FACULDADE DE ENGENHARIA DA UNIVERSIDADE DO PORTO

# Upper Limb Functional Rehabilitation Using Inertial Sensors

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# Resumo

Todos os anos, aproximadamente 15 milhões de pessoas no mundo sofrem um AVC, tratando-se portanto de um grave problema de saúde global. Sabe-se que o principal impacto de um AVC são os danos a longo prazo, principalmente a nível motor, uma vez que os pacientes ficam limitados em termos de controlo muscular e movimento. Os cuidados pós-AVC recaem maioritariamente sob reabilitação, que se trata de um caminho longo e difícil que requer semanas ou mesmo meses de exercícios repetitivos. Devido à escassez de recursos humanos nos serviços de saúde, há uma necessidade de arranjar soluções de reabilitação fora do ambiente clínico. No entanto, é preciso evitar a necessidade da presença física do terapeuta e ser capaz de avaliar automaticamente a qualidade dos movimentos, de maneira a permitir que o paciente realize os exercícios de maneira autónoma.

A tecnologia pode ser bastante útil tanto para uniformizar a avaliação durante o processo de reabilitação, como para complementar os recursos humanos. Em particular, a grande variedade de tecnologias existentes para análise de movimento humano, como é o caso dos sensores inerciais, permite a quantificação do movimento através de variáveis e sinais cinemáticos. O objectivo final desta dissertação foi, portanto, desenvolver algoritmos capazes de converter os dados cinemáticos dos segmentos e articulações em métricas com significado, que permitam avaliar a qualidade do movimento em exercícios de reabilitação funcional.

O presente documento começa por apresentar os conceitos fundamentais, assim como as soluções propostas na literatura para a avaliação da qualidade do movimento do membro superior, de forma a dar uma visão geral do panorama do estado da arte nesta área. De seguida, é feita uma descrição da metodologia adoptada para chegar ao conjunto de métricas proposto, incluindo todos os passos desde a saída dos sensores inerciais até ao cálculo das métricas em si. Posteriormente, descreve-se o estudo que foi desenvolvido para validar a capacidade das métricas propostas para distinguir movimentos saudáveis de movimentos não saudáveis, assim como os resultados do mesmo. Por fim, o documento termina com as principais conclusões e futuros melhoramentos ao trabalho desenvolvido.

# Abstract

Stroke is a very serious global health care problem since each year, approximately 15 million people suffer from a stroke worldwide. The biggest health impact of stroke is long-term impairment, specially at the motor level, as patients become limited in terms of muscle control and movement. Post-stroke care mainly relies on rehabilitation, which is a long and difficult path and requires repetitive practice for several weeks or even months. Due to the staffing shortages in health services, there is a need to provide solutions for rehabilitation outside the clinical setting. However, this requires avoiding the need for the physical presence of the therapist and being able to automatically assess quality of movement and performance, allowing the patient to perform the exercises autonomously.

Technology can be really helpful to both standardize the assessment of rehabilitation and complement human resources. In particular, the wide variety of existing technologies for human motion tracking, like inertial sensors, allows for the quantification of movement through several kinematic variables and signals. Thus, the final aim of this dissertation was to develop algorithms capable of converting raw kinematic data from several joints into meaningful metrics that allow the quality assessment of upper limb movement during functional rehabilitation exercises.

This document starts by presenting the fundamental concepts, as well as the proposed solutions existing in the literature for quality assessment of upper limb movement, so as to provide an overview of the state of the art in this field. Then, the methodology adopted to achieve the set of proposed metrics is described, including all the steps from the output of the inertial sensors to the calculation of the metrics per se. Next, there is a description of the study that was carried out to validate the ability of the proposed metrics to discriminate between healthy and unhealthy movements. Additionally, the results of the study are also presented. Finally, the document ends with the main conclusions and future refinements of the developed work.

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Não poderia também deixar de agradecer aos meus pais, por me proporcionarem a oportunidade de tirar este curso e, claro, por tudo o resto. Ao Cobra, por me aturar nos momentos mais difíceis, apesar de fazer questão de me dizer que devia ter ido para Biológica. A Metal&Bio, pelos momentos de refúgio e diversão pois, de outra forma, estes cinco anos tinham sido apenas uma continuação do ensino secundário, e não me teria tornado na pessoa que sou hoje. Estarei para sempre grata a este curso e a esta faculdade.

