordelaar et al., 2012a) as seen in strategies C1, C2, C4, C5, and C6. Furthermore, grip strength sensors can be useful in measuring strategy C3 (Ye et al., 2014). Compensation using trunk movement during reaching is seen quite often and influences reaching performance (Cirstea and Levin, 2000; Schwarz et al., 2020; Suvada et al., 2020). Recently, using fMRI, Bani-Ahmed and Cirstea studied the relation between ipsilateral primary Motor Cortex (iM1) activity and its relation with compensation of the paretic arm (BaniAhmed and Cirstea, 2020). They concluded that dynamic recruitment of iM1 is associated with trunk motion in chronic stroke, which is not seen in healthy participants (Bani-Ahmed and Cirstea, 2020). They further speculated that the instead of directly controlling the impaired arm, the iM1 area is involved in compensating brain damage (Bani-Ahmed and Cirstea, 2020). These initial
results concluded that kinematics in addition to being objective also enhance scope and reliability of fMRI studies.

Compensatory strategies in hemiparetic gait during the swing phase includes, amongst others, pelvis hiking, reduced knee flexion, and circumduction due to limited ankle dorsiflexion on the paretic side (De Luca et al., 2019; Kerrigan et al., 2000; Olney and Richards, 1996). Additionally, persons with stroke may also exhibit flat foot landing during initial contact, and knee hyperextension and excessive knee flexion during the stance phase on the paretic side (Olney and Richards, 1996). Although these strategies improve walking speed, they may affect long term recovery, and result in weakness of the underutilized muscles (Levin, 1996). Therefore, it is unclear whether it is optimal to avoid these strategies or embrace them as they help improve parameters such as walking speed. Further, as these strategies involve movement of different joints or lower extremity segments, they require measurement of biomechanics across different joints. Hence, measuring compensation in the lower extremity can be an involved process. Further research is required in order to concur how compensation should be best measured in the lower extremity.

### 11.3. MEASURING MOVEMENT QUALITY OUTSIDE THE LAB

We see in the previous sections that biomechanics are well poised to assist clinicians to measure differences in behavioural restitution and compensation post stroke. However, the gold standard for measuring movement currently is marker based optical motion capture systems. These systems have low ecological validity (Colyer et al., 2018) and do not allow quick measurement of the persons with stroke or home monitoring. Therefore, suitable wearable sensors need to be developed.

### 11.3.1. Wearables for the Upper Extremity

An ideal wearable system for measuring movement of the upper extremity should be light weight, inconspicuous, and integrated into the clothing or a watch (Bergmann and McGregor, 2011). Thus, Inertial Measurement Units (IMUs) find potential uses in this direction.


IMU data could be exploited to estimate biomechanics that provide objective information regarding the upper extremity movement such as reaching or during clinical assessments such as the Fugl-Meyer assessment (FM) (Bhagubai et al., 2021). The measurement setup of Bhagubai and colleagues was able to provide objective information about changes in joint angles and presence of pathological synergies during each of the FM tasks (Bhagubai et al., 2021). Instrumented gloves or arm wear can be useful in measuring compensations used in the hand during fine movements, and grasping or gripping (Raghavan et al., 2010; Schwarz et al., 2020). These setups can help clinicians measure objective changes in kinematic metrics of the upper limb and distinguish behavioural restitution from compensation during the initial weeks post stroke.

In the AMBITION project, efforts have been taken towards developing a minimal sensor setup for measuring quality of upper limb movement. In a limited study, the feasibility of a three IMU approach to detect reaching and to subsequently measure its quality was tested (Jafarzadeh Esfahani, 2019). The IMUs were placed on each wrist, and one on the chest. The study showed the feasibility of the setup for measuring smoothness of the reaching events using the SPARC metric. In a recent study on persons with stroke, MelendezCalderon and colleagues (Melendez-Calderon et al., 2021) concluded that IMU based estimation of SPARC is not recommended due to the issue of drift that occurs when processing IMU data. However, they avoided exploring drift correction techniques and state that velocity reconstruction is almost always erroneous due to incorrect orientation correction. Nevertheless, other studies show, in situations where we can confidently identify the movement task being made, a good assumption regarding the initial and final velocities of reaching can be made (Bhagubai et al., 2021; Jafarzadeh Esfahani, 2019). This allows us to use appropriate drift correction techniques which provides a better estimate of reaching kinematics. Furthermore, sensor fusion techniques may be used to optimize the estimated velocity of reaching based on expected error margins associated with the measurements. Therefore, we recommend setting up studies on persons with stroke that test the feasibility of a minimal sensing setup (preferably three IMUs; one on each wrist, and one on the chest) to detect reaching tasks during ADL, and thereafter measure its quality.

The feasibility of a minimal three IMU system (one on each wrist, and one on the chest) must be studied for detecting
 reaching and measuring reaching quality post stroke.

Apart from reaching, measuring recovery of finger individuation is also important post stroke (Kwakkel et al., 2019). There have been efforts in developing wearable systems for this purpose. The Powerglove consists of a series of IMUs placed at different finger segments, and provides a comprehensive visualization of finger movement (Kortier et al., 2014; van den Noort et al., 2016). However, the system employs 17 IMUs, and that increases the cost and complexity of the device. The system can rather be minimized when the movements we wish to measure require the hand and finger tips
move together (Schwarz et al., 2020; Yang et al., 2020). This is also an area of active research.

Measuring forces during finger individuation, grasping or gripping using wearables is rather non-trivial. Nonetheless, there have been several attempts in this direction. Kortier and colleagues studied the manipulation of loads at the finger tips using miniature 3D force sensors (Kortier et al., 2016). However, these sensors mask the natural tactile feedback at the fingertips. Wolterink and colleagues designed a 3D printed shear force sensor that can help reduce the loss of touch sensation (Wolterink et al., 2019). The commercially available Myo ${ }^{\text {TM }}$ band can be explored as an alternative that can measure forearm muscle activity and model it to estimate the forces exerted by the fingers.

Thus, further development on minimal wearable sensor systems is required for measuring finger individuation, and grasp/grip forces. Such systems would help measure performance assays of the upper extremity post stroke.

Further development of wearable systems for measuring finger individuation and grasping/grip forces will be useful
 in studying upper extremity recovery post stroke.

### 11.3.2. Wearables for the Lower Extremity

The second section of the thesis focused on developing wearable sensors for estimation of gait and gait quality. Tracking gait quality helps us understand recovery post stroke, and therefore, these solutions were provided within the context of stroke research. Nevertheless, the wearable solutions presented in this thesis can be applied to populations other than stroke.

In Chapter IV, we showed that pressure sensors can be used to extract more information than simply the pressure profiles of the feet. Changes in pressure profiles under the feet were related to measurement of shear forces using machine learning models. We also showed that measurement of balance metrics is feasible even when only the changes in pressure profile under the heel and metatarsal region are available.

### 11.3.3. Portable Gait Lab (PGL)

A major part of the thesis focuses on translating the data from IMUs to useful gait parameters using a three IMU based Portable Gait Lab (PGL) setup (Chapters V - X).

IMUs measure 3D linear accelerations, and 3D angular velocities of the object they are attached to. One approach to extract gait parameters is to employ physical models. Parameters such as orientation, linear velocity, and position of the object can be estimated from IMU data using strapdown inertial navigation (Woodman, 2007). Strapdown inertial navigation introduces drift in the estimated variables, which are usually removed by employing principles of gait biomechanics. This approach is influenced by errors associated with strapdown inertial navigation, and assumptions regarding the gait models used. The estimated variables can be used to extract gait parameters of interest. For instance, IMU data has been used to estimate gait events (Pacini Panebianco et al., 2018), walking speed (Sabatini et al., 2005), joint angles (Muro-de-la-Herran et al., 2014; Tham et al., 2021), foot pose and trajectory (Okkalidis et al., 2020a) etc. We also employ this 'physical model' approach in Chapters VI - X for estimating ground reaction forces, Centre of Mass (CoM) velocity, and relative movement of feet and CoM.

Additionally, there are other methods in literature to extract gait and balance parameters from IMU data. We could classify them into the following broad categories. Although these categories can also apply to estimation of upper extremity kinematics, we restrict our discussion to the lower extremity:

- Employing raw IMU data: Using smart heuristics, the angular velocities and accelerations of the IMUs can be used to obtain spatiotemporal parameters. Using this approach, temporal and symmetry parameters are relatively easier to measure (Pacini Panebianco et al., 2018; Storm et al., 2016; Zhang et al., 2018). This method offers relatively lower processing complexity and could be applicable in real time.
- Employing machine learning models: Machine learning methods automatically build a black box model of the gait parameters of interest from IMU data without needing any knowledge of the underlying physical models. The advantage of this approach is that it allows us to extract data from sensors that are not directly measured by them. For instance,
using machine learning models applied to sparse IMUs, we can extract 3D ground reaction forces (Ancillao et al., 2018; Revi et al., 2020; Wouda et al., 2018a), full body joint kinematics (Weygers et al., 2020; Wouda et al., 2018a), CoM velocity (Sabatini and Mannini, 2016), Centre of Pressure (CoP) trajectory (Podobnik et al., 2020) etc. A drawback of this method is that the machine model cannot be related to an underlying physical model of motion. Furthermore, in order to create new models, training datasets are required.
- Employing correlation models: Finally, instead of building any of the above models, correlates for gait parameters of interest can be extracted from IMU data. For instance, Fino and colleagues use an average of the acceleration over each step as a correlate for lateral Margin of Stability (MoS) (Fino et al., 2020). Such an approach may be suitable when measuring complex measures using a limited sensor setup and limited processing. Although this offers a simple approach to estimate relevant gait parameters, this approach may not provide a mechanistic underpinning and must be tested for reliability in cases of variable gait.

Therefore, in order to measure gait parameters of interest, the approach may depend on the parameter itself, or complexity of the setup. Usually, optical motion capture systems are considered to be gold standards for kinematic measures. However, they do not measure orientations directly, and require proper marker placement and segment modelling. The choice of the underlying biomechanical model influences the joint angles being measured (Wouda et al., 2018b). Therefore, in case of joint kinematics, IMUs could be considered as a more reliable alternative, as they measure rate of change of joint angle directly.

Measuring spatiotemporal metrics that rely on movement of just one foot, or temporal metrics relative to both feet have been shown in literature (Okkalidis et al., 2020a; Pacini Panebianco et al., 2018; Schepers et al., 2010b; Storm et al., 2016). This includes parameters such as stance time, stride length etc. However, measuring spatiotemporal metrics with a three IMU setup that require knowledge of relative foot movement is not trivial. In Chapters IX and $\mathbf{X}$, we show that the PGL is able to measure the different gait parameters including those that require knowledge about relative foot movement.

The PGL employs a number of assumptions and biomechanical constraints in order to track the relative movement of the feet and CoM. It employs the simplified inverted pendulum model of walking, which allows us to ignore knee joint kinematics. Furthermore, we assumed that the CoM is bounded by the pelvis (Devetak et al., 2019; Floor-Westerdijk et al., 2012), which allows us to estimate accelerations of the CoM by placing an IMU on the pelvis.

The Centroidal Moment Pivot (CMP) point constraint was central for the PGL. Although the CMP point is used in humanoid gait (Popovic et al., 2005), we considered that the assumptions of CMP point are also valid in human gait (Chapter IV). This helped us approximate the relative movement of feet and CoM as the IMUs cannot measure this directly. The uncertainty in the assumptions of the CMP point can be reduced if we can model foot roll during stance and estimate moments around the CoM.

Additional portable sensors such as pressure insoles or an additional sternum IMU can be used to solve the issues above. Employing a sparse pressure sensor layout under the metatarsal and heel should be sufficient to estimate the CoP given that the dimensions of the feet are known (Chapter IV). This helps as the trajectory of the CoP overlaps that of the CMP point (Chapter V). Furthermore, pressure insoles can improve our estimations of foot contact, gait cycle phases, and 3D ground reaction forces (Chapter IV). A recent study showed that the foot can be modelled as a multi-segment model, simply by adding IMUs to different locations on the foot (Okkalidis et al., 2020b). Furthermore, the uncertainty in CMP assumptions is expected to increase during turns due to trunk rotations. Using simple models, the sternum IMU can be used to estimate the moments around the CoM, which can help reduce the uncertainty with CMP point (Chapter X). Another biomechanical constraint used in the PGL is the use of zero height during stance phases (Chapters IX, $\mathbf{X )}$. This makes it unsuitable for measuring gait on uneven terrain, such as stair climbing, up or down hill walking. Barometers and ultrasound sensors have been used to measure changes in height of the IMUs (Jao et al., 2020). These may help reduce the drift during stair or slope climbing whilst keeping the size of sensors small. In these cases, we recommend studying the inclusion of adding portable sensors to the PGL (preferably a pressure insole and a sternum IMU). We expect these changes to only minimally compromise the portability and inconspicuousness of the envisioned minimal sensing setup.

The accuracy of spatiotemporal parameters measured by the Portable Gait Lab system due to inclusion of portable sensors such as pressure insoles or sternum IMU must be studied.

To deal with uncertainties of the different biomechanical constraints used in the PGL, we used sensor fusion techniques. Particularly, the error extended Kalman filter, and extended Kalman filter approaches were used (Chapters VI - X). The Kalman filter is essentially a Bayesian fusion model, that fuses different sources of information whilst assuming that the noise associated with each information is known, and thereby, an optimal estimate can be derived. Other sensor fusion techniques may be employed as long as the dependent parameters are tuned well (Caruso et al., 2021). Thus, the relative estimations of foot and CoM distances within the PGL are an optimal estimate. This is unlike a true measure of relative distances as is the case in the work of Weenk and colleagues (Weenk et al., 2015). Therefore, the PGL estimates the most optimal output given the errors associated with the IMUs, process of integration, as well as biomechanical models of gait are known.

## Usability of the Portable Gait Lab (PGL) in the clinic and daily life

We tested the PGL in persons with stroke walking in a straight line (Chapter X). Although the results are not generalizable due to the limited dataset used, the study shows the feasibility of using the PGL in stroke population. A subsequent study is currently being setup at the Roessingh Research and Development with more persons with stroke performing variable walking tasks by Roelien Russcher.

The results of the PGL were optimized using the reference systems (VICON© or ForceShoes ${ }^{\mathrm{TM}}$ ) for validating the 3D ground reaction forces, and kinematics of the CoM and feet (Chapters VI - IX). In Chapter X, we make efforts to reduce this dependency on the reference system, by identifying parameters that can be measured easily in the clinic such as total distance travelled, and distance between either foot at the end of walking task. Additional measures that can be explored for this purpose include average CoM velocity. These efforts can help translate the PGL into a standalone system that be commercialized. The Dutch sensor product development company 2M Engineering Ltd., also a
partner of the AMBITION project, has developed a prototype of the PGL that can be used in actual practice. This helps us bridge the gap between academia and clinical application.

The PGL has potential to be developed as a home monitoring system. The system must be optimized for use by persons with stroke, i.e., the wearability and setup must be simple. The users could wear the three IMUs that form the PGL during training or exercise sessions that they perform at home. Predefined set of instructions must be provided so that they can calibrate and perform the tasks themselves. The gait metrics that will be measured by the PGL in these tasks can be used by clinicians to track performance during daily life. This could help clinicians and users optimize ADL such that they promote rehabilitation.

## Framing movement right

Anatomical reference frames are used in order to express changes in joint kinematics, as they are clinically relevant. Data from optical marker based systems are calibrated in order to derive these special frames. However, when we study kinematics using IMUs, we have the opportunity to explore a bodyfixed reference frame, as the IMUs move along with the body. For instance, Fino and colleagues use the average inclination with respect to gravity to define a body-fixed frame (Fino et al., 2020). Rebula and colleagues estimate the average heading from a number of strides in order to define the body-fixed frame with respect to the foot movement (Rebula et al., 2013). In Chapters VI - X, we extend the concept of body-fixed frame to define reference frames that changes per step. Applying this step-wise reference frame allows us to compare gait kinematics across all steps, including turning or shuffling steps. This approach offers us a new perspective in studying gait biomechanics. These body-fixed reference frames could be closer to the somatosensory reference frame used by the body when planning motion (Burdet et al., 2013). This could provide an avenue for studying changes in planning or control of limbs in the presence of a perturbation (Burdet et al., 2013; Vlutters et al., 2018).

## IMU Calibration: good initialization begets reliable kinematics

IMUs are essentially sensors of change, as they measure changes in angular and linear kinematics. Therefore, good calibration of the initial state is necessary for subsequent optimal estimation of gait biomechanics. In this thesis, we calibrate the initial orientation of the foot sensors using the first step made by the user. For the pelvis sensors, additional movements were incorporated to estimate the initial orientation. In Chapters VI and VII, we show the use of a bowing task that allowed estimation of the medio-lateral axes of the pelvis. In Chapter $\mathbf{X}$, we explored the sit to stand movement during the Timed Up and Go test for the same purpose. If we wish to move towards using the PGL in clinical or home applications, the calibration procedure must be extracted from movements in ADL that are comfortable for persons with balance issues. As ADL is rich with variable movement, activity classifiers may be employed to select movements appropriate for the calibration. This problem of movement classification using wearable sensors has been studied commonly in literature (Attal et al., 2015; Lara and Labrador, 2013; Liu and Schultz, 2019; van Meulen et al., 2016a).