Cristina Martins

*“Sê todo em cada coisa. Põe quanto és no mínimo que fazes.”*

Ricardo Reis (Heterónimo de Fernando Pessoa)

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# Abbreviations and Symbols

| | |
|---|---|
| 3D | Three Dimensional |
| ADL | Activities of Daily Living |
| BI | Barthel Index |
| CI | Confidence Interval |
| CIMT | Constraint-Induced Movement Therapy |
| DF | Degree of Freedom |
| EKF | Extended Kalman Filter |
| EPE | End-Point Error |
| FAS | Functional Ability Ranking Scale |
| FIM | Functional Independence Measure |
| FM | Fugl-Meyer Assessment |
| IJC | Interjoint Coordination |
| IMU | Inertial Measurement Unit |
| KF | Kalman Filter |
| MEMS | MicroElectronic Mechanical Systems |
| PV | Peak Velocity |
| TD | Trunk Displacement |
| TMT | Total Movement Time |
| WMFT | Wolf Motor Function Test |

# Chapter 1

# Introduction

## 1.1 Context

Every year, approximately 15 million people suffer from a stroke worldwide. Of these, 5 million die and another 5 million are left permanently disabled [1]. Stroke is a very serious global health care problem which has been reported as one of the main causes of adult disability in developed and low-mortality developing regions [2].

As the majority of patients usually survives a first stroke, the biggest problem and consequent health impact of a stroke is long-term impairment. Particularly, motor impairment is the most common form of impairment caused by stroke. It can be defined as a loss or limitation of function in muscle control and movement, and normally affects the face, arm and leg of one side of the body [3].

Despite the efforts and developments that have been made to find a widely applicable or effective medical treatment for stroke repercussions, most post-stroke care continues to rely on rehabilitation interventions [4].

Post-stroke rehabilitation is a restorative learning process that aims at helping patients recover the functions associated to the affected limbs and prepare them to reintegrate as fully as possible into community life [5, 6]. However, it is a long and difficult path and requires repetitive practice for a period that can last several weeks or even months [5].

Functional deficits are often referred to as disabilities and are measured in terms of functions such as activities of daily living (ADLs). Hence, functional recovery is defined as an improvement in mobility and ADLs and has long been known to be influenced by rehabilitation [7].

## 1.2 Motivation

Classical rehabilitation mainly relies on physiotherapy, which depends on therapists' training and past experience and lacks objective standardized analysis for evaluating the performance of the patient and the effectiveness of the therapy. This raises the need for quantifying movement during rehabilitation and thus finding appropriate instruments for quantitative measurements so as to capture motion and specific details of task execution [8].

Besides that, there is also a problem of staffing shortages in health services. As rehabilitation is a long process and often requires one-on-one manual interaction with patients, it reflects in a burden on hospitals and physiotherapists and patients end up not receiving enough treatment and attention [9].

In the end, technology can be really helpful to both standardize the assessment of rehabilitation and complement human resources. In particular, the wide variety of existing technologies for human motion tracking allows for the quantification of movement through several kinematic variables and signals. These variables and signals can be used to develop metrics that characterize quality of movement and are useful to provide feedback on performance during the execution of rehabilitation exercises.

However, even though kinematic analysis has been widely used for gait analysis and its validity has been well established, its clinical use for the assessment of upper limb movement is in its early stages and is still not well established [10]. This is mainly due to the variable and idiosyncratic movements that characterize upper limb movement [11].

Thus, there is a need to develop objective metrics that rely on the fundamentals of clinical reasoning. Additionally, since patients need to exercise functional tasks and ADLs that usually require several degrees of freedom (DOFs), these metrics have also to take in consideration kinematic data from different joints and segments.

It can be easily noted that these metrics are specially useful for systems that aim at facilitating stroke rehabilitation through the use of technology, complementing the work of the therapists. In particular, they could be used to provide real-time feedback to the patient about his/her performance during the rehabilitation exercises. Additionally, the metrics could also be included on reports about the results of the patient, for further analysis by the therapist. For that reason, the metrics need to be easy to interpret [12].

## 1.3 Objectives

The main goal of this dissertation is therefore to develop algorithms capable of converting raw kinematic data from several joints into meaningful metrics that allow the quality assessment of upper limb movement during functional rehabilitation exercises. The algorithms should be also able to give real-time feedback to the patient on his/her performance and progress.

This requires understanding which parameters are most clinically relevant for the analysis of upper limb movement during functional tasks and ADLs, which are characterized by several DOFs and demand the use of several joints and segments.

The algorithms will be developed based on the output signals of inertial measurement units properly placed on the upper limb of the subject.

## 1.4 Structure of the Dissertation

This document contains four more chapters. Chapter 2 provides a review of the existing literature on the important topics regarding upper limb functional rehabilitation and the possibility of performing said rehabilitation using inertial sensors. In chapter 3, the developed algorithms to calculate the set of suggested metrics are described, covering all the steps since the output of the inertial sensors. Afterwards, chapter 4 describes the study that was carried out to validate the ability of the proposed metrics to discriminate between healthy and unhealthy movements, as well as its results. The document finalizes with chapter 5, where the main conclusions of the work are presented, as well as suggestions for further improvements.

# Chapter 2

# Literature Review

## 2.1 Overview

This chapter presents a review of the existing literature on all the important topics regarding upper limb functional rehabilitation and the possibility of monitoring said rehabilitation using inertial sensors, without the need for the physical presence of the therapist.

While developing a system or algorithm for any kind of medical purpose, it is of utmost importance to have a strong clinical foundation behind it. Hence, the aim of the first section is to provide an overview of the clinical basis for functional upper limb rehabilitation. Then, there is a section about the basic concepts of upper limb functional anatomy and biomechanics, including its bones and joints and the movements allowed by those joints.

In order to avoid the need for the physical presence of the therapist, it is necessary to automatically assess the performance and progress of the patient during the rehabilitation exercises. First of all, this requires using some kind of technology that is capable of tracking human movement. Thus, the next section provides a summary of the existing motion tracking systems and their advantages and disadvantages, followed by a more detailed explanation about the technology that will be used in this work: the Inertial Measurement Unit. Finally, in the last section before the conclusions, examples of the use of technology for rehabilitation purposes are provided. The section starts by describing several kinematic measures proposed in the literature for quantitative assessment of functional impairments. Then, some examples of commercially available systems for real-time feedback on rehabilitation are provided.

## 2.2 Functional Recovery After Stroke

A stroke occurs when blood flow to an area of the brain is disrupted and brain cells are left oxygen deprived. It may result from either blockage (ischaemic stroke) or rupture of a blood vessel (haemorrhagic stroke) [1]. Motor impairment is the most common form of impairment caused by stroke. It can be defined as a loss or limitation of function in muscle control and movement, and normally affects the face, arm and leg of one side of the body [3]. The recovery of functions associated to the affected limbs mainly relies on rehabilitation, which is a restorative learning process [5, 6].

This section begins with presenting the existing approaches for stroke rehabilitation. Then, an overview of the requirements of functional movement is provided, along with the clinical reasoning behind the evaluation of movement. Lastly, there is a summary of the existing scales for performance evaluation and recovery assessment.

### 2.2.1 Neurophysiological Aspects of Recovery and Therapy Protocols

When it comes to stroke rehabilitation, there are several approaches/theories that try to explain the neurophysiological aspects of recovery [13]. Some of these approaches, as it is the case of the Bobath Concept, are based on theories of motor learning, which is defined as the permanent change in an individual's motor performance as a result of practice [14].

Nevertheless, this is only possible because motor recovery is influenced by neurological recovery, namely through functional and structural reorganization of the brain. In particular, brain plasticity (or neuroplasticity) is the ability of the brain, both healthy and injured, to reorganize itself through plastic changes in response to sensory input, experience and learning [15]. Therefore, the Bobath Concept sees the potential for plasticity as the basis for development, learning and recovery within both the nervous and muscular systems [14].

A study was performed to analyze the motor cortical representation of the hand on a group of healthy subjects while they learned a one-handed, five-finger exercise on the piano. It was observed that, as subjects became more skilled on this new task, the size of the motor cortical representation of the hand increased. However, these changes were not verified in subjects who played the piano at will for the same amount of time but were not taught the exercise [16]. Similar findings were reported in studies reviewed in [17]. Therefore, the evidence suggests that cortical reorganization is greater if the practice method is meaningful or, in other words, has a specific goal. For example, in order to improve elbow extension, one could practice reaching for a glass of water, instead of simply performing elbow flexion and extension [13]. Consequently, rehabilitation produces better results when the tasks are meaningful to the patient [17].