## Passing the baton: New avenues for Portable Gait Lab (PGL)

We attempted to protect the concepts introduced in Chapters $\mathbf{V}-\mathbf{X}$ by filing a patent (Mohamed Refai et al., 2021). The principles of the PGL are additionally available for the scientific community in the form of the different publications included in this thesis (Mohamed Refai et al., 2020a, 2020b, 2020c, 2020d, 2019a, 2019b). However, we believe that the functionality and applicability of the PGL can be broader than those identified in this thesis and the patent.

Sy and colleagues measured joint kinematics of the lower extremity during gait using only three IMUs and a number of biomechanical constraints (Sy et al., 2020). It would be fruitful to include their model with the PGL to develop a minimal system that provides a complete picture of gait including biomechanics of the feet and CoM, as well as joint kinematics for the lower extremity.

Ankle push-off propels the CoM during gait (Zelik and Adamczyk, 2016), and is a clinically relevant kinetic parameter that must be studied post stroke (Alingh et al., 2020; Roelker et al., 2019; Yang et al., 2018). Push-off power is measured
as the product of ankle velocity and ankle torque (Caputo and Collins, 2014). Ankle joint angles could be approximated using the three IMU setup and the method of Sy and colleagues (Sy et al., 2020). Using simple approximations, the total ground reaction forces acting on the body as estimated using the PGL (Chapter VI) can be approximated to forces acting under each foot (Karatsidis et al., 2016; Ren et al., 2008). Alternatively, using pressure insoles, we can measure the ground reaction forces and moments of each foot during walking (Chapter IV). Therefore, it might be feasible to measure ankle push-off power during gait using the PGL by applying additional biomechanical constraints and including pressure insoles.

The minimal sensing setup has to be further developed for additional gait patterns seen in daily life such as climbing stairs, side stepping, walking a slope etc. The approach is further complicated if the person with stroke employs walking aids such as a cane. The aids may also be instrumented in order to measure its movement (Sprint et al., 2016). We have to be aware that parameters such as gait events, Base of Support (BoS), and Margin of Stability (MoS) have to be redefined for this special case. The inverted pendulum model of walking can no longer be employed. Additionally, if the person leans on the cane, the CoM moves further from the pelvis and may oscillate outside the body during this period. Therefore, the underlying assumptions and models used in the PGL have to be revisited.

Nonetheless, interesting efforts have been made by Eleonora Costamagna in her PhD thesis in this direction. In her studies, she instrumented a walking frame with force sensors, placed pressure sensors under the feet of the participants, and measured movement using optical motion capture system (Costamagna et al., 2019, 2017). She developed a combined stability margin that includes the frame of the walking aid in measuring the stability during stance (Costamagna et al., 2017). IMUs were later added to the instrumented walkers developed by Costamagna (Cheng et al., 2016; Sun et al., 2019). The IMU data was only used to understand gait patterns of walker (rollator) users, and to estimate gait speed and distance travelled. Therefore, further work is required to estimate gait stability using only IMUs. IMUs placed on the user can be used to measure the relative movement of the user and the walking aid. However, the distance between them cannot be measured directly, and this
requires additional sensors. An infrared, ultrasound, or ultra wide band based time of flight sensor may offer a simple approach in determining the distance between the walker and the user. It is wise to begin with an extended set of sensors before exploring avenues for minimization. Similar attempts can also be made when the user relies on a single walking cane. However, the combined stability margin has to be redefined for this case too (Costamagna et al., 2017).

Developing the Portable Gait Lab system to measure gait quality in persons using walking aids or other relevant metrics such as ankle push off would improve the usability of the system.

### 11.3.4. Marker-less motion capture systems

Motion capture systems that use markers and are powered by artificial intelligence pose a potential competition to the advancement of IMUs in the measurement of gait biomechanics. The root mean square of errors in estimating 3D joint angles using a marker-less system varied per movement task, and was at best 2 degrees for the lower extremity for walking tasks when compared to marker based systems (Colyer et al., 2018). In comparison, a full body suit of IMUs showed similar errors (Zhang et al., 2013). DeepLabCut ${ }^{\text {TM }}$ is an example of an open access software that helps tracking motion in animal models (Nath et al., 2019), and efforts to track human movement are underway. Another system, DensePose, can track several human poses at the same time (Güler et al., 2018). However, these systems depend on existing models of pose, line of sight, and require processing power. Nevertheless, they may also offer an approach where the user doesn't have to wear any sensors and can perform unrestricted movements either at the clinic, or at home.

### 11.4. AUGMENTED MOVEMENT FEEDBACK

The human body constantly receives intrinsic feedback when we navigate or interact in our environment. This feedback is derived from the perceptual information from sensory processes such as vision, proprioception, and audition that sense movement (Molier et al., 2010). In persons with stroke, intrinsic feedback may be affected, and in such cases, augmented feedback
can be useful. Feedback regarding the progress of undergoing therapy can be provided to the clinician or the patient themselves. They could be used to assist the disturbed intrinsic feedback or be used to tailor patient specific therapies. For instance, if we could conclude that motor recovery does not take place anymore for a person with stroke, feedback may be used to improve a functional ability using compensatory strategies. Regardless, the different fundamental ways of feedback or aspects that can be identified are (Molier et al., 2010):

- Nature: Feedback can be provided about the movement itself i.e., Knowledge of Performance (KP) or about the outcome of the movement i.e., Knowledge of Results (KR).
- Timing: Feedback can be delivered during the movement i.e., concurrent or can be postponed until after the movement has been completed i.e., terminal.
- Frequency: The feedback frequency aspect could either be summary or faded. Summary feedback is provided at fixed intervals, for instance after every ' $x$ ' trials. Faded feedback on the other hand follows a schedule, for instance, first feedback is provided after the ' x 'th trial, then after the ' 3 x 'th trial, and so on.

The sources of augmented feedback or types can be categorised as follows (Molier et al., 2010; Sigrist et al., 2013):

- Auditory: includes verbal encouragements or beeps,
- Sensory: includes force, tactile and position feedback,
- Visual: includes vision of own movement, virtual or augmented realities, or simply scores and reports on a screen.
- Multimodal: A mixture of different modalities.

Aspects of augmented feedback must be clearly discerned before applying them in clinical rehabilitation (Molier et al., 2010). Metrics that track recovery of the upper extremity and identify compensation strategies are required in order to develop feedback paradigms. For instance, concurrent feedback can be provided in order to warn participants about possible compensatory strategies. At the end of the movement, KR feedback can be provided to summarize the
goals that were achieved as part of the movement. For instance, when the participant is reaching, tactile sensors may be placed on the arm or chest. When the participant employs the alternative hand, or bends the trunk, the tactile sensors may warn them. At the end of the task, the smoothness or the movement quality of the task may be reported to the clinician who keeps a periodic tab on the progress and advises the participant to change movements if necessary. There has been progress in this direction, for example, detecting trunk compensation using wearable systems have already been reported in literature (Ranganathan et al., 2017).

In persons with gait impairment, joint angle was commonly measured to provide feedback, and feedback was most commonly provided by touch (Shull et al., 2014). Feedback during gait was provided in order to improve walking stability and to reduce joint loading (Shull et al., 2014). In cases of persons with stroke, the clinician may use the spatiotemporal parameters measured using the PGL in order to track changes over time. This information can help clinicians or therapists tweak the therapies such that it optimizes lower extremity function post impairment. However, care must be taken while defining feedback aspects and paradigms for the lower extremity. For instance, concurrent feedback during gait post stroke might be risky as it may affect balance and may lead to falls.

Note that auditory, sensory, or visual feedback requires active attention by the user, and subsequent cognitive effort by the user to translate it to the desired movement. Contrarily, intuitive feedback can be provided by providing opposing forces or torques that correct the movement of the user. There are solutions such as the GyroGlove ${ }^{\mathrm{TM}}$ that helps reduce hand tremors (Panisse et al., 2016), or the GyBAR that helps with balance issues (Lemus et al., 2020). The GyBAR is a gyroscope installed into a backpack (Lemus et al., 2020), and has been shown to improve the user's ability to walk further on a thin beam, and also standing balance for persons with stroke.

Finally, future studies must focus on first measuring movement quality post stroke, and then identifying patient specific therapy goals. This can help develop feedback paradigms that either promote behavioural restitution over compensation strategies or vice versa.

Knowledge of metrics that measure movement quality can help develop patient tailored feedback paradigms.

### 11.5. FUTURE RESEARCH QUESTIONS

Based on the knowledge gained in this thesis, its limitations, and the inspiring discussions with the project partners that took place during the AMBITION meetings, we highlight a number of different research goals that may be explored as a follow up of this thesis:

### 11.5.1. Behavioural restitution versus compensation:

- Identifying biomechanical metrics that are capable of measuring movement quality and distinguishing behavioural restitution from compensation post stroke.
- Identifying feedback paradigms that are patient specific and can individually target behavioural restitution or compensatory strategies post stroke.


### 11.5.2. Upper Extremity:

- Studying the feasibility of a minimal three IMU system (one on each wrist, and one on chest) in detecting reaching and measuring reaching quality post stroke.
- Developing minimal and wearable sensing systems for measuring finger individuation and grasping/gripping forces.


### 11.5.3. Lower Extremity:

- Improving the relative distance estimation by the Portable Gait Lab system by including additional portable sensors such as pressure insoles, or sternum IMU.
- Studying the feasibility of the Portable Gait Lab system in measuring variable walking in persons with stroke including turns, shuffling, backward stepping, climbing stairs etc.
- Developing models to measure push-off during gait using the Portable Gait Lab system in healthy populations and those with neurological disorders.
- Developing models that enable the use of the Portable Gait Lab system in measuring gait quality in persons using walking aids such as crutches or wheeled walkers.


### 11.6. GENERALIZABILITY OF THE FINDINGS

In this thesis, movement quality was provided within the context of differentiating recovery from compensatory strategies post stroke. However, movement quality is also affected in other populations with neurological disorders such as Parkinson's, Huntington's, Multiple sclerosis, cerebral palsy, etc. (Centonze et al., 2020; Mañago et al., 2020; Tosserams et al., 2020). Our findings regarding the kinematics of reaching can be applied to other populations that study changes in reaching quality (Connell and Tyson, 2012). Nevertheless, the underlying spontaneous recovery pattern seen in stroke may not apply to other neurological disorders (Langhorne et al., 2011). Moreover, the compensatory strategies used may differ based on the area or severity of damage done in the central nervous system (Nonnekes et al., 2019). Also, in persons with lower extremity amputation, compensation strategies were observed on both the intact and amputated leg (Prinsen et al., 2011). Therefore, biomechanical metrics that reflect movement quality must be studied specifically for each population.

Furthermore, our efforts in developing minimal systems, including the PGL, can be applicable to other fields that perform gait analysis. As we validated the PGL mostly with healthy gait performed at self-selected walking speeds, the system has potential applications for commercial wearables that track gait. The system could also be applicable to gait in elderly to monitor risk of fall using the spatiotemporal and balance metrics that PGL can measure. The PGL could be used to design smarter prosthesis or exoskeletons. In case of exoskeletons, the CMP point can be used to control foot placement (Hamza et al., 2020), and using the ideas presented in this thesis, the CMP point can be used to estimate parameters such as step length and relative foot distances.

In case of neurological populations other than stroke, variability in gait patterns that may affect the application of PGL must be first considered.

For instance, persons with Parkinson's suffer from Freezing of Gait (FoG). During these instances, there is no clear swing phase, and therefore the CMP constraint cannot be used (Chapter IX). This is because we employ the CMP constraint during the stance phase when the contralateral leg is in swing. Nonetheless, the IMUs could be used to detect FoG, and the CMP constraint could be applied accordingly (Shi et al., 2020). The PGL may be used in rehabilitation after trauma or corrective surgery of the lower extremity. In these situations, the PGL could help track changes in gait quality during the course of recovery and offer indications for selection of appropriate patient tailored therapies.

The PGL may be used to improve estimation of relative foot distances during running. However, it would be useful to first validate the assumptions of the CMP point during running before applying the PGL. Therefore, the PGL has potential across different fields, if the variations in gait are studied within the context of the constraints used.

### 11.7. CONCLUDING REMARKS

This thesis offers a platform through which we can address future avenues for standardization of stroke rehabilitation and integration of technology in practice and care. We reviewed our understanding of movement recovery in the upper extremity and developed wearable solutions for measuring gait quality. We also identified questions that need to be addressed in order to apply these findings in actual practice. In the far future, we might be able to pre-emptively prevent stroke or are able to regrow our lost brain cells after a stroke. In this utopia, we do not need to concern ourselves with hemiparesis. Hitherto, we have to rely on extracting the best outcome from the current state of the art and optimize them for use in daily life.

## Appendices

## Appendices related to Chapter II:

A Search strategy used in Chapter II
B Definitions and psychometric analyses of metrics identified in Chapter II
C Assessing if the studies identified in Chapter II agreed with international recommendations

## Appendices related to Chapter III:

D Search strategy used in Chapter III
E Modelling reach-to-grasp movement in healthy participants
F Models for reach-to-point and reach-to-grasp movements
G Mathematical definition of selected smoothness metrics
H Simulation analyses performed for reach-to-grasp movement
I Influence of the velocity profile model on monotonicity in the submovement simulation

# APPENDIX A: SEARCH STRATEGY USED IN CHAPTER II 

Search strategy in PubMed July 1, 2020 (read from bottom-up).



Search strategy in EMBASE July 1, 2020 (read from bottom-up).

[^6]‘cerebrovascular accident’/exp OR cva:ab,ti OR cvas:ab,ti OR stroke:ab,ti OR apoplex*:ab,ti OR poststroke*:ab,ti OR ((brain*:ab,ti OR cerebr*:ab,ti OR cerebell*:ab,ti OR intracran*:ab,ti OR intracerebral*: ab,ti OR vertebrobasilar":ab,ti) AND vascular*:ab,ti AND (disease:ab,ti OR diseases:ab,ti OR accident*:ab,ti OR disorder*:ab,ti)) OR (cerebrovascular*:ab,ti AND (disease:ab,ti OR diseases:ab,ti OR accident*:ab,ti OR disorder*:ab,ti)) OR ((brain*:ab,ti OR cerebr":ab,ti OR cerebell*:ab,ti OR intracran*:ab,ti OR intracerebral*:ab,ti OR vertebrobasilar*:ab,ti) AND (haemorrhag*:ab,ti OR hemorrhag*:ab,ti OR ischemi":ab,ti OR ischaemi*:ab,ti OR infarct*:ab,ti OR haematoma*:ab,ti OR hematoma*:ab,ti OR bleed*:ab,ti))

Search strategy in Scopus July 1, 2020 (read from bottom-up).

## Set Search terms

\#4 AND (LIMIT-TO ( SRCTYPE, "j" ) ) AND (LIMIT-TO ( DOCTYPE, "ar") OR LIMIT-TO
\#5 ( DOCTYPE, "re" ) OR LIMIT-TO ( DOCTYPE, "ip" ) ) AND (LIMIT-TO (LANGUAGE , "English"))
\#4 \#1 AND \#2 AND \#3
(TITLE-ABS-KEY ( movement OR motion OR mechanical OR biomechanic* OR kinematic*
\#3 OR kinetic* OR angle* OR force* OR motion OR acceler* OR deceler* OR rotation OR velocity* OR speed* OR spatiotemporal ) )
( TITLE-ABS-KEY ( pronation OR supination OR hand AND strength OR reach* OR coordination OR grasp" OR grip* OR pinch AND strength OR "Upper Extremit"" OR "Upper Limb*" OR arm OR arms OR shoulder OR elbow* OR forearm* OR wrist* OR hand OR hands OR finger* OR thumb* ) )
( ( TITLE-ABS-KEY ( cva OR cvas OR poststroke* OR stroke* OR apoplex* ) OR TITLE-ABS-KEY ( ( brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar*) AND vascular* AND ( disease OR diseases OR accident* OR disorder*) )) OR TITLE-ABS-KEY ( ( (brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar* ) AND ( haemorrhag* OR hemorrhag* OR ischemi* OR ischaemi* OR infarct* OR haematoma* OR hematoma* OR bleed* ) ) ) )

Search strategy in the Cochrane Library July 1, 2020 (read from bottom-up).
Set Search terms
\#4 \#1 AND \#2 AND \#3 in Cochrane Reviews (Reviews and Protocols), Other Reviews and Trials
Movement or Motion or Mechanical or biomechanic* or Kinematic* or kinetic* or
\#3 angle* or force* or motion or acceler* or deceler* or rotation or velocity* or speed* or spatiotemporal:ti,ab,kw