Additionally, in order to induce and preserve brain changes, repetition and consistent practice are required [17, 18]. Thus, stroke rehabilitation methods should consist of intensive and repetitive practice of meaningful tasks [13]. Some authors also highlight the importance of feedback to the patient, specially for motivation purposes [3].

There are several movement therapy protocols that rely on principles of motor learning and neuroplasticity, inducing both neural and motor recovery. Among these protocols, (i) task-specific training; (ii) constraint-induced movement therapy (CIMT) and (iii) motor imagery have demonstrated preliminary but promising evidence of their impact on functional recovery [13].

Task-specific training consists of goal-directed repetitive practice of motor tasks to improve the patient's functional abilities [13, 15]. This therapy protocol focuses on training specific tasks since "the best way to learn any task is to practice that particular task" [13]. Functional recovery is achieved due to the recruitment of unused parts of the brain that are usually close to the lesion or whatever function is present elsewhere (proximal or distal) [15, 18]. Additionally, the chosen tasks must be relevant to the patient in order to be motivating [18].

Constraint-induced movement therapy can be considered an extension of task-specific training since it combines intensive practice of the affected upper limb with restricted use of the other (unaffected) limb [19]. This can be achieved by wearing a sling or a mitt. The idea behind this protocol is to counter the common tendency of stroke patients to use the unaffected limb for every task, even if they are minimally capable of using the affected one [13]. This is often called "learned non-use" and can be due to pain, frustration, or simply because it is easier for the patient to use the healthy limb [18]. However, this therapy protocol presents some disadvantages, namely the fact that tasks are only performed unilaterally, which automatically excludes some tasks that can be meaningful to the patient. Additionally, only patients who are able to carry out $20^\circ$ of wrist extension and $10^\circ$ of finger extension are eligible for CIMT [15].

Mental imagery can be defined as the cognitive process of creating any experience (auditory, visual, tactile, and kinesthetic) in the mind without its actual presence. In particular, motor imagery is the act of producing an internal representation of a movement without actually generating any motor output. Brain mapping techniques have shown that this technique can activate brain areas and pathways responsible for the movement even in the absence of the movement itself. This can be particularly helpful in early stages of recovery, when it is almost impossible for patients to perform movements. However, this method cannot be used alone, and therefore should be combined with others like the ones mentioned above. Moreover, there might be some patients who are unable to generate such images since it is considered a quite complex cognitive skill [13].

In the end, there is not a widely accepted approach due to the lack of compelling evidence for the majority of the approaches, specially for upper limb interventions [13]. Consequently, therapists do not usually go for a single specific approach or technique but instead combine several sources and ideas, resulting on an eclectic approach [19]. They also tend to choose their interventions as a result of their own judgment and experience and not regarding results from clinical studies [20]. However, the main general recommendations seem to be that stroke rehabilitation should (as much as possible) focus on high-intensity, repetitive task-specific practice with feedback on performance [3].

### 2.2.2 Functional Movement and Clinical Reasoning

During the course of rehabilitation, the therapist is responsible not only for prescribing the rehabilitation exercises, but also for assessing the patient when he/she is performing the exercises. A simple clinical reasoning would be to assess whether or not the patient can perform the exercise. However, recovery achieved through motor learning may be either true or compensatory. True motor recovery happens when undamaged or alternative pathways transport commands to the same muscles that were used before the injury. On the other hand, compensation is the use of alternative muscles to accomplish the task goal [13]. Thus, the patient might be capable of performing the exercise simply due to compensatory mechanisms. For this reason, the Bobath Concept defends

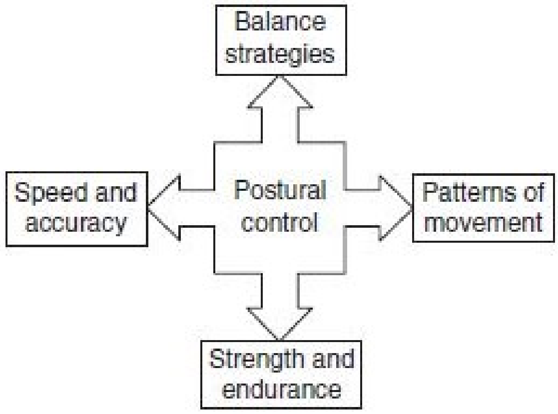



Figure 2.1: Requirements for efficient functional movement (Adapted from [14]).

that quality of movement must be taken into consideration during the clinical reasoning process, which requires a deep understanding of functional human movement [14].