Pronation or Supination or Hand Strength or reach* or coordination or grasp* or grip*
\#2 or pinch strength or "Upper Extremit"" or "Upper Limb"" or arm or arms or shoulder or elbow* or forearm* or wrist* or hand or hands or finger* or thumb*:ti,ab,kw
cva or cvas or poststroke* or stroke* or apoplex* or ((brain* or cerebr* or cerebell* or intracran* or intracerebral* or vertebrobasilar*) and vascular* and (disease or diseases
\#1 or accident* or disorder*)) or (cerebrovascular* and (disease or diseases or accident* or disorder*)) or ((brain* or cerebr* or cerebell* or intracran* or intracerebral* or vertebrobasilar*) and (haemorrhag* or hemorrhag* or ischemi* or ischaemi* or infarct* or haematoma* or hematoma* or bleed*)):ti,ab,kw
APPENDIX B: DEFINITIONS AND PSYCHOMETRIC ANALYSES OF METRICS IDENTIFIED IN CHAPTER II
Table B. 1 Reported outcomes regarding the investigated kinematic metrics.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | As stated by the authors | As stated by the authors | Degree to which the metric is an adequate reflection of the construct measured(Mokkink et al., 2010) | Degree to which the metric is free from measurement error(Mokkink et al., 2010) | Significant change over time (yes/no); time period (T1-T2) or passed time ( $\Delta T$ ) | Measurement time point; Clinical measure it has been associated with, strength |
| Platz et al., 2001 | Movement time | Time between start and end of each aimed movement | Differences between groups studied (discriminative validity) | NR | Yes; 3w | NR |
|  | Accuracy | Distance from center of target at movement termination |  | NR | Yes; 3w | NR |
| Rohrer et al., 2002 | Mean Speed | Total distance travelled over total movement duration | Differences between groups studied (discriminative validity) | NR | NR | Results combined sub-acute and chronic participants. <br> Longi: FM-UE: Jerk (fair), Speed Metric (fair), MAPR (fair), Tent (poor), Peaks (poor), other metrics: NR |
|  | Peak Speed | NR |  | NR | NR |  |
|  | Movement Duration | NR |  | NR | NR |  |
|  | Jerk Metric | Negative of mean jerk magnitude divided by peak speed |  | NR | NR |  |
|  | Speed Metric | Mean speed divided by peak speed |  | NR | NR |  |
|  | Mean Arrest <br> Period Ratio <br> (MAPR) | Proportion of time that movement speed exceeds a given percentage of peak speed |  | NR | NR |  |
|  | Peaks Metric | Number of peaks in a speed profile |  | NR | NR |  |
|  | Tent Metric | Ratio of area under the speed curve to the area under a curve stretched over its top |  | NR | NR |  |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Lang et al., 2006a | Reach speed | Peak wrist velocity | Correlation of change with ARAT was used to denote construct validity of ARAT | NR | NR | *0d: ARAT fair <br> *14d: ARAT NS <br> *90d: ARAT moderately strong |
|  | Reach efficiency | Reach path ratio: ratio between length of travelled path to a straight line between start and end position. |  | NR | NR | *0/90d: ARAT fair <br> *14d: ARAT moderately strong |
|  | Reach accuracy | Endpoint error: distance from index finger to target at the end of movement |  | NR | NR | *0d: ARAT moderately strong <br> *14/90d: ARAT fair |
|  | Aperture speed | Maximum aperture rate, how fast thumb and index finger opened/ closed |  | NR | NR | *0d: ARAT moderately strong <br> *14/90d: ARAT fair |
|  | Aperture efficiency | Aperture path ratio: ratio of the length of the aperture curve to an ideal straight line between the first peak of the aperture trace and the aperture at the end of movement. |  | NR | NR | *0/90d: ARAT fair <br> *14d: ARAT moderately <br> strong |
|  | Peak aperture | Distance between thumb and index finger tips during the movement |  | NR | NR | ```*0/14d: ARAT moderately strong *90d: ARAT fair``` |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Lang et al., 2006b | Reach speed | Peak wrist velocity | NR | NR | Yes; 1w-90d | NR |
|  | Reach efficiency | Reach path ratio: ratio between length of travelled path to a straight line between start and end position. | NR | NR | Yes; 1w-90d | NR |
|  | Reach accuracy | Endpoint error: distance from index finger to target at the end of movement | NR | NR | Yes; 1w-90d | NR |
|  | Aperture speed | Maximum aperture rate, how fast thumb and index finger opened/ closed | NR | NR | Yes; 1w-90d | NR |
|  | Aperture efficiency | Aperture path ratio: ratio of the length of the aperture curve to an ideal straight line between the first peak of the aperture trace and the aperture at the end of movement. | NR | NR | No; 1w-1y | NR |
|  | Aperture accuracy | Aperture at touch: distance between thumb and index fingertip at the end of the movement | NR | NR | No; 1w-1y | NR |
|  | Peak aperture | NR | NR | NR | Yes; 1w-90d | NR |
|  | Time of peak aperture | Percentage of movement time when peak aperture occurred | NR | NR | No; 1w-1y | NR |
|  | Movement time | NR | NR | NR | Yes; 1w-90d | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Wagner et al., 2007 | Peak wrist velocity | Max. Tangential linear velocity of the wrist between the start and end of the first phase of reaching | Differences between groups studied (discriminative validity) | NR | Yes; 9d-109d | 109d: C-AROM fair; <br> 109d: C-STR moderately <br> strong |
|  | Endpoint error | Distance from index finger to center of target at the end of the first phase of reaching |  | NR | Yes; 9d-109d | 109d: C-AROM NS; <br> 109d: C-STR fair |
|  | Reach path ratio | Ratio of the length of the actual wrist path travelled to an ideal straight line between start position and target |  | NR | Yes; 9d-109d | 109d: C-AROM fair; <br> 109d: C-STR fair |
|  | Movement time | Time from start of movement to target touch |  | NR | Yes; 9d-109d | NR |
| Konczak et al., 2010 | Max hand velocity | Maximum hand velocity during the large transport phase of the hand | Differences between groups studied (discriminative validity) | NR | Yes; 2w-4w | NR |
|  | Max hand acceleration | Maximum hand acceleration during the large transport phase of the hand |  | NR | Yes; 2w-4w | NR |
|  | Acceleration time | The time between movement onset and peak resultant velocity |  | NR | NR | NR |
|  | Deceleration time | The time between peak resultant velocity and movement end |  | NR | NR | NR |
|  | Total movement time | Sum of acceleration and deceleration time |  | NR | Yes; 2w-4w | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Edwards et al., 2012 | Peak wrist velocity | Maximum resultant velocity of the wrist | Metric used to assess construct validity of WMFT | NR | NR | *0d: WMFT function, time and grip: moderately strong *14d: WMFT function and grip: fair; WMFT time: NS *90d: WMFT function and time: fair. WMFT grip: moderately strong |
|  | Reach efficiency | Reach path ratio: ratio of the length of the path actually travelled to an ideal straight line between the start and end positions. |  | NR | NR | *0/14/90d: WMFT function: fair <br> *0/14/90d: WMFT time: <br> moderately strong <br> *0d: WMFT grip: poor <br> *14/90d: WMFT grip: fair |
|  | Reach accuracy | Endpoint error: total distance from the index finger to the target at the end of movement |  | NR | NR | * $0 / 14 \mathrm{~d}$ : WMFT function and time: moderately strong *90d: WMFT function and time: fair *0/14/90d: WMFT grip: fair |
|  | Aperture speed | Maximum aperture rate: velocity of opening/closing thumb and index finger tips |  | NR | NR | *0d: WMFT function, time and grip: moderately strong *14d: WMFT function, time and grip: fair *90d: WMFT function and grip: NS, time: fair. |
|  | Aperture efficiency | Aperture path ratio: ratio of the length of the aperture curve actually travelled to an ideal straight line between the first peak of the aperture trace and the aperture at the end of movement. |  | NR | NR | *0/14/90d: WMFT function and time: moderately strong, grip: fair |
|  | Peak aperture | Maximum distance between thumb and index finger tips during movement |  | NR | NR | *0/14d: WMFT function: moderately strong *90d: WMFT function: fair *0/14/90d: WMFT time and grip: moderately strong |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{aligned} & \text { Tan et al., } \\ & 2012 \end{aligned}$ | Total movement time | Total time it took to complete the task | No between group differences | NR | Yes; 2w | NR |  |
| Dipietro <br> et al., $2012$ | movement mean speed | NR | NR | NR | Yes; NR | NR |  |
|  | movement peak speed | NR | NR | NR | Yes; NR | NR |  |
|  | movement duration | NR | NR | NR | Yes; NR | NR |  |
|  | speed shape | mean speed divided by peak speed | NR | NR | Yes; NR | NR |  |
|  | number of peaks | Negative of the number of peaks in the speed profile | NR | NR | Yes; NR | NR |  |
|  | jerk | Negative mean jerk magnitude divided by the peak speed | NR | NR | Yes; NR | NR |  |
| van <br> Kordelaar <br> et al., $2013$ | Trunk rotation | Defined by ISB, forward/backward trunk rotation, lateral trunk rotation toward the paretic/non-paretic side, axial trunk rotation toward the nonparetic/paretic side | NR | NR | NR | NR |  |
|  | Shoulder rotation | Defined by ISB, horizontal shoulder adduction/abduction, upward/ downward shoulder rotation, internal/external shoulder rotation. | NR | NR | NR | NR |  |
|  | Elbow rotation | Defined by ISB, elbow flexion/ extension | NR | NR | NR | NR |  |
|  | Forearm rotation | Defined by ISB, forearm pronation/ supination | NR | NR | NR | NR | 空 |
|  | Wrist rotation | Defined by ISB, wrist flexion/ extension, ulnar/radial rotation | NR | NR | NR | NR | 苋 |
|  | Movement duration | Time between the start and end of reach-to-grasp | NR | NR | Yes; 14d-57d | NR |  |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Duret and Hutin 2013 | Movement efficacy | $1=$ target reached, $0=$ not reached | NR | NR | Yes; 40d | NR |
|  | Root-meansquare | RMS error between the trajectory and the virtual linear trajectory | NR | NR | No; 80d | NR |
|  | Hand velocity | NR | NR | NR | Yes; 40d | NR |
|  | Number of hand trajectory reversals | Number of direction changes on the trajectory | NR | NR | Yes; 80d | NR |
| Metrot et al., 2013a | Movement time | Time between begin and end of movement | NR | NR | Yes; 2w, 3w | NR |
|  | Number of velocity peaks | NR | NR | NR | Yes; 2w, 3w | NR |
|  | Max reaching velocity | Maximal amplitude of the velocity peak | NR | NR | Yes; NR | NR |
|  | Trajectory directness | Trajectory/distance ratio | NR | NR | Yes; NR | NR |
| Colombo et al., 2013 | Active movement index | The percentage of trajectory travelled by means of the patient's voluntary activity. | NR | NR | Yes; 3w | NR |
|  | mean velocity | The mean value of the velocity of the end-effector. | NR | NR | Yes; 3w | NR |
|  | normalized path length | Path length of the trajectory travelled by the patient to reach the target, normalized to the theoretical path. | NR | NR | Yes; 3w | NR |

Table B. 1 Continued.

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Interval of submovements | NR |  |  |  |  |
|  | Skewness of submovements | NR |  |  |  |  |
| Van <br> Kordelaar et al., 2014 | Movement duration | Time between the start and end of reach-to-grasp movement | NR | Yes(van Kordelaar et al., 2012b) | Yes; 1w-5w | NR |
|  | Normalized hand displacement Jerk | $3^{\text {rd }}$ derivative of hand displacement was squared and integrated over the total movement duration, from start of reach to grasp to end, normalized to ( $\mathrm{L}^{\wedge} 2 /\left(\mathrm{MD}^{\wedge} 5\right)$ ), L is shortest distance between start and end position of hand, MD is movement duration. | NR | Yes(van Kordelaar et al., 2012b) | Yes; 1w-5w | NR |
|  | Jerk grasp aperture | $3^{\text {rd }}$ derivative of hand grasp aperture was squared and integrated over the total movement duration, from start of reach to grasp to end, normalized to (L^2/(MD^5)) | NR | Yes(van Kordelaar et al., 2012b) | Yes; 1w-5w | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Van <br> Dokkum <br> et al., <br> 2014 | Movement time | NR | Discriminative validity | NR | NR | Longi; FM-UE NS |
|  | Peak hand velocity | NR |  | NR | NR | Longi; FM-UE NS |
|  | Mean velocity | NR |  | NR | *Yes; NR | NR |
|  | Time of max velocity | NR |  | NR | NR | Longi; FM-UE NS |
|  | Trajectory length | NR |  | NR | NR | Longi; FM-UE NS |
|  | Trajectory directness | Curvature index: ratio between actual hand path and the straight link between beginning and end-point. |  | NR | *Yes; NR | Longi; FM-UE NS |
|  | Number of velocity peaks | NR |  | NR | *Yes; NR | Longi; FM-UE NR |
|  | Movement irregularity | Ratio between peak and mean speed, which is the inverse of smoothness. |  | NR | NR | Longi; FM-UE NS |
| $\begin{aligned} & \text { Yoo et al., } \\ & 2015 \end{aligned}$ | Smoothness | Smoothness is calculated as the ratio of mean velocity/max velocity. | NR | NR | Yes; 4w | NR |
|  | Reach error | difference between the patients' actual reach endpoints and the endpoint targets | NR | NR | Yes; 4w | NR |
|  | Displacement | patients' ability to move the arm against resistance in each of eight compass directions | NR | NR | No; 4w | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Semrau et al., 2015 | Composite score | All scores were normalized to a z-score distribution, based on: posture speed, reaction time, initial direction error, initial distance ratio, speed maxima count, min/max speed difference, movement time, path length ratio, max speed. | Criterion validity | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Posture speed | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Reaction time | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Initial direction error | NR |  | NR | Yes; NR | All: FIM, PP, CMSA; all time points strength fair |
|  | Initial distance ratio | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Speed maxima count | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Min/max speed difference | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Movement time | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |
|  | Path length ratio | NR |  | NR | Yes; NR | All: FIM, PP, CMSA; strength NR |
|  | Max speed | NR |  | NR | NR | All: FIM, PP, CMSA; strength NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{aligned} & \text { Li et al., } \\ & 2015 \end{aligned}$ | Reaction time | Time between the go cue and the moment when the index finger was lifted off the starting point. | Concurrent and predictive validity tested | NR | NR | Pre: FM-UE Sig for both conditions; strength NR Post: FM-UE Sig for unconstrained; strength $N R$ |
|  | Movement time | Time between movement onset and end. Represents temporal efficiency. |  | NR | NR | Pre: ARAT, FM-UE; Sig for both conditions; strength $N R$ Post: FM-UE; Sig for both conditions; strength $N R$ |
|  | Endpoint displacement | Length of the trajectory in 3D space from movement onset to end |  | NR | NR | Pre: ARAT; Sig for constrained; strength $N R$ Post: ARAT; Sig for both conditions; strength $N R$ |
|  | Peak velocity | Highest tangential velocity used to characterize velocity during reaching |  | NR | NR | Post: ARAT; Sig for constrained; strength NR |
|  | Percentage of peak velocity | time from the movement onset to the moment where peak velocity occurred divided by the total task time. |  | NR | NR | Post: ARAT; Sig for unconstrained; strength $N R$ |
|  | Shoulder flexion | sagittal plane: the angle between the vector joining the ipsilateral acromionlateral epicondyle markers and the vector joining the C7 and T4 markers. |  | NR | NR | NR |
|  | Shoulder adduction | frontal plane: was determined by the angle between the vector joining the ipsilateral acromion-lateral epicondyle markers and the vector joining the C7 and T4 markers. |  | NR | NR | Pre: FM-UE; Sig for unconstrained; strength $N R$ Post: ARAT; Sig for unconstrained; strength NR Post: FM-UE; Sig for both conditions; strength $N R$ |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Elbow extension | sagittal plane: the angle between the vector formed by the ipsilateral acromion-lateral epicondyle markers and a vector defined by the lateral epicondyle and the styloid process of the ulna. |  | NR | NR | Pre: ARAT; Sig for unconstrained; strength $N R$ |
| Prange et al., 2015 | Reach distance | Horizontal distance between start position (as close to their sternum as possible) and end position (as far as possible in a forward direction) | NR | NR | Yes; 6w | NR |
| Bang et al., 2015 | Maximal elbow extension angle during reaching | Defined as the dot product of 2 vectors formed by lateral epicondyle of the humerus and styloid process of the ulna markers, and lateral epicondyle of the humerus and ipsilateral greater trochanter of the humerus. The elbow angle was defined as zero in full flexion and $180^{\circ}$ in full extension. We recorded the maximum extension angle of elbow during reaching. | NR | NR | Yes; 4w | NR |
| Buma et <br> al., 2016 | Normalized jerk grasp | third derivative in the grasp aperture signal (between thumb and index finger), normalized for movement duration and net change in grasp aperture during the reach-to-grasp movement. | Significantly correlated with brain activation and ARAT | NR | Yes; 6w-29w | 6w: ARAT (moderately strong); NS with FM-UE or NHPT; fMRI (moderately to very strong) |
|  | Movement duration | time between start and end of reach-to-grasp movement. |  | NR | Yes; 6w-29w | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Duret et al., 2016 | mean movement speed | NR | NR | NR | Yes; 35d | Pre: FM-UE and MSS, moderately strong Longi: FM-UE and MSS, poor |
|  | peak movement speed | NR | NR | NR | Yes; 35d | Pre: MSS, moderately strong; <br> FM-UE, NS <br> Longi: FM-UE and MSS, poor |
|  | path error | Movement accuracy: mean deviation from the straight path towards the target. | NR | NR | Yes; 35d | Pre: FM-UE and MSS, moderately strong. Longi: change of FM-UE (moderately strong) and MSS (fair) was related to change of path error |
|  | reach error | Efficacy: ability to precisely reach the target | NR | NR | Yes; 35d | Pre: FM-UE and MSS, very strong <br> Longi: FM-UE and MSS, poor |
|  | speed shape | Smoothness metric calculated as mean speed divided by peak speed. | NR | NR | Yes; 35d | Pre: FM-UE and MSS, moderately strong Longi: FM-UE and MSS, poor |
| Cortes et al., 2017 |  | $A M D^{2}$ is a measure of the statistical distance between entire reaching |  |  |  |  |
|  | Average squared Mahalanobis Distance (AMD ${ }^{2}$ ) | trajectories made by each stroke participant and healthy controls, using functional principal component analysis; hence it is a global kinematic measure. | NR | NR | Yes; 1w-5w | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| $\begin{aligned} & \text { Pila et al., } \\ & 2017 \end{aligned}$ | Distance Index | mean distance travelled by the participants hand from the starting position in percent of the controls | NR | NR | $\begin{aligned} & \text { Yes; } 2 m-3 m, \\ & 2 m-4 m, 2 m-5 m \end{aligned}$ | NR |
|  | Velocity Index | distance travelled divided by movement time in percent of controls | NR | NR | $\begin{aligned} & \text { Yes; } 2 m-3 m, \\ & 2 m-4 m, 2 m-5 m, \\ & 3 m-5 m \end{aligned}$ | NR |
|  | Accuracy Index | inverse of root mean square error from straight line in percent of controls | NR | NR | Yes; 2m-5m | NR |
|  | Smoothness Index | inverse of mean number of zero crossings in the velocity profile in percent of controls | NR | NR | $\begin{aligned} & \text { Yes; } 2 m-3 m, \\ & 2 m-4 m, 2 m-5 m \end{aligned}$ | NR |
| Palermo et al., 2018 | Movement time (MT) | Total execution time of the task (between onset and offset) measured in seconds | NR | NR | Yes; 4w | Longi: NS: FIM, BI, FAT, FM-UE |
|  | Peak velocity (PV) | maximum value of the speed profile curve of the hand marker, measured in $\mathrm{m} / \mathrm{s}$ | NR | NR | No | Longi: NS: FIM, BI, FAT, FM-UE |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Time to PV <br> (TtPV) | Percentage of time from the beginning of the movement to the peak speed | NR | NR | No | Longi: NS: FIM, BI, FAT, FM-UE |
|  | Normalized Jerk (NJ) | Non-dimensional quantity which corresponds to the square root of the jerk (third derivative of the position of the hand marker with respect to time), mediated over the entire duration of the movement, and normalized with respect to MT and to the total displacement of the onset and offsets | NR | NR | Yes; 4w | Longi: NS: FIM, BI, FAT, FM-UE |
|  | Trunk <br> Displacement <br> (TD) | Measured in meters to identify compensation movements, calculated as the difference between the maximum displacement of the trunk marker and its initial position in space, normalized with respect to distance C7-sacrum, expressed as a percentage | NR | NR | Yes; 4w | Longi: NS: FIM, BI, FAT, FM-UE |
|  | Hand Path Ratio (HPR) | Ratio of the distance travelled by the hand between the movement onset and offset and the straight-line distance between the starting and destination targets, expressed as a percentage | NR | NR | Yes; 4w | Longi: FAT (strength NR, mentioned as strong), NS: FIM, BI, FM-UE |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Mazzoleni et al., 2018 | Mean Velocity | NR | NR | NR | Yes (ab/ad component during forward and backward direction, fl/ ex component during left/right direction); 6w | NR |
|  | normalized jerk | The normalized jerk is a unitfree metric used to evaluate the smoothness of movements: the lower the values of this index, the smoother the movement | NR | NR | Yes (forward and backward direction); 6w | NR |
|  | Quality index | Reflects the accuracy of movements. Smaller QI values, correspond to more accurate movements. | NR | NR | Yes (forward, backward and left direction); 6w | NR |
| Duret et <br> al., 2019 | Mean movement speed | measured in centimeters per second | NR | NR | Yes; 5w | NR |
|  | movement path error | mean deviation from the straight line | NR | NR | Yes; 5w | NR |
|  | active range of motion | calculated as the average distance between the movement end point and the peripheral target in centimeters | NR | NR | Yes; 5w | NR |
|  | smoothness | calculated from the average speed divided by peak speed. | NR | NR | Yes; 5w | NR |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Mazzoleni et al., 2019 | mean velocity | NR | NR | NR | Yes (forward, backward and left direction); 5w | NR |  |
|  | normalized reaching speed | peak velocity minus mean velocity normalized to peak velocity | NR | NR | Yes (abduction component during reaching in forward direction); 5w | NR |  |
|  | normalized jerk | unit-free metrics used to evaluate the smoothness of movements. Smaller values of the normalized jerk indicate a smoother movement. | NR | NR | Yes (abduction component during reaching in forward direction); 5w | NR |  |
|  | Movement Error | reflects the accuracy of movements. Smaller ME values, correspond to more accurate movements. (same as QI, see Mazzoleni et al., 2018) | NR | NR | Yes (forward, backward and left direction); 5w | NR |  |
| Goffredo et al., 2019 | Movement accuracy | Absolute value of the minimum distance of each point of the actual path travelled by the participant from the ideal straight line connecting the targets | NR | NR | No | NR |  |
|  | Movement speed | Mean value of the resultant velocities in the xy plane | NR | NR | Yes, NR | NR |  |
|  | Number of peak speed | Smoothness, defined as the number of peaks of the resultant velocity | NR | NR | Yes, NR | NR | 完 |
|  | Task completion time | Time required to carry out each single point-to-point trajectory from the central target to the peripheral one | NR | NR | Yes, NR | NR | 花 |

Table B. 1 Continued.

| Authors | Metrics | Definition | Validity | Reliability | Responsiveness | Clinical association |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Hussain et al., 2020 | Movement time | time taken to complete one movement segment | NR | NR | NR | 10d/4w: ABILHAND, NS <br> 3/6m: ABILHAND, fair <br> 12m: ABILHAND, moderately <br> strong |
|  | Mean velocity | NR | NR | NR | NR | 10d/4w/3m/6m: ABILHAND, NS <br> 12m: ABILHAND, moderately strong |
|  | Peak velocity | maximum absolute velocity recorded during each movement segment | NR | NR | NR | All: ABILHAND, NS |
|  | Number of velocity peaks | counting the number of velocity peaks in a movement segment as reflection of movement smoothness | NR | NR | NR | 10d: ABILHAND, fair 4w/3m: ABILHAND, $N S$ 6/12m: ABILHAND, moderately strong |
| Thrane et al., 2020 | peak hand velocity | Maximal tangential velocity during the reaching phase $(\mathrm{cm} / \mathrm{s})$ | NR | NR | Yes; 3d-6m | NR |
|  | relative time to peak velocity | Percentage of time to peak hand velocity during the reaching phase | NR | NR | Yes; 3d-3m | NR |
|  | peak angular velocity | Peak angular velocity of the elbow joint during reaching | NR | NR | Yes; 3d-6m | NR |

[^7]
# APPENDIX C: ASSESSING IF THE STUDIES IDENTIFIED IN CHAPTER II FOLLOWED INTERNATIONAL RECOMMENDATIONS 



Figure C. 1 For each of the recently provided international recommendations on stroke (Kwakkel et al., 2019) by the Stroke Recovery and Rehabilitation Roundtable (SRRR), the percentage of studies identified in Chapter II that followed them is shown. We see (Table C.2) that none of the studies followed all the recommendations of the SRRR. Abbreviations: w: week, m: months, NA: not applicable, NR: not reported, UK: unknown or unclear.
Table C. 2 Overview of whether studies are in agreement with the recent recommendations of SRRR.

|  | Measurement time points |  |  |  | Measurement methods |  |  |  |  | Performed analyses |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | Inclusion in or before early sub-acute phase ( $\leqslant 3$ months) post stroke | Inception cohort from stroke onset onwards ( $\leqslant 1$ week) | Measurements at fixed time points post stroke | s Measurement moments at least at: w1, w12 and w26 | Age matched healthy control group | High speed and high resolution digital optoelectronic system used | Sample frequency 60 Hz | >15 repetitions per task | In addition, a performance assay was investigated to identify behavioral restitution | Changes of kinematics investigated | Changes of clinical scores investigate | Association between metrics and clinical assessments investigated |
| Platz et al., 2001 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| Rohrer et al., 2002 | 1 | 0 | 0 | 0 | 0 | 0 | NR | NR | 0 | 1 | 0 | 1 |
| Lang et al., 2006a | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 |
| Lang et al., 2006b | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 |
| Wagner et al., 2007 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 0 | 1 | 1 | 1 | 1 |
| Konczak et al., 2010 | 1 | 0 | 0 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| Edwards et al., 2012 | 1 | 1 | 1 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 1 | 1 |
| Tan et al., 2012 | 0 | 0 | 0 | 0 | 1 | 0 | NA | 0 | 0 | 1 | 0 | 0 |
| Dipietro et al., 2012 | 1 | 0 | 0 | 0 | 0 | 0 | NR | 1 | 0 | 1 | 1 | 0 |
| Van Kordelaar et al., 2013 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 1 | 0 |
| Colombo et al., 2013 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | NR | 0 | 1 | 1 | 0 |
| Duret and Hutin 2013 | 1 | 0 | 0 | 0 | 0 | NR | NR | 0 | 0 | 1 | 1 | 0 |
| Metrot et al., 2013a | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| Van Kordelaar et al., 2014 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| Van Dokkum et al., 2014 | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 1 |

Table C. 2 Continued.

|  | Measurement time points |  |  |  | Measurement methods |  |  |  |  | Performed analyses |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Krebs et al., 2014 | 1 | 1 | 1 | 0 | 0 | 0 | NR | UK | 0 | 0 | 0 | 1 |
| Yoo et al., 2015 | 0 | 0 | 0 | 0 | 0 | 0 | NR | NR | 0 | 1 | 1 | 0 |
| Semrau et al., 2015 | 1 | 1 | 1 | 1 | 0 | 0 | NR | NR | 0 | 1 | 1 | 1 |
| Li et al., 2015 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 | 1 |
| Bang et al., 2015 | 0 | 0 | 0 | 0 | 0 | 1 | NR | 0 | 0 | 1 | 1 | 0 |
| Prange et al., 2015 | 1 | 0 | 0 | 0 | 0 | 0 | NR | 0 | 0 | 1 | 1 | 0 |
| Buma et al., 2016 | 1 | 0 | 1 | 0 | 0 | 0 | 1 | 0 | 0 | 1 | 1 | 1 |
| Duret et al., 2016 | 0 | 0 | 0 | 0 | 0 | 0 | NR | 1 | 0 | 1 | 1 | 1 |
| Cortes et al., 2017 | 1 | 0 | 1 | 0 | 1 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| Pila et al., 2017 | 1 | 0 | 1 | 0 | 1 | 0 | NR | 1 | 0 | 1 | 1 | 0 |
| Palermo et al., 2018 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 1 | 1 | 1 |
| Mazzoleni et al., 2018 | 1 | 0 | 0 | 0 | 0 | 0 | NR | 0 | 0 | 1 | 1 | 0 |
| Duret et al., 2019 | 1 | 0 | 0 | 0 | 0 | 0 | NR | 1 | 0 | 1 | 1 | 0 |
| Mazzoleni et al., 2019 | 1 | 0 | 0 | 0 | 0 | 0 | NR | 0 | 0 | 1 | 1 | 0 |
| Goffredo et al., 2019 | 1 | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 |
| Hussain et al., 2020 | 1 | 0 | 1 | 0 | 0 | 0 | NR | 1 | 0 | 0 | 0 | 完1 |
| Thrane et al., 2020 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | 0 | 0 | 1 | 0 | 号 |

W Table C. 2 Continued.

|  | Measurement time points |  |  |  | Measurement methods |  |  |  |  | Performed analyses |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| TOTAL (yes/total) | 25/32 | 8/32 | 13/32 | 3/32 | 8/32 | $\begin{gathered} 8 / 32 \\ (1 \mathrm{NR}) \end{gathered}$ | 15/17 <br> (14NR, 1NA) | 8/27 <br> (4NR, <br> 1UK) | 1/32 | 27/32 | 23/32 | 12/32 |

## APPENDIX D: SEARCH STRATEGY USED IN CHAPTER III

Table D. 1 Search string per database

| PubMed | \#1 Stroke | "Stroke"[Mesh] OR "Stroke Rehabilitation"[Mesh] OR cva[tiab] OR cvas[tiab] OR poststroke"[tiab] OR post-stroke*[tiab] OR stroke*[tiab] OR apoplex*[tiab] OR cerebrovascular diseas*[tiab] OR cerebrovascular accident*[tiab] OR cerebrovascular disorder*[tiab] OR ((brain*[tiab] OR cerebr*[tiab] OR cerebell*[tiab] OR intracran*[tiab] OR intracerebral*[tiab] OR vertebrobasilar*[tiab]) AND vascular*[tiab] AND (disease[tiab] OR diseases[tiab] OR accident*[tiab] OR disorder*[tiab])) OR ((brain*[tiab] OR cerebr"[tiab] OR cerebell*[tiab] OR intracran*[tiab] OR intracerebral*[tiab] OR vertebrobasilar*[tiab]) AND (haemorrhag*[tiab] OR hemorrhag*[tiab] OR ischemi*[tiab] OR ischaemi*[tiab] OR infarct*[tiab] OR haematoma*[tiab] OR hematoma*[tiab] OR bleed*[tiab])) |
| :---: | :---: | :---: |
|  | \#2 Kinetics <br> and <br> kinematics | (("Movement"[Mesh:NoExp] OR "Motion"[Mesh] OR "Spatio-Temporal Analysis"[Mesh] OR "Kinetics"[Mesh] OR Kinematic*[tiab] OR kinetic*[tiab] OR angle*[tiab] OR motion[tiab] OR acceler*[tiab] OR deceler*[tiab] OR rotation[tiab] OR velocity*[tiab] OR speed*[tiab] OR spatiotemporal[tiab])) |
|  | \#3 Upper limb kinetics and kinematics | OR "Upper Extremity"[Mesh] OR Upper Extremit*[tiab] OR Upper Limb*[tiab] OR arm[tiab] OR arms[tiab] OR shoulder[tiab] OR elbow*[tiab] OR forearm*[tiab] OR wrist*[tiab] OR hand[tiab] OR hands[tiab] OR finger*[tiab] OR thumb*[tiab] |
|  | \#4 <br> Smoothness | Smooth* |
| Scopus | \#1 Stroke | TITLE-ABS-KEY (cva OR cvas OR poststroke* OR stroke* OR apoplex* OR ( ( brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar* ) AND vascular* AND ( disease OR diseases OR accident* OR disorder*) ) OR ( cerebrovascular* AND (disease OR diseases OR accident* OR disorder* ) ) OR ( ( brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar**) AND ( haemorrhag* OR hemorrhag* OR ischemi* OR ischaemi* OR infarct* OR haematoma* OR hematoma* OR bleed* ) )) |
|  | \#2 Kinetics <br> and kinematics | TITLE-ABS-KEY ( movement OR motion OR kinematic* OR kinetic* OR angle* OR motion OR acceler* OR deceler* OR rotation OR velocity* OR speed* OR spatiotemporal ) |
|  | \#3 Upper limb kinetics and kinematics | TITLE-ABS-KEY ("Upper Extremit*" OR "Upper Limb*" OR arm OR arms OR shoulder OR elbow* OR forearm* OR wrist* OR hand OR hands OR finger* OR thumb* ) |
|  | \#4 <br> Smoothness | TITLE-ABS-KEY ( smooth*) |


| Cochrane | \#1 Stroke | cva OR cvas OR poststroke* OR stroke* OR apoplex* OR ((brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar*) AND vascular* AND (disease OR diseases OR accident* OR disorder*)) OR (cerebrovascular* AND (disease OR diseases OR accident* OR disorder*)) OR ((brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar*) AND (haemorrhag* OR hemorrhag* OR ischemi* OR ischaemi* OR infarct* OR haematoma* OR hematoma* OR bleed*)) |
| :---: | :---: | :---: |
|  | \#2 Kinetics <br> and kinematics | reach* OR coordination OR grasp* OR grip* OR "Upper Extremit"" OR "Upper Limb"" OR arm OR arms OR shoulder OR elbow* OR forearm* OR wrist* OR hand OR hands OR finger* OR thumb* |
|  | \#3 Upper limb kinetics and kinematics | Movement OR Motion OR Mechanical OR biomechanic* OR Kinematic* OR kinetic* OR angle* OR motion OR acceler* OR deceler* OR rotation OR velocity* OR speed* OR spatiotemporal |
|  | \#4 <br> Smoothness | Smooth* |
| Embase | \#1 Stroke | 'cerebrovascular accident'/exp OR cva:ab,ti OR cvas:ab,ti OR stroke:ab,ti OR apoplex*:ab,ti OR poststroke*:ab,ti OR ((brain*:ab,ti OR cerebr*:ab,ti OR cerebell*:ab,ti OR intracran*: ab,ti OR intracerebral*:ab,ti OR vertebrobasilar*:ab,ti) AND vascular*:ab,ti AND (disease:ab,ti OR diseases:ab,ti OR accident*:ab,ti OR disorder*:ab,ti)) OR (cerebrovascular*:ab,ti AND (disease:ab,ti OR diseases:ab,ti OR accident*:ab,ti OR disorder*:ab,ti)) OR ((brain*:ab,ti OR cerebr*: ab,ti OR cerebell*: ab,ti OR intracran*:ab,ti OR intracerebral*:ab,ti OR vertebrobasilar*:ab,ti) AND (haemorrhag*:ab,ti OR hemorrhag*:ab,ti OR ischemi*:ab,ti OR ischaemi*: ab,ti OR infarct*:ab,ti OR haematoma*:ab,ti OR hematoma*:ab,ti OR bleed*:ab,ti)) |
|  | \#2 Kinetics and kinematics | reach*:ti,ab OR coordination:ti,ab OR grasp*:ti,ab OR grip":ti,ab OR ‘upper limb'/exp OR 'Upper Extremit"':ti,ab OR ‘Upper Limb"':ti,ab OR arm:ti,ab OR arms:ti,ab OR shoulder:ti,ab OR elbow*:ti,ab OR forearm*:ti,ab OR wrist*:ti,ab OR hand:ti,ab OR hands:ti, ab OR finger*:ti, ab OR thumb*:ti,ab |
|  | \#3 Upper limb kinetics and kinematics | 'movement (physiology)'/de OR 'limb movement'/de OR 'arm movement'/exp OR 'hand movement'/exp OR 'motion'/de OR 'velocity'/exp OR 'mechanics'/de OR 'biomechanics'/exp OR 'force'/exp OR 'kinematics'/exp OR 'kinetics'/de OR 'torque'/ $\exp$ OR 'temporal analysis'/exp OR 'spatial analysis'/de OR torque*:ti,ab OR biomechanic*:ti, ab OR Kinematic*:ti, ab OR kinetic*:ti,ab OR angle*:ti, ab OR force":ti, ab OR motion:ti,ab OR acceler*:ti,ab OR deceler*:ti,ab OR rotation:ti,ab OR velocity*:ti,ab OR speed*:ti,ab OR spatiotemporal:ti,ab |
|  | \#4 <br> Smoothness | Smooth*:ti,ab |


| CINAHL | \#1 Stroke | (cva OR cvas OR poststroke* OR stroke* OR apoplex) OR ( brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar**) AND vascular* AND ( disease OR diseases OR accident* OR disorder*) OR (cerebrovascular* AND ( disease OR diseases OR accident* OR disorder* ) ) OR (brain* OR cerebr* OR cerebell* OR intracran* OR intracerebral* OR vertebrobasilar* ) AND ( haemorrhag* OR hemorrhag* OR ischemi* OR ischaemi* OR infarct* OR haematoma* OR hematoma* OR bleed* ) |
| :---: | :---: | :---: |
|  | \#2 Kinetics and kinematics | reach* OR coordination OR grasp* OR grip* OR "Upper Extremit"" OR "Upper Limb"" OR arm OR arms OR shoulder OR elbow* OR forearm* OR wrist* OR hand OR hands OR finger* OR thumb* |
|  | \#3 Upper limb kinetics and kinematics | Movement OR Motion OR Mechanical OR biomechanic* OR Kinematic* OR kinetic* OR angle* OR motion OR acceler* OR deceler* OR rotation OR velocity* OR speed* OR spatiotemporal |
|  | \#4 <br> Smoothness | smooth* |

All articles with \#1 AND \#2 AND \#3 AND \#4 NOT ('animal'/exp NOT 'human'/exp) were retrieved.

## APPENDIX E: MODELLING REACH-TO-GRASP MOVEMENT IN HEALTHY PARTICIPANTS

As reach-to-grasp movement does not follow a minimal jerk profile (Hughes et al., 2013), here, we model a base velocity profile for reach-to-grasp movements required for testing the different simulations proposed in Chapter II. For this, data from the EXPLICIT study containing 12 healthy participants performing reach-to-grasp a block as part of the ARAT using the dominant hand was used. The study was registered at the Netherlands National Trial Register (NTR1424), approved by the Medical Ethics Committee of the VU University Medical Centre, Amsterdam, The Netherlands and carried out in accordance with the Code of Ethics of the World Medical Association, Declaration of Helsinki. The average age of the participants was $64.2 \pm 5.8$ years, and seven of them identified as males. Fig. E. 1 shows all 28 trials of reach-to-grasp movement performed by a healthy participant. The profile, unlike a minimal jerk model is skewed and the peak speed is not at half of the reaching duration.

Using Fig. E.1, we can define requirements for the shape of the asymmetric profile. For instance, the velocity at the beginning and end of the movement should be zero. Further, the velocity peaks at $32.7 \%$ of the total reaching time. Using these constraints, a polynomial model of the reaching velocity can be generated using six variables of the form

$$
y(x)=a+b x+c x^{2}+d x^{3}+e x^{4}+f x^{5}
$$

The polynomial fit using the equation and the aforementioned constraints can be seen in Fig. E. $2(g=0)$. Although this velocity profile satisfies all the requirements, it does not have the desired profile of Fig. E.1. An additional variable $g$ was added and tuned to improve the profile. The new polynomial equation is therefore

$$
y(x)=a+b x+c x^{2}+d x^{3}+e x^{4}+f x^{5}+g x^{6}
$$

Multiple solutions were found while solving the above equation due to redundancy (seven variables, six equations). Therefore, a cost function was introduced to optimize the parameter $g$ :


Figure E. 1 Twenty-eight reaching profiles measured on the dominant hand of a single healthy participant.

$$
\text { error }=\frac{\int\left|v-v_{f i t}\right| d t}{\int v d t},
$$

with $v$ as the average velocity profile of participant 1 and $v_{f i t}$ the modelled polynomial velocity profile. $v_{f i t}$ was adjusted based on the distance and duration of the reaching movement $v . v$ was derived by normalizing all trails to movement distance and duration. The error term was minimized using the interior-point algorithm (implemented using MATLAB ${ }^{\text {TM }}$ function fmincon). A $g$ value of 54 was found to be most optimum. This fit will be referred to as 'Polynomial 1'.

To generalize the polynomial model for all participants, all trails of all healthy participants were normalized, and averaged after removing outlies. This velocity profile did not however have a zero velocity and zero acceleration at the end and beginning of the movement.

Using the average profile, the error cost function was minimized by tuning variable $g$, and also the location of the peak value, using fmincon. This resulted in a value of 81.5 for the $g$ parameter and 0.3157 for the peak location. The error between the new found profile and the normalized mean velocity profile was 0.04 . This model had a lower steep slope following the peak velocity, and this polynomial will be referred as 'Polynomial 2'.

It was found that the difference between the two polynomial profiles is not that large. Over all trails, Polynomial 1, had an average error of 0.2369 while Polynomial 2 had an slightly lower average error of 0.2169 . Polynomial 2 will be used in the analysis and can also been seen in Fig. F.1.

Comparison of shapes with a change in g


Figure E. 2 Influence of varying the parameter ' $g$ ' on the polynomial fit. A value of 81.5 provided the closest fit with the reach-to-grasp movement in healthy participants.

## APPENDIX F: MODELS FOR REACH-TO-POINT AND REACH-TO-GRASP MOVEMENTS



Figure F. 1 The velocity profiles $\left(\mathrm{v}_{\text {symm }}\right.$ and $\left.\mathrm{v}_{\text {asymm }}\right)$ used in Chapter III are shown here. Here, they are plotted with a duration of 1 s , and a reaching distance of 0.3 m . The response of each metric to different types of simulated perturbations applied to these profiles were studied.

## APPENDIX G: MATHEMATICAL DEFINITION OF SELECTED SMOOTHNESS METRICS

- Number of sub-movements (NOS) (Rohrer and Hogan, 2006): This algorithm fits the velocity profile by a combination of minimal jerk velocity profiles. This is done by using interior-point algorithm (fmincon in MATLAB) and minimizing the error function:

$$
\begin{aligned}
& \epsilon=\frac{\int|F(t)-G(t)| d t}{\int|G(t)| d t}, \quad \begin{array}{l}
\text { where } \mathrm{G}(\mathrm{t}) \text { is the movement speed } \\
\text { profile and } \mathrm{F}(\mathrm{t}) \text { is the fitted speed } \\
\text { profile. }
\end{array} \\
& F(t)=\sum_{i=1}^{N s} v_{\mathrm{mj}_{\mathrm{i}}}(t) \text { where, } \\
& v_{\mathrm{mj}_{\mathrm{i}}}(t)=\left\{\begin{array}{l}
0 \text { if } t<T_{s_{i}} \\
0 \text { if } t>T_{s_{i}}+T_{i} \\
\text { else } \Delta_{i}\left(\frac{30\left(t-T_{s_{i}}\right)^{4}}{T_{i}^{5}}-\frac{60\left(t-T_{s_{i}}\right)^{3}}{T_{i}^{4}}+\frac{30\left(t-T_{s_{i}}\right)^{2}}{T_{i}^{3}}\right)
\end{array}\right.
\end{aligned}
$$

where Ns denotes the number of sub-movements, $\mathrm{v}_{\mathrm{mj}}$ the minimal jerk speed profile, $\Delta$ the sub-movement distance, $T$ the sub-movement duration and $\mathrm{T}_{\mathrm{s}}$ the sub-movement time shift. Subscript $i$ denotes the $\mathrm{i}^{\text {th }}$ sub-movement. $\Delta, \mathrm{T}_{\mathrm{s}}$ and T are minimized, while the function was initialized ten times at random points within the solution space, with $\mathrm{Ns}=1$. For $\Delta$, the solution space is between 0 and 1 m , for T between 0.01 and 3 s and for $\mathrm{T}_{\mathrm{s}}$ between 0 s and the total duration of the movement. If the error was below 0.02 , the optimization ends, otherwise, a 1 is added to Ns and the optimization continues. Further, the minimization was aborted if Ns was greater than 7. In that case, it was assumed that there was no optimized solution. Finally, NOS gives the number of subtracted sub-movements Ns, which is the measure for smoothness.

- Speed metric (SM) (Rohrer et al., 2002): $S M=\frac{v_{\text {mean }}}{v_{\text {peak }}}$, where $\mathrm{v}_{\text {mean }}$ and $\mathrm{v}_{\text {peak }}$ are respectively the mean and peak velocity of the whole movement.
- Normalized reaching speed (NRS) (Mazzoleni et al., 2011): $N R S=\frac{v_{\text {peak }}-v_{\text {mean }}}{v_{\text {peak }}}$
- Movement arrest period ratio (MAPR) (Beppu et al., 1984): $M A P R=\frac{t\left(v \geq F \cdot v_{\text {peak }}\right)}{T}$ where F is the fraction that is taken from the peak velocity to calculate the threshold and T is the total duration. Rohrer and colleagues (Rohrer et al., 2002) used a F-value of 0.1.
- Velocity arc length (VAL) (Balasubramanian et al., 2012):

$$
\begin{aligned}
V A L & =-\ln \left(\int_{t_{1}}^{t_{2}} \sqrt{\left(\frac{1}{t_{2}-t_{1}}\right)^{2}+\left(\frac{d \hat{v}}{d t}\right)^{2}} \mathrm{~d} t\right) \\
\hat{v}(t) & =\frac{v(t)}{v_{\text {peak }}}
\end{aligned}
$$

Here, $t_{1}$ and $t_{2}$ are the time points at the start and end of the movement.

- Correlation metric (CM) (Krebs et al., 2001): First, the minimum jerk speed profile is calculated by

$$
v_{\mathrm{mj}}(t)=\Delta\left(\frac{30 t^{4}}{T^{5}}-\frac{60 t^{3}}{T^{4}}+\frac{30 t^{2}}{T^{3}}\right), v_{\text {norm }}(t)=\frac{v(t)}{v_{\text {peak }}},
$$

where $v(t)$ is the hand speed, $v_{\mathrm{mj}}(t)$ is the minimal jerk speed profile. $\Delta$ is the distance of the reaching movement. T is the duration of the reaching movement. Then, the correlation coefficient is calculated in the standard form as

$$
\rho=\frac{\sum\left[\left(v_{n o r m}-\bar{v}_{n o r m}\right)\left(v_{m j}-\bar{v}_{m j}\right)\right]}{\sqrt{\left(\sum\left[\left(v_{n o r m}-\bar{v}_{n o r m}\right)^{2} \sum\left(v_{m j}-\bar{v}_{m j}\right)^{2}\right]\right)}}
$$

where $\bar{v}_{\text {norm }}$ and $\bar{v}_{m j}$ are the mean values of the normalized hand speed and minimum jerk speed profile.

- Peaks metric (Peaks) (Brooks, 1974): This metric counts the number of $v_{\text {maxima }}$, where $\mathrm{v}_{\text {maxima }}$ is defined as $v(t): \dot{v}(t)=0$ and $\ddot{v}(t)<0$, where $v(t), \dot{v}(t)$, and $\ddot{v}(t)$ are respectively the first, second and third time derivative of position.
- Number of Peaks normalized by movement duration (NPt) (Kahn et al., 2006):

$$
P M_{m d}=\frac{P M}{T}
$$

- Number of peaks normalized by movement distance (NPd) (Abdul Rahman et al., 2017):

$$
P M_{p s}=\frac{P M}{\Delta}
$$

- Inverse number of peaks and valleys (IPV) (Pila et al., 2017) is defined by $P M_{i n v}=\frac{1}{(P M * 2)-1}$, where PM is the number of peaks, defined earlier, $\mathrm{v}_{\text {peak }}$ is the peak velocity within the movement and T is the total movement duration. Note here that the number of peaks and valleys is defined as $(P M * 2)-1$.
- Acceleration metric (AM) (Mazzoleni et al., 2011): $A M=\frac{\ddot{x}_{\text {mean }}}{\ddot{x}_{\text {peak }}}$, where $\ddot{x}$ is the second derivative of $x(t)$ with respect to time, which is the acceleration.
- Integrated absolute jerk (IAJ) (Duff et al., 2010): $\eta_{\mathrm{iaj}}=\int_{t 1}^{t 2}|\dddot{x}(t)| d t$, where $\dddot{x}(t)$ is the third derivative of $x(t)$ with respect to time, which is the jerk.
- Mean absolute jerk (MAJ) (Bigoni et al., 2016): $\eta_{\text {maj }}=\frac{1}{t_{2}-t_{1}} \int_{t 1}^{t 2}|\dddot{x}(t)| d t$
- Mean absolute jerk, normalized by peak speed (MAJPS) (Rohrer et al., 2002):

$$
\eta_{\text {majps }}=\frac{1}{v_{\text {peak }}\left(t_{2}-t_{1}\right)} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t
$$

- Integrated squared jerk (ISJ) (Laczko et al., 2017): $\eta_{\mathrm{isj}}=\int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t$.
- Root mean squared jerk (RMSJ) (Young and Marteniuk, 1997):

$$
\eta_{\mathrm{rmsj}}=\sqrt{\frac{1}{\left(t_{2}-t_{1}\right)} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t}
$$

- Normalized integrated jerk (NIJ) (Adamovich et al., 2009):

$$
\eta_{\mathrm{NIJ}}=\sqrt{\frac{1}{2} \frac{\left(t_{2}-t_{1}\right)^{3}}{v_{\text {mean }}^{2}}} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t
$$

- Dimensionless squared jerk (DSJt) (Teulings et al., 1997):

$$
\eta_{\mathrm{DSJt}}=\sqrt{\frac{1}{2} \frac{\left(t_{2}-t_{1}\right)^{3}}{v_{\text {mean }}^{2}} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t}
$$

- Log dimensionless squared jerk (LDSJt) (van Kordelaar et al., 2014):

$$
\eta_{\mathrm{LDSJt}}=\ln \left(\sqrt{\frac{1}{2} \frac{\left(t_{2}-t_{1}\right)^{3}}{v_{\text {mean }}^{2}} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t}\right) .
$$

- Dimensionless squared jerk (DSJ ${ }_{m}$ ) (Marini et al., 2017):

$$
\eta_{\mathrm{DSJm}}=\frac{1}{2} \sqrt{\frac{\left(t_{2}-t_{1}\right)^{3}}{v_{\text {mean }}^{2}} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t}
$$

Note that although this is similar to the DSJt (Teulings et al., 1997), there is an additional $1 / 2$ in the equation.

- Dimensionless squared jerk (DSJb) (Balasubramanian et al., 2012):

$$
\eta_{\mathrm{DSJb}}=\frac{\left(t_{2}-t_{1}\right)^{3}}{v_{\text {peak }}^{2}} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t
$$

- Log dimensionless squared jerk (LDSJb) (Balasubramanian et al., 2012):

$$
\eta_{\mathrm{LDSJb}}=\ln \left(\frac{\left(t_{2}-t_{1}\right)^{3}}{v_{\text {peak }}^{2}} \int_{t_{1}}^{t_{2}} \dddot{x}(t)^{2} d t\right)
$$

- Rotational jerk (RJ) (Repnik et al., 2018):

$$
\eta_{\text {rot }}=\log \sqrt{\frac{\left(t_{2}-t_{1}\right)^{5}}{2 \theta^{p}}} \int_{t_{1}}^{t_{2}}\left\|\frac{d^{2} \omega(t)}{d t^{2}}\right\|^{2} d t
$$

where $t_{1}$ is the beginning of the movement, $t_{1}$ the end of the movement, $\omega(t)$ is the hand angular velocity vector and parameter $\theta^{p}$ normalizes the jerk index with angular displacement of the rotation movement.

- Spectral metric (SPMR) (Strohrmann et al., 2013):

$$
\begin{aligned}
& V(\omega)=\operatorname{fft}(v(t)) \\
& \bar{V}(\omega)=\frac{V(\omega)}{\sum_{\forall \omega}\{V(\omega)\}} \\
& S P M R=\max _{\forall \omega}\{V(\omega)\},
\end{aligned}
$$

where $f f t(v(t))$ is the fast Fourier transform operation. The parameters are in this transformation are chosen such that each bin in the frequency domain is equal to 0.2 Hz

- Spectral method (SPM) (Balasubramanian et al., 2009):

$$
\begin{aligned}
V(\omega) & =f f t(\tilde{v}(t)) \\
\bar{V}(\omega) & =\frac{V(\omega)}{\max _{\forall \omega}\{V(\omega)\}} \\
S P M & =\sum \operatorname{Maxima}_{\bar{V}(\omega)} \in\left[0, \omega_{c}\right] \text { with }, \\
\omega_{c} & =\min (\omega) \mid \bar{V}(\omega)<0.01
\end{aligned}
$$

where $\tilde{v}(t)$ is the zero padded version of $v(t), \mathrm{V}(\omega)$ is the Fourier magnitude spectrum of $\tilde{v}(t)$, and $\left[0, \omega_{\mathrm{C}}\right]$ is the frequency band occupied by the given movement. Before detecting the maxima, spectral smoothing was done using a moving average filter using a window size of 5 samples.

- Spectral arc length 2012 (SPAL) (Balasubramanian et al., 2012):

$$
\begin{aligned}
S P A L & =-\int_{0}^{\omega_{c}} \sqrt{\left(\frac{1}{\omega_{c}}\right)^{2}+\left(\frac{d \hat{V}(\omega)}{d \omega}\right)^{2}} \mathrm{~d} \omega \\
\hat{V}(\omega) & =\frac{V(\omega)}{V(0)}
\end{aligned}
$$

where $\mathrm{V}(\omega)$ is the Fourier magnitude spectrum of $\mathrm{v}(\mathrm{t})$, and $\left[0, \omega_{\mathrm{c}}\right]$ is the frequency band occupied by the given movement.

- Spectral arc length (SPARC) (Balasubramanian et al., 2015) uses the same formula as the SPAL. However, to determine $\omega_{\mathrm{C}}$ the following additional formula is used:

$$
\omega_{c} \triangleq \min \left\{\omega_{c}^{\max }, \min \{\omega, \hat{V}(r)<\bar{V} \forall r>\omega\}\right\}
$$

- Combined smoothness metric (CSM) (Kostić and Popović, 2013):

$$
C S M=e^{\left(J_{h}+J_{i}\right)}+e^{\left(P_{h}+P_{i}\right)}+\frac{V_{i}}{V_{h}}+\frac{T_{i}}{T_{h}}
$$

where $J_{i}$ is the mean negative jerk, normalized by peak velocity, $P_{i}$ is the number of peaks in the velocity profile, $V_{i}$ is the ratio of mean velocity and peak velocity and $T_{i}$ is the ratio of area under the velocity profile and its convex hull. The terms $J_{h}, P_{h}, V_{h}$ and $T_{h}$ are the normal values, which were $1.15,1,0.5$ and 0.9 respectively (Kostić and Popović, 2013).
APPENDIX H: SIMULATION ANALYSES PERFORMED FOR REACH-TO-GRASP MOVEMENT

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${ }_{[-1}^{-\infty}$

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 $\stackrel{\circ}{\circ} \mathrm{in}$

 $\begin{array}{llll} & 0 & 0 & 0.2 \\ \text { Movement duration (s) Movement distance (m) }\end{array}$




$\begin{array}{ccc}0 & 0 & 0.2 \\ & \text { SPM }\end{array}$

Figure H. 1 Shape simulation (SS): The vertical axis represents the metric value, ranging from yellow to blue in descending order. The horizontal axes represent the movement duration and movement distance. Metrics included are NOS (number of sub-movements), SM (speed metric), MAPR (movement arrest period ratio), $V A L$ (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), DSJt and DSJb (Dimensionless squared jerk), LDSJb and LDSJt (log of DSJt and DSJb), CM (correlation metric), SPMR (spectral metric), SPM (spectral method), SPAL (spectral arc length 2012), and SPARC (spectral arc length). SM, MAPR, IPV, CM, SPM, SPMR, SPAL and SPARC should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. $D S J t, D S J b$ and $L D S J b$ showed significant change from the base profile only when testing with the the $\mathrm{v}_{\text {asymm }}$.









$$
\begin{array}{lllllllll}
\hline 20 & 10 & 0 & 0 & 0.05 & 0.1 & 0.15 & 0.2 \\
& & & \text { SPM } & & & & \\
& & & & & & & & \\
\hline
\end{array}
$$


Figure H. 2 Harmonic Disturbances simulation: The color represents the value on the z -axis, with yellow being the highest value. Metrics included are NOS (number of sub-movements), $S M$ (speed metric), MAPR (movement arrest period ratio), VAL (velocity arc length), Peaks (number of peaks), IPV (inverse of number of peaks and valleys), $D S J t$ and $D S J b$ (Dimensionless squared jerk), $L D S J b$ and $L D S J t(\log$ of $D S J t$ and $D S J b$ ), $C M$ (correlation metric), SPMR (spectral metric), $S P M$ (spectral method), $S P A L$ (spectral arc length 2012), and SPARC (spectral arc length). $S M, M A P R, I P V, C M, S P M, S P M R, S P A L$ and $S P A R C$ should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness.

[-]
U 0.5

[-]

[-]


| 0 |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: |
| 0 | 0.02 | 0.04 | 0.06 | 0.08 |
| 0 | LDSJt |  |  |  |

[-]

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Figure H. 3 Noise simulation: The thick blue line represents the mean value of 25 different realizations of the noise for each noise RMS, and shaded area is the corresponding standard deviation. The dotted lines denote the minimum and maximum value of the metric found at that RMS value. The dashed blue line shows mean value of the filtered noise sets. Metrics included are NOS (number of sub-movements), SM (speed metric), MAPR (movement arrest period ratio), $V A L$ (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), $D S J t$ and $D S J b$ (Dimensionless squared jerk), $L D S J b$ and LDSJt (log of DSJt and DSJb), CM (correlation metric), SPMR (spectral metric), SPM (spectral method), SPAL (spectral arc length 2012), and SPARC (spectral arc length). $S M, M A P R, I P V, C M, S P M, S P M R, S P A L$ and $S P A R C$ should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. Peaks and $I P V$ were less sensitive to measurement noise when the base velocity profile used was $\mathrm{v}_{\text {asymm }} \mathrm{rather}$ than $\mathrm{v}_{\text {symm }}$.


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## APPENDIX I - INFLUENCE OF THE VELOCITY PROFILE MODEL ON MONOTONICITY IN THE SUB-MOVEMENT SIMULATION

A preliminary analysis showed that for the sub-movement simulation, the monotonicity of jerk based metrics depended on the base velocity profile for the symmetric velocity profile. Therefore, the influence of base velocity profiles on the monotonicity was assessed with additional simulations performed using Hann and Blackman window as the base symmetric velocity profile. Both windows had a total duration of 1 s , and a total reaching distance of 0.3 m .

It was found that the monotonicity of jerk based metrics depends on the design of the base velocity profile for the $\mathrm{v}_{\text {symm }}$. Further, the choice of normalization used influenced the monotonicity. The (L)DSJb metric is normalized by peak velocity while (L)DSJt is normalized by mean velocity. Using a Hann velocity profile, it was seen that only (L)DSJt increased monotonically. However, when employing a Blackman window, all jerk metrics changed monotonically with increasing sub-movements and delay between them respectively.

Table I. 1 Monotonicity of change in the valid Jerk metrics for the Sub-movements simulation

| Base Profiles |  | Shows Monotonic Change |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
|  |  | DSJt | LDSJt | DSJJ | LDSJb |
| $\mathbf{v}_{\text {symm }}$ | Minimum Jerk | No | No | No | No |
|  | Hann | Yes | Yes | No | No |
|  | Blackman | Yes | Yes | Yes | Yes |
| $\mathbf{v}_{\text {asymm }}$ | Polynomial | Yes | Yes | Yes | Yes |

Metrics included: Dimensionless Squared jerk (DSJt and DSJb), and log of DSJt and DSJb (LDSJb and LDSJt)

Appendix

## Summary

Stroke, ischemic or haemorrhagic, is the second cause of death worldwide (Avan et al., 2019), and the prevalence for stroke is expected to increase (Stevens et al., 2017). Most persons with stroke suffer from motor impairment on one side of the body, which includes restricted muscle movement or mobility (Langhorne et al., 2009a). These affect the independency of the persons with stroke, and also subject them to issues of balance, and risk of falls (Kwakkel et al., 2019; Li et al., 2018; Morris et al., 2013).

We need to measure recovery in order to develop appropriate therapy post stroke. Clinical outcomes suffer from ceiling effects, low resolution, and subjectivity (Gladstone et al., 2002; Hsueh et al., 2008; Kwakkel et al., 2017; Levin et al., 2009). Contrarily, kinematic and kinetic metrics of movement can provide an objective measure of movement quality. These metrics can also help distinguish behavioural restitution from compensation strategies post stroke (Jones, 2017; Kwakkel et al., 2017). These differences can be used to identify tailored therapies that optimally target individual recovery in persons with stroke. However, metrics that measure motor recovery and help differentiate it from compensation strategies are yet to be identified.

Measuring kinematic and kinetic metrics accurately requires large laboratory setups that are not portable. Sensing systems that are wearable can help reduce the hassle in setting up measurements, and increase the number of measurements performed post stroke. This can offer a better picture of motor recovery (Kwakkel et al., 2019). Moreover, minimal systems are better suited for clinicians if they wish to measure recovery of the person with stroke in their home environment during functional activities (van Meulen et al., 2016a). Therefore, there is a need to develop and adapt wearable sensing systems to measure metrics of interest.

Based on these gaps, the goal of the thesis was 'To identify metrics that reflect movement quality of upper and lower extremities after stroke and develop wearable minimal systems for tracking the proposed metrics'. This broad goal was split into
several sub-questions identified within two sections throughout the thesis: Section Upper Extremity and Section Lower Extremity.

## SECTION UPPER EXTREMITY

In the first section on the Upper Extremity, we focused on identifying kinematic and kinetic metrics that can provide objective measures of movement quality of the upper extremity. In Chapter II, we identified longitudinal studies that used kinematic and/or kinetic metrics to investigate post-stroke recovery of reaching using a systematic literature search. We identified 32 studies that fit our inclusion criteria, and extracted 46 different kinematic metrics. Majority of these studies studied the changes in kinematics within the scope of movement quality, but they did not explicitly address the differences between behavioural restitution and compensation. This issue needs to be addressed urgently. The Stroke Recovery and Rehabilitation Roundtable (SRRR) taskforce provided a list of criteria in order to standardize measurement of motor recovery post stroke. These criteria could be a useful starting point for setting up future studies that identify kinematic and/or kinetic metrics that measure movement quality and can distinguish between behavioural restitution and compensation.

Of the several objective measures studied post stroke, smoothness has commonly been used to measure movement quality of the upper paretic limb during reaching tasks (Balasubramanian et al., 2015). However, we found that the definition for smoothness of reaching task varied amongst studies (Balasubramanian et al., 2015; Rohrer et al., 2002), and therefore, a 'valid' metric was hard to find. In order to address this ambiguity, we analysed all metrics used in stroke research to measure smoothness of reaching by the upper paretic limb in Chapter III. After a systematic review, we found 32 different definitions for smoothness. We assessed each of their mathematical definitions and excluded 17 metrics that did not satisfy a set of pre-defined criteria. Finally, we assessed the response of the remaining 15 smoothness metrics to simulated changes associated with smoothness deficits in the reaching profile. Eventually, we found that, for reach-to-point movements, the Correlation Metric, and the Spectral Arc Length (SPARC) are valid metrics. For reach-to-grasp movements, only SPARC was found to be a valid metric. In
a follow up study, that is not included in this thesis, we investigated the time course of smoothness deficits early post stroke using the SPARC metric (Saes et al., n.d.). We found that recovery from motor impairment reflected by FuglMeyer followed a similar time course to the recovery of smoothness reflected by SPARC for reach-to-grasp tasks (Saes et al., n.d.). Therefore, SPARC shows promise as a valid smoothness metric for reaching tasks of the upper limb after stroke and can be used to study motor recovery post stroke.

Chapters II and III offer us insights into our current understanding of kinematics that can reflect movement quality in the upper paretic limb especially during reaching. In these chapters and in Chapter XI (General Discussion), we offer recommendations for setting up future studies to identify metrics that should be tracked post stroke, and also recommend development of minimal and wearable systems that can measure these objective metrics.

## SECTION LOWER EXTREMITY

In the case of the Lower Extremity, there are a number of different spatiotemporal and balance parameters that have been related to gait quality (Bruijn et al., 2013; Punt et al., 2017b; van Meulen et al., 2016c). Nevertheless as measuring gait quality requires extensive laboratory setups, we rather focused on developing wearable solutions in this section. We envision that the portability of wearable systems can help accelerate studies that aim to study gait recovery.

Measuring gait quality using metrics such as Extrapolated Centre of Mass (XCoM) requires knowledge of 3D Ground Reaction Forces (GRF), and relative foot positions. As part of an earlier project, the Forceshoes ${ }^{\text {TM }}$ was conceptually designed and evaluated at the Biomedical Signals and Systems group, University of Twente, and built at Xsens Technologies B.V., The Netherlands. It consisted of two 3D Force and Moment (F\&M) sensors, and Inertial Measurement Units (IMUs) on each shoe.

However, the F\&M sensors were thick, and heavy, thereby making the Forceshoes ${ }^{\text {TM }}$ cumbersome. In Chapter IV, we explored the feasibility of pressure insoles as an alternative to the bulky Force and Moment (F\&M)
sensors for measuring 3D GRF. We used subject specific regression models that could estimate 3D F\&M from 1D plantar pressures and found that the approach was applicable for variable walking speeds. We also studied different configurations of sensors within the pressure insoles to optimise system complexity and accuracy. We found that sensors only under the toe and heel were sufficient to estimate the XCoM with an average Root Mean Square (RMS) error of $2.2 \pm 0.3 \mathrm{~cm}$ in the walking direction while walking at a preferred speed. Recommendations for minimizing the Forceshoes ${ }^{\mathrm{TM}}$ were also provided in this chapter.

## Portable Gait Lab

The IMUs on-board the Forceshoes ${ }^{\mathrm{TM}}$ measured movement kinematics. Nonetheless, the kinematics are prone to drift due to strapdown integration, and additionally, the IMUs cannot measure relative foot distances. Therefore, ultrasound sensors were added to the Forceshoes ${ }^{\mathrm{TM}}$ (Weenk et al., 2015). However, the additional ultrasound sensors do not help with the portability of the setup. Therefore, we developed a minimal sensing setup that employed only IMUs to measure kinematics and kinetics of gait.

Existing studies attempted to solve the issue of drift associated with the IMU only setup using artificial mathematical constraints (Bancroft et al., 2008; Niu et al., 2019; Skog et al., 2012; Sy et al., 2020; Zhao et al., 2018). However, these studies do not comment on relative foot distances or may fail during variable gait. Therefore, in Chapter V, we explored the Centroidal Moment Pivot (CMP) point as a realistic biomechanical principle that can relate movement of the foot with that of the Centre of Mass (CoM). The CMP point assumes that the net moment around the CoM is zero for 'stable' gait (Popovic et al., 2005; Schepers et al., 2009), and thus provides:

$$
\begin{equation*}
\boldsymbol{c} \boldsymbol{m} \boldsymbol{p}_{a x}^{f}=\boldsymbol{p}_{a x}^{C}-\left(\boldsymbol{p}_{Z}^{C} \cdot \frac{F_{a x}}{F_{Z}}\right) \tag{S.1}
\end{equation*}
$$

where $\boldsymbol{c m p} p_{a x}^{f}$ is the virtual CMP point on the ground in the anterio-posterior (AP) or medio-lateral (ML) direction. $f$ corresponds to the foot that is in stance phase, when the contralateral foot is in swing. In (S.1), we require prior knowledge of CoM positions in 3D $\left(\boldsymbol{p}_{a x}^{C}\right.$, and $\left.\boldsymbol{p}_{Z}^{C}\right)$, and GRF $(F)$ in 3D.

We studied the relation between the cmp $\boldsymbol{p}_{a x}^{f}$ and Centre of Pressure (CoP) in Chapter V. We saw that the mean distance between CMP and CoP was $10.5 \pm 1.2 \%$ of the foot length over the gait cycle. When IMUs are employed, estimating the CoP requires a model of foot rolling during stance, and weight shift between the left and right side. Therefore, we simplified (S.1) by assuming that the $\boldsymbol{c m} \boldsymbol{p}_{a x}^{f}$ overlaps with the foot trajectory measured by the IMUs, and that the equation is valid during single stance phase. We analysed this in Chapter V and found an average error between the CMP and foot positions measured by VICON® markers of $9.4 \pm 0.1 \mathrm{~cm}$ and $1.6 \pm 0.4 \mathrm{~cm}$ in the AP and ML directions respectively. Therefore, we concluded that, after accounting for the error margins, the relative movement of the feet and CoM can be modelled during gait using (S.1).

From Chapters VI - X, we pursued the idea proposed above. We developed a three IMU setup; one on each foot, and one on the pelvis, called the Portable Gait Lab (PGL) that employed the CMP point assumptions to estimate relative foot and CoM distances. We employed sensor fusion techniques to handle the uncertainties with regards to the measurements and assumptions. In Chapter VI, we first showed the feasibility of the PGL in estimating 3D GRF from the accelerations at the CoM that were measured by the pelvis IMU. We validated the approach on data collected from eight healthy participants performing variable over ground gait. The results were compared with the reference Forceshoes ${ }^{\mathrm{TM}}$. The mean and standard deviation of error between the estimated and the reference values of 3D GRF, normalized against the range of the reference, was $12.1 \pm 3.3 \%$ across all walking tasks, in the horizontal plane.

The foot movement measured by the foot IMUs was additionally used to express the measured GRF with respect to the moving and turning body. The changing reference frame was called the current step frame and was defined using the change in foot positions. In Chapter VII, we showed the feasibility of estimating the changing reference frame using information from the pelvis IMU alone. This could be useful for later studies that wish to measure 3D GRF using only a single pelvis IMU.

Next, we require 3D CoM positions for (S.1). CoM positions can be derived from CoM velocity, which in turn can be estimated from the CoM accelerations. Therefore, we first improved the estimations of CoM velocity using a complementary filter method in Chapter VIII. This method fused two sources of information regarding the CoM velocity. The RMS of the error between the CoM velocity estimated from PGL against the reference VICON® measurement was found to be $0.1 \pm 0.02 \mathrm{~m} / \mathrm{s}$ across three healthy participants performing six variable walking tasks.

In Chapter IX, we employed the approaches described so far to track relative foot and CoM distances. Here, we designed a Kalman filter that fused information from strapdown integration of IMU data, and biomechanical constraints such as zero velocity, zero height, CoM velocity (Chapter VII), and relative segment distances from the CMP assumption; to eventually track relative foot and CoM positions. We validated the methods for variable over ground gait in six healthy participants. We were able to estimate step lengths and step widths with an average absolute error of $4.6 \pm 1.5 \mathrm{~cm}$, and $3.8 \pm 1.5 \mathrm{~cm}$ respectively when compared against the reference VICON©. Additionally, we showed that the approach helped identify asymmetric gait patterns.

Finally, in Chapter $\mathbf{X}$, we validated the use of the PGL to measure spatiotemporal and balance measures in four persons with chronic stroke performing the 10 metre walk test. We compared the estimated values with reference Forceshoes ${ }^{\text {TM }}$ (Weenk et al., 2015). The PGL was able to track foot and CoM trajectories with an RMS of the differences of $2.9 \pm 0.2 \mathrm{~cm}$ and $4.6 \pm 3.6 \mathrm{~cm}$ respectively. The distances between either foot at the end of the walking task, and step lengths were estimated by PGL with an average error with the reference of $1.98 \pm 2.2 \mathrm{~cm}$ and $7.8 \pm 0.1 \mathrm{~cm}$ respectively across participants. We showed that the PGL estimated the foot and CoM positions, stance times and step lengths well. Therefore, the PGL offers a portable alternative for measuring spatiotemporal gait parameters post stroke. Nonetheless, the study in Chapter $\mathbf{X}$ is limited in the number of participants, and we recommend setting up measurements with participants with varying levels of severity.

Finally, in Chapter XI (General Discussion), we offer recommendations for improving the PGL and its applicability for gait analysis in other populations.

We summarize future research directions that must be addressed as a follow up of this thesis.

## CONCLUSION

This thesis lays one brick towards building knowledge in improving the quality of life post stroke. We focused on understanding movement quality post stroke. In Section Upper Extremity, we assess our current understanding of the use of biomechanical metrics for movement quality during reaching in the upper extremity. Further work is required before we can reach consensus on metrics that can measure movement quality and help distinguish behavioural restitution from compensation. The same can be said for the lower extremity. However, in Section Lower Extremity, the thesis contributes to developing novel techniques for developing wearable sensing systems for assessing the quality of variable gait in daily life. These offer clinicians and researchers tools to increase measurement times post stroke or move towards home monitoring after discharge. We hope the ideas and arguments presented in this thesis can contribute to standardizing stroke recovery research.

## Samenvatting

Beroerte (ischemisch of hemorragisch) is wereldwijd de tweede doodsoorzaak (Avan et al., 2019) en de verwachting is dat de prevalentie van beroerte zal toenemen (Stevens et al., 2017). De meeste mensen met een beroerte hebben een motorische beperking aan één kant van het lichaam, waaronder beperkte spierbeweging of mobiliteit (Langhorne et al., 2009). Dit beïnvloedt de onafhankelijkheid van de personen en stelt hen ook bloot aan balansproblemen en het risico op vallen (Kwakkel et al., 2019; Li et al., 2018; Morris et al., 2013).

We moeten het herstel meten om een geschikte therapie na een beroerte te ontwikkelen. Klinische uitkomstmaten hebben echter problemen zoals 'ceiling effects', lage resolutie en subjectiviteit (Gladstone et al., 2002; Hsueh et al., 2008; Kwakkel et al., 2017; Levin et al., 2009). Kinematische en kinetische bewegings-metrieken kunnen daarentegen een objectieve maatstaf zijn voor de bewegingskwaliteit. Deze metrieken kunnen ook helpen om 'behavioural restitution' of herstel te onderscheiden van compensatiestrategieën na een beroerte (Jones, 2017; Kwakkel et al., 2017). Deze verschillen kunnen worden gebruikt om therapieën op maat te identificeren die optimaal gericht zijn op individueel herstel bij personen die een beroerte hebben gehad. Metrieken die motorherstel meten en helpen dit te onderscheiden van compensatiestrategieën, moeten echter nog worden geïdentificeerd.

Het nauwkeurig meten van kinematische en kinetische metrieken vereist grote laboratoriumopstellingen die niet draagbaar zijn. Aangezien minimale draagbare detectiesystemen het opzetten van de metingen eenvoudiger maakt, kunnen er na een beroerte meer metingen uitgevoerd worden. Dit kan een beter beeld geven van motorisch herstel (Kwakkel et al., 2019). Bovendien zijn minimale systemen geschikter voor clinici als ze het herstel van de persoon na een beroerte in hun thuisomgeving willen meten tijdens dagelijkse activiteiten (van Meulen et al., 2016a). Daarom is er behoefte aan de ontwikkeling van draagbare detectiesystemen die metrische gegevens meten die van belang zijn.

Op basis van deze hiaten, was het doel van het proefschrift 'Het identificeren van metrieken die de bewegingskwaliteit van de bovenste en onderste extremiteit
na een beroerte kunnen identificeren en het ontwikkelen van draagbare minimale systemen voor het meten van de voorgestelde metrieken'. Dit brede doel werd opgesplitst in verschillende deelvragen die in twee secties in het proefschrift zijn geïdentificeerd; Secties Boventse Extremiteit (Upper Extremity) en Onderste Extremiteit (Lower Extremity).

## Sectie Bovenste Extremiteit

In de eerste Sectie Bovenste Extremiteit hebben we ons gericht op het identificeren van kinematische en kinetische metrieken die objectieve maatstaven kunnen geven van de bewegingskwaliteit van de bovenste extremiteit. In Hoofdstuk II hebben we longitudinale studies geïdentificeerd die kinematische en/of kinetische metrieken gebruikten om het herstel van reiken met de paretische arm na een beroerte te onderzoeken met behulp van een systematisch literatuuronderzoek. Van de 32 studies die voldoen aan de inclusiecriteria, hebben we 46 verschillende kinematische metrieken geëxtraheerd. De meerderheid van deze studies onderzocht de veranderingen in de kinematica in het kader van bewegingskwaliteit, maar ze gingen niet expliciet in op de verschillen tussen herstel en compensatie. Dit probleem moet dringend worden aangepakt. De taskforce Stroke Recovery and Rehabilitation Roundtable (SRRR) heeft een lijst met criteria opgesteld om het meten van motorisch herstel na een beroerte te standaardiseren (Kwakkel et al., 2019). Deze criteria zouden een nuttig uitgangspunt kunnen zijn voor het opzetten van toekomstige studies die kinematische en/of kinetische metrieken identificeren die de bewegingskwaliteit meten en die onderscheid kunnen maken tussen gedragsherstel en compensatie.

Van de verschillende objectieve metrieken die na een beroerte zijn bestudeerd, wordt 'smoothness' vaak gebruikt om de bewegingskwaliteit van de paretische arm te meten tijdens de taken om naar iets te reiken (Balasubramanian et al., 2015). We ontdekten echter dat de definitie voor smoothness in taken om naar iets te reiken, varieerde tussen de studies (Balasubramanian et al., 2015; Rohrer et al., 2002), waardoor een 'geldige’ metriek moeilijk te vinden was. Om deze probleem aan te pakken, hebben we in Hoofdstuk III een rigoureuze analyse uitgevoerd van de smoothness metrieken die worden gebruikt in het onderzoek naar beroertes. Dit werd gedaan door eerst systematisch de literatuur te herzien. We vonden 32 verschillende definities
voor de smoothness metriek tijdens het reiken van de paretische arm. We hebben elk van hun wiskundige definities beoordeeld aan de hand van een reeks vooraf gedefinieerde criteria en 17 metrieken uitgesloten. Ten slotte hebben we de respons beoordeeld van de resterende 15 smoothness maten op gesimuleerde veranderingen die verband houden met smoothness tekorten tijdens het reiken van de arm. Uiteindelijk ontdekten we dat, voor reiken met de arm naar iets te wijzen, de Correlation Metric en de Spectral Arc Length (SPARC) geldige metrieken zijn. Voor reiken met de arm naar iets gepakt moet worden, bleek alleen SPARC een geldige metriek. In een vervolgstudie, die niet in dit proefschrift is opgenomen, hebben we het tijdsverloop van smoothness tekorten kort na een beroerte onderzocht met behulp van de SPARC-metriek (Saes et al., n.d.). We ontdekten dat het herstel van motorische beperking weerspiegeld door Fugl-Meyer, een vergelijkbaar tijdsverloop volgde als het herstel van smoothness weerspiegeld door SPARC, voor taken van reiken met de arm naar iets gepakt moet worden (Saes et al., n.d.). Daarom is SPARC veelbelovend als een geldige metriek voor smoothness voor taken van reiken met de arm na een beroerte, en kan het worden gebruikt om motorisch herstel na een beroerte te bestuderen.

Hoofdstukken II en III bieden ons inzicht in onze huidige kennis van kinematica die de kwaliteit van de beweging in de paretische arm vooral tijdens reik-taken kan reflecteren. In deze hoofdstukken en in Hoofdstuk XI (Generale Discussie) doen we aanbevelingen voor het opzetten van toekomstige studies om metrieken te identificeren die na een beroerte moeten worden bijgehouden, en bevelen we ook de ontwikkeling aan van minimale en draagbare systemen die deze objectieve metrieken kunnen meten.

## Sectie Onderste Extremiteit

In het geval van de onderste extremiteit zijn er een aantal verschillende spatiotemporale en balansparameters die gerelateerd zijn aan de gangkwaliteit (Bruijn et al., 2013; Punt et al., 2017; van Meulen et al., 2016b). Omdat het meten van de gangkwaliteit echter uitgebreide laboratoriumopstellingen vereist, hebben we ons in deze sectie eerder gericht op het ontwikkelen van draagbare oplossingen. We stellen ons voor dat de draagbaarheid van draagbare systemen kan helpen bij het versnellen van onderzoeken die gericht zijn op het bestuderen van loopherstel.

Het meten van de loopkwaliteit met behulp van meetgegevens zoals het geëxtrapoleerde zwaartepunt (XCoM) vereist kennis van 3D Ground Reaction Forces (GRF) en relatieve voetposities. Als onderdeel van een eerder project, de Forceshoes ${ }^{\mathrm{TM}}$ is conceptueel ontworpen en geëvalueerd door de Biomedische Signalen en Systemen groep, Universiteit Twente, en gebouwd door Xsens Technologies BV, Nederland. Het bestond uit twee 3D Force and Moment (F\&M)-sensoren en twee 'Inertial Measument Units' (IMUs) op elke schoen.

De F\&M-sensoren waren echter dik en zwaar, wat de Forceshoes ${ }^{\text {TM }} \log$ maakte. In Hoofdstuk IV hebben we de haalbaarheid onderzocht van drukzolen als alternatief voor de omvangrijke F\&M-sensoren voor het meten van 3D F\&M. We gebruikten gebruiker specifieke regressiemodellen die 3D F\&M konden inschatten op basis van 1D druk informatie, en ontdekten dat de benadering toepasbaar was voor variabele loopsnelheden. We hebben ook verschillende configuraties van sensoren in de drukzolen bestudeerd om de complexiteit en nauwkeurigheid van het systeem te optimaliseren. We ontdekten dat sensoren onder de teen en hiel voldoende waren om de XCoM te schatten met een gemiddelde Root Mean Square (RMS) fout van $2,2 \pm 0,3 \mathrm{~cm}$ in de looprichting tijdens het lopen met een voorkeurssnelheid. Hoofdstuk IV belichtte ook de bijdrage van voetkinematica en -kinetiek bij het schatten van de XCoM. In dit hoofdstuk werden ook aanbevelingen gegeven voor het minimaliseren van de Forceshoes ${ }^{\mathrm{TM}}$.

## Portable Gait Lab

De IMU's aan de Forceshoes ${ }^{\text {TM }}$ hebben bewegingskinematica gemeten. De kinematica is echter vatbaar voor drift als gevolg van de strapdown-integratie en bovendien kunnen de IMU's de relatieve voetafstanden niet meten. Daarom werden een echografiesysteem toegevoegd aan de Forceshoes ${ }^{\mathrm{TM}}$. Het extra echografiesysteem helpt echter niet bij aan de draagbaarheid van het systeem. Er zijn eerdere onderzoeken geweest die de drift tussen de voetIMU's verminderden zonder het gebruik van extra afstandssensoren, door kunstmatige wiskundige beperkingen te gebruiken (Bancroft et al., 2008; Niu et al., 2019; Skog et al., 2012; Sy et al., 2020; Zhao et al., 2018). Deze onderzoeken geven echter geen commentaar op relatieve voetafstanden of geven fouten tijdens variabel lopen. Daarom is, in Hoofdstuk V, het Centroidal Moment Pivot (CMP) punt geïdentificeerd als een realistisch biomechanisch
principe dat beweging van de voet kan relateren aan dat van de CoM. Het CMP punt neemt aan dat de netto momenten rond de CoM nul zijn voor een stabiele gang (Popovic et al., 2005; Schepers et al., 2009), en geeft:

$$
\begin{equation*}
\boldsymbol{c} \boldsymbol{m} \boldsymbol{p}_{a x}^{f}=\boldsymbol{p}_{a x}^{C}-\left(\boldsymbol{p}_{Z}^{C} \cdot \frac{F_{a x}}{F_{Z}}\right) \tag{S.1}
\end{equation*}
$$

waar $\boldsymbol{c m p} \boldsymbol{p}_{a x}^{f}$ is het virtuele CMP punt op de grond in de anteroposteriore (AP) of mediolaterale (ML) richting. $f$ verwijst naar de voet die zich in de standfase bevindt, wanneer de contralaterale voet in swingfase is. In (S.1) hebben we voorkennis nodig van de CoM posities in 3D ( $\boldsymbol{p}_{a x}^{C}$, en $\boldsymbol{p}_{Z}^{C}$ ), en de grondreactiekrachten $(F)$ in 3D.

We bestudeerden eerst de relatie tussen $\mathbf{c m p} \boldsymbol{p}_{a x}^{f}$ en het drukmiddelpunt (CoP) in Hoofdstuk V. We zagen dat de gemiddelde afstand tussen de CMP en CoP $10,5 \pm 1,2 \%$ van de voetlengte over de gangcyclus was. Wanneer IMU's worden gebruikt, vereist het schatten van de CoP een model van het rollen van de voet tijdens het standfase en het verschuiven van het gewicht tussen de linkeren rechterkant. Daarom hebben we (S.1) vereenvoudigd door aan te nemen dat de cmp $\boldsymbol{p}_{a x}^{f}$ overlapt met de voetposities gemeten door de IMU's, en dat de vergelijking geldig is tijdens de standfase van enkele voet. We analyseerden dit in Hoofdstuk V en vonden een gemiddelde fout tussen de CMP- en voetposities gemeten door VICON© markers van respectievelijk $9,4 \pm 0,1 \mathrm{~cm}$ en $1,6 \pm 0,4 \mathrm{~cm}$ in de AP- en ML-richting. Daarom hebben we geconcludeerd dat, na het in acht nemen van de foutmarges, de relatieve beweging van de voeten en CoM tijdens het lopen gemodelleerd kan worden met behulp van (S.1).

Vanaf de Hoofdstukken VI - X, hebben we het hierboven voorgestelde idee verder ontwikkeld. We hebben een configuratie met drie IMU's ontwikkeld; één op elke voet en één op het bekken, genaamd de Portable Gait Lab (PGL) dat de CMP punt aannames gebruikte om relatieve voet- en CoM-afstanden te schatten. We hebben sensorfusietechnieken gebruikt om met de onzekerheden met betrekking tot de metingen en aannames om te gaan. In Hoofdstuk VI hebben we eerst de haalbaarheid van de PGL laten zien om 3D GRF te schatten van de versnellingen bij de CoM die werden gemeten door de IMU op het bekken. We hebben de aanpak gevalideerd op basis van gangmeten die zijn verzameld bij acht gezonde proefpersonen die verschillende looptaken
uitvoerde. De resultaten werden vergeleken met de referentiekrachten gemeten door de Forceshoes ${ }^{\mathrm{TM}}$. Het gemiddelde en de standaarddeviatie van de fout tussen de geschatte 3D GRF en de referentiewaarden, genormaliseerd ten opzichte van het referentiebereik, was $12,1 \pm 3,3 \%$ in het horizontale vlak, voor alle looptaken.

De voetbeweging gemeten door de voet-IMU's werd aanvullend gebruikt om de gemeten GRF uit te presenteren met betrekking tot het bewegende lichaam. Het veranderende referentieframe werd het huidige stappenframe ('current step frame') genoemd en werd gedefinieerd met behulp van de verandering in voetposities. In Hoofdstuk VII hebben we de haalbaarheid laten zien van het schatten van het veranderende referentieframe met alleen informatie van de bekken-IMU. Dit kan nuttig zijn voor latere studies die 3D GRF willen meten met slechts één IMU op het bekken.

Vervolgens hebben we 3D CoM posities nodig voor (S.1). De CoM posities zijn afgeleid van CoM snelheid, die worden geschat op basis van de CoMversnellingen. Daarom hebben we eerst de schattingen van CoM-snelheid verbeterd met behulp van een 'complementary filter' methode in Hoofdstuk VIII. Deze methode combineert twee bronnen die aanvullende informatie over de CoM snelheid leverden. De RMS van de fout tussen de CoM snelheid geschat op basis van PGL en de VICON© referentiemeting bleek $0,1 \pm 0,02 \mathrm{~m} / \mathrm{s}$ te zijn voor drie gezonde proefpersonen die zes verschillende looptaken uitvoerden.

In Hoofdstuk IX hebben we de tot dusver beschreven benaderingen gebruikt om relatieve voet- en CoM afstanden te volgen. Hier hebben we een Kalman filter ontworpen dat informatie van de strapdown integratie van IMU data en biomechanische randvoorwaarden zoals 'zero velocity', 'zero height', CoM snelheid (Hoofdstuk VII), en relatieve segmentafstanden van de CMPaanname samenvoegde, om uiteindelijk de relatieve voet- en CoM- posities te meten. We valideerden de methodes voor verschillende looppatronen bij zes gezonde proefpersonen. We waren in staat om staplengtes en stapbreedtes te schatten met een gemiddelde absolute fout van respectievelijk $4,6 \pm 1,5 \mathrm{~cm}$ en $3,8 \pm 1,5 \mathrm{~cm}$ in vergelijking met de referentie VICON©. Bovendien toonden we aan dat de aanpak hielp bij het identificeren van een asymmetrisch looppatroon.

Tenslotte hebben we in Hoofdstuk X het gebruik van de PGL gevalideerd om spatiotemporale en balansparameters te meten bij vier mensen met een beroerte in de chronische fase die de 10 meter looptest uitvoerden. We vergeleken de geschatte waarden met Forceshoes ${ }^{\mathrm{TM}}$ als de referentiesysteem (Weenk et al., 2015). De PGL was in staat om voet- en CoM- trajecten te meten met een RMS van de verschillen met de referentie van $2,9 \pm 0,2 \mathrm{~cm}$ en 4,6 $\pm 3,6 \mathrm{~cm}$. De afstanden tussen beide voeten aan het einde van de looptaak en staplengtes werden geschat door de PGL met een gemiddelde fout van respectievelijk $1,98 \pm 2,2 \mathrm{~cm}$ en $7,8 \pm 0,1 \mathrm{~cm}$ ten opzichte van de referentie, over de deelnemers. We toonden aan dat de PGL de voet- en CoM- posities, staptijden, en staplengtes goed inschatte. Daarom biedt de PGL een draagbaar alternatief voor het meten van spatiotemporale gangparameters na een beroerte. Desalniettemin is onze studie in Hoofdstuk $\mathbf{X}$ beperkt in het aantal proefpersonen, en we raden aan om metingen uit te voeren met deelnemers uit verschillende (herstel-)fases na een beroerte.

Ten slotte doen we in Hoofdstuk XI (General Discussion) aanbevelingen voor het verbeteren van de PGL en de toepasbaarheid ervan voor ganganalyse in andere populaties. We vatten toekomstige onderzoeksrichtingen samen die als vervolg op dit proefschrift moeten worden aangepakt.

## CONCLUSIE

Dit proefschrift legt een steen voor het opbouwen van onze kennis om de kwaliteit van leven na een beroerte te verbeteren. We hebben ons gericht op het begrip van bewegingskwaliteit na een beroerte. In de Sectie Bovenste Extremiteit beoordelen we onze huidige kennis van het gebruik van biomechanische metrieken voor bewegingskwaliteit tijdens het reiken in de bovenste extremiteit. Onze studies tonen aan dat verdere werk is nodig voordat we consensus kunnen bereiken over specifieke metrieken die de bewegingskwaliteit kunnen meten en helpen om onderscheid te maken tussen herstel en compensatie. Hetzelfde kan gezegd worden voor de onderste extremiteit. In de Sectie Onderste Extremiteit draagt het proefschrift echter bij aan de ontwikkeling van nieuwe technieken voor het ontwikkelen van draagbare detectiesystemen voor het beoordelen van de kwaliteit van verschillende lopen in het dagelijks leven. Deze bieden clinici en onderzoekers
hulpmiddelen om het aantal metingen na een beroerte te verhogen of om na ontslag over te gaan op thuismonitoring. We hopen dat de ideeën en argumenten die in dit proefschrift worden gepresenteerd, kunnen bijdragen aan het standaardiseren van het onderzoek van herstel na een beroerte.

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## Author Biography

Mohamed Irfan Mohamed Refai (or Irfan Refai) was born in Chennai, India, and grew up in Riyadh, Saudi Arabia. He returned to his birth town and obtained his Bachelor degree in Biomedical Engineering at the SSN College of Engineering in 2012. In 2017, he received his Master degree in Electrical Engineering with Research Honours from the University of
 Twente, The Netherlands. During his master thesis, he investigated the feasibility of 1D pressure insole for measuring 3D forces and moments during gait. Between 2017-2021, he pursued his PhD as part of the Dutch AMBITION project at the Department of Biomedical Signals and Systems at University of Twente. During this period, he contributed towards understanding how to measure reaching quality post stroke, and developed minimal sensing setups for measuring gait quality. Currently, he is working as a Teacher at the Department of Biomechanical Engineering at the same University and is looking for a post-doctoral position. For a complete overview of his profile, visit irfanrefai.com.

## Public Dissemination

Journal Publications

## Published

Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H., 2020. Portable Gait Lab: Tracking Relative Distances of Feet and CoM Using Three IMUs. In IEEE Transactions on Neural Systems and Rehabilitation Engineering. 28, 2255-2264. (included as Chapter IX).

Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H., 2020. Portable Gait Lab: Estimating Over-Ground 3D Ground Reaction Forces Using Only a Pelvis IMU. In Sensors (Basel). 20. (included as Chapter VII).

Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H., 2020. Portable Gait Lab: Estimating 3D GRF Using a Pelvis IMU in a Foot IMU Defined Frame. In IEEE Transactions on Neural Systems and Rehabilitation Engineering. 28, 1308-1316. (included as Chapter VI).

Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H., 2018. Gait and Dynamic Balance Sensing Using Wearable Foot Sensors. In IEEE Transactions on Neural Systems and Rehabilitation Engineering. 27, 218-227. (included as Chapter IV).

## Submitted

Saes, M.*, Mohamed Refai, M.I.*, van Beijnum, B.-J.F., Bussmann, J.B.J., Jansma E.P., Veltink, P.H., Buurke, J.H., van Wegen, E.E.H., Meskers, C.G.M., Krakauer J.W., Kwakkel, G., Quantifying quality of reaching movements longitudinally post stroke - a systematic review. (included as Chapter II). *authors contributed equally

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Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H. Centroidal Moment Pivot for ambulatory estimation of relative feet and CoM movement post stroke: Portable Gait Lab. (included as Chapter X).

## Conference Proceedings and Abstracts

Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H., 2021. Portable Gait Lab: Tracking Gait Kinetics And Kinematics using only Three Inertial Measurement Units. Abstract from 8th Dutch Bio-Medical Engineering Conference, BME 2021, Virtual Conference.

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Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Saes, M., Bussmann, J.B.J., Meskers, C.G.M., van Wegen, E.E.H., Kwakkel, G., Veltink, P.H., 2019. Portable Gait Lab: Zero Moment Point for Minimal Sensing of Gait*, In 2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). IEEE, pp. 2077-2081. (included as Chapter V).

Wang, H., Mohamed Refai, M. I., \& van Beijnum, B.-J.F., 2019. Measuring UpperExtremity Use with One IMU. In Proceedings of the 12th International Joint Conference on Biomedical Engineering Systems and Technologies - Volume 4: BIOSIGNALS, pages 93-100.

Mohamed Refai, M. I., Saes, M., Visser, I., Bussmann, J.B.J., Buurke, J.H., Kwakkel, G., Veltink, P.H., van Wegen, E.E.H., Meskers, C.G.M., \& van Beijnum, B.-J.F., 2018. Ambition: What has been done so far?. Poster session presented at Symposium Enabling Technology for Active Life and Better Health 2018, Enschede, Netherlands.

Mohamed Refai, M. I., van Beijnum, B.-J.F., Buurke, J.H., \& Veltink, P.H., 2018. Ambulatory Estimation of XCoM using Pressure Insoles and IMUs. Abstract from 15th International Symposium on 3D Analysis of Human Movement, 3D-AHM 2018, Manchester, United Kingdom. Received best student award.

## Patents

Mohamed Refai, M.I., Veltink, P.H., van Beijnum, B.-J.F., Buurke, J.H., 2021. A method, a system and a computer program product for estimating positions of a subject's feet and centre of mass relative to each other (Patent) (No. WO 2021/010832 A1). University of Twente.

'As our tools improve, so does our understanding of nature.'

## Invitation

You are kindly invited to attend the public defense of my doctoral dissertation

Moving On: measuring movement remotely after stroke
date
wednesday 7th july 2021
at 16:30
location
(online)
vimeo.com/universityoftwente
paranymphs
Boudewijn van den Berg
Ashwini Uthrapathi Shakila

Mohamed Irfan
Mohamed Refai
m.r.m.irfan12@gmail.com
+31 684389579


[^0]:    The metrics belonged to either *G1: those that reflect the ability to recover from small perturbations or ${ }^{+} \mathrm{G} 2$ : those that reflect the ability to recover from larger perturbations. The cited references mention the first studies to use them in defining stability in human gait. The advantages and disadvantages are derived from the work of Bruijn and colleagues (Bruijn et al., 2013).

[^1]:    Submitted as:
    Saes, M.*, Mohamed Refai, M.I.", van Beijnum, B.-J.F., Bussmann, J.B.J., Jansma E.P., Veltink, P.H., Buurke, J.H., van Wegen, E.E.H., Meskers, C.G.M., Krakauer J.W., Kwakkel, G., Quantifying quality of reaching movements longitudinally post stroke - a systematic review.
    *authors contributed equally

[^2]:    Abbreviations: ${ }^{1-5}$ partial overlap of included patients, NR: not reported, NA: not applicable. C: healthy controls, S: Stroke patients, SD: standard deviation; I: ischaemic, H: haemorrhagic; L: left, R: right; D: Dominant, ND: Non-Dominant. d: days, w: weeks, m: months, PS: Post Stroke, PI: Post Inclusion. Intervention groups: CIMT: Constrain Induced Movement Therapy, AAT: arm ability training, KR: Knowledge of results, AS: Arm Support; CON: Conventional; TBI: Traumatic Brain Injury; Segments: Th: thumb, IF: Index Finger, H: Hand, W: Wrist, FA: Forearm, E: Elbow, UA: Upper Arm, Tr: Trunk, Sh: Shoulder, Sc: Scapula, T: Target. Clinical measures: clinical tests) ARAT: Action Research Arm Test, AROM: Active Range of Motion, (M)BI: (Modified) Barthel Index, CMSA: Chedoke-McMaster Stroke Assessment, FA: Functional Ability, FIM: Functional Independence Measure, FM-UE: Fugl-Meyer motor assessment of the Upper Extremity, FM Fensation $^{\text {: Fugl-Meyer domain for sensation, }}$ MAL: Motor Activity Log, MAS: Modified Ashworth Scale, MCS: motor control scores, MFS: Modified Frenchay Scale, MP: Motor Power, MSS: Motor Status Scores, NHPT: Nine Hole Peg Test, NIHSS: National Institutes of Health Stroke Scale, SIS: Stroke Impairment Scale, SULCS: Stroke Upper Limb Capacity Scale, TEMPA: Test Evaluant les Membres superieurs de Personnes Agees, TLT: Thumb Localization Test, WMFT: Wolf Motor Function Test. (neurophysiological techniques) MRI: Magnetic Resonance Imaging, fMRI: functional MRI.

[^3]:    Responsiveness was noted as change between two moments post stroke, or the passed time when measurement moments were not fixed post stroke. Abbreviations: x: not investigated; Longi: longitudinal association; Cross: cross-sectional association; Pre: pre-intervention; Post: Post-intervention; d: days post stroke; w: weeks post stroke; m: months post stroke; y: years post stroke; NR: Not reported; NS: Not significant, *Interpreted from graph; Clinical assessments: ABILHAND: ABILHAND questionnaire, ARAT: Action Research Arm Test, C-AROM: composite score Active Range of Motion, CMSA: ChedokeMcMaster Stroke Assessment, C-STR: composite score muscle strength, FM-UE: Fugl-Meyer motor assessment of the upper extremity, FIM: Functional Independence Measure, MSS: Motor Status Scale, NHPT: Nine Hole Peg Test, PP: Purdue Pegboard, WMFT: Wolf Motor Function Test. When available, the strength of the relation was provided, R: Pearson correlation coefficient, $\rho$ : Spearman rank correlation coefficient.

[^4]:    [] meant the metric was unit-less. ${ }^{\text {a }}$ Number of articles in the systematic review that used the metric. ${ }^{\text {b }}$ Units were not available. Exclusion criteria include E1: metric units containing m and/or s ; E2: metric not reproducible from the literature; E3: metric not based on velocity or its derivative; and E4: metric linearly related to another metric (shown in brackets) by (a) scaling or (b) addition of a constant.

[^5]:    Published as:
    Mohamed Refai, M.I., van Beijnum, B.-J.F., Buurke, J.H., Veltink, P.H., 2020. Portable Gait Lab: Estimating 3D GRF Using a Pelvis IMU in a Foot IMU Defined Frame.

[^6]:    Set Search terms
    \#5 \#4 AND ('article'/it OR 'article in press'/it OR 'review'/it) AND [english]/lim
    \#4 \#1 AND \#2 AND \#3
    'movement (physiology)'/de OR 'limb movement'/de OR 'arm movement'/exp OR 'hand movement'/exp OR 'motion'/de OR 'velocity'/exp OR 'mechanics'/de OR 'biomechanics'/exp OR 'force'/exp OR 'kinematics'/exp OR 'kinetics'/de OR 'torque'/exp OR 'temporal analysis'/ exp OR ‘spatial analysis'/de OR torque*:ti, ab OR biomechanic":ti, ab OR kinematic*:ti, ab OR kinetic*:ti,ab OR angle*:ti,ab OR force*:ti,ab OR motion:ti,ab OR acceler*:ti,ab OR deceler":ti,ab OR rotation:ti,ab OR velocity*:ti,ab OR speed":ti,ab OR spatiotemporal:ti,ab 'pronation'/exp OR 'supination'/exp OR 'hand strength'/exp OR reach*:ti,ab OR coordination:ti,ab OR grasp":ti,ab OR grip":ti,ab OR 'hand strength':ti,ab OR 'pinch
    \#2 strength':ti,ab OR 'upper limb'/exp OR ‘upper extremit"’:ti, ab OR 'upper limb"':ti,ab OR arm:ti,ab OR arms:ti,ab OR shoulder:ti,ab OR elbow":ti,ab OR forearm*:ti,ab OR wrist*:ti,ab OR hand:ti,ab OR hands:ti,ab OR finger*:ti,ab OR thumb*:ti,ab

[^7]:    Responsiveness was noted as change between two moments post stroke, or the passed time when measurement moments were not fixed post stroke. Abbreviations: NR: Not Reported; NS: Not significant, d: days, w: weeks, m: months, *Interpreted from graph, Longi: longitudinal association. Clinical measures: (clinical tests): ABILHAND: ABILHAND questionnaire, ARAT: Action Research Arm Test, C-AROM: Composite score Active Range of Motion, CMSA: Chedoke-McMaster Stroke Assessment, C-STR: Composite score muscle strength, FM-UE: Fugl-Meyer Motor assessment for Upper Extremity, FIM: Functional Independence Measure, MSS: Motor Status Scale, NHPT: Nine Hole Peg Test, PP: Purdue Pegboard, WMFT: Wolf Motor Function Test. (neurophysiological techniques) MRI: magnetic resonance imaging, fMRI: functional MRI. If available, the strengths of the clinical associations were obtained from the manuscripts or classified based on the provided correlation coefficient (<0.3: poor, 0.3-0.5: fair, 0.5-0.8:moderately strong; >0.8: very strong) (Chan, 2003).

[^8]:    Figure H. 4 Sub-movements simulation: The colors denote the number of sub-movements that is used. Metrics included are NOS (number of sub-movements), $S M$ (speed metric), $M A P R$ (movement arrest period ratio), $V A L$ (velocity arc length), Peaks (number of peaks), $I P V$ (inverse of number of peaks and valleys), $D S J t$ and $D S J b$ (Dimensionless squared jerk), $L D S J b$ and $L D S J t$ (log of $D S J t$ and $D S J b$ ), CM (correlation metric), SPMR (spectral metric), SPM (spectral method), $S P A L$ (spectral arc length 2012), and $S P A R C$ (spectral arc length). $S M, M A P R, I P V, C M, S P M, S P M R, S P A L$ and $S P A R C$ should decrease with decreasing smoothness of movement, while the others should increase with decreasing smoothness. Although CM changed monotonically when testing with $\mathrm{v}_{\text {symm }}$, here they change non monotonically and thus do not respond as expected.