The natural human movement develops from the interaction of three different systems: (i) the perceptual system, which is related with the integration of sensory information; (ii) the action system, which concerns the actual motor output of the muscles and (iii) the cognitive system, which includes attention, motivation and other emotional aspects of motor control [14]. However, after a stroke, the harmonious interaction between the systems is affected. This leads to a number of deficits, namely the weakness of specific muscles, abnormal postural adjustments, lack of mobility, deflection of trajectories from a straight line, slowness and incorrect timing of components within a movement pattern and loss of interjoint coordination (segmented movements). Thus, when trying to perform a certain movement, the stroke patient faces all these problems and naturally tries to compensate with the available motor strategies [21].

An example of a compensatory strategy is the fixation of specific body segments, decreasing the number of DOFs of the movement, which requires the control of fewer motor elements by the central nervous system. These patterns can happen in response to the inability of maintaining balance and posture. For example, the fixation of the scapula[1] can result in a limitation of the normal kinematics of upper limb movement [21].

Postural control can be defined as the ability to orientate and stabilize the body within the force of gravity using appropriate balance mechanisms and is associated with the variability of human movement. For that reason, postural control is a crucial consideration in the Bobath Concept and is the foundation for the requirements of efficient functional movement [14]. These requirements can be found in the schematic representation of Figure 2.1.

Balance strategies allow for the organization of movement and are a fundamental requirement since they directly influence postural control. Additionally, all movements occur in coordinated patterns that follow an appropriate trajectory according to the task and the environment. These patterns are characterized by timing and sequencing and also play an important role on efficient

[1] The scapula is one of the bones of the shoulder girdle (see Section 2.3).

functional movement. Another important aspect is the ability to achieve the appropriate speed and accuracy. This is particularly important for postural control since a greater speed results in a greater torque at adjacent body parts, which requires more stability. Finally, strength and endurance are also required to appropriately perform functional tasks since muscles must be able to generate sufficient force and tension to overcome the resistance of the activity [14].

In conclusion, clinical reasoning behind the assessment of quality of movement requires understanding the relationships between these components and particular emphasis must be given to the assessment of postural alignment. However, this is not an easy task, especially for the upper limb, since it is characterized by variable and idiosyncratic movements [11].

### 2.2.3 Clinical Scales for Stroke Rehabilitation

The efficacy and outcome of stroke rehabilitation, as any other therapeutic practice, needs to be accurately evaluated [22]. Moreover, assessment is also important to initially choose the adequate intervention for the patient and to compare results from the application of the same therapy protocol to different patients and by different therapists, which is often done through scientific trials [23].

However, stroke recovery is extremely difficult to measure because it depends on several factors, namely the type of stroke, the size and location of the lesion and the type, severity and number of neurological deficits. Additionally, the rate and degree of spontaneous recovery is also different from patient to patient [24].

It becomes necessary to have some kind of numerical notation or score that adequately reflects changes in the rate and quality of patients' performance during the course of recovery, making the assessment process easier and less subjective [24]. Even though there is not a universally accepted instrument, there is a wide variety of assessment practices, which often rely on scales [23].

Depending on the purpose, the assessment method can have different levels of specificity, that range from muscle force quantification to quality of life estimation. Between these two extremes, there is firstly muscle strength and tendon jerk analysis, followed by the assessment of partial functions, like the ability to use the affected arm. Then, there is the assessment of patient function as a whole, for which there are disability indexes that measure ability to perform activities of daily living or, even more general, scales that measure patient independence (or level of handicap) [25].

The Barthel Index [26] and the Functional Independence Measure [22] are examples of disability indexes that measure independence. The patient performs a set of activities of daily living and gets a score depending on whether he/she is independent while performing each activity. This level can be based on time and amount of help required. The Barthel Index includes 10 different tasks and a specific score is given for each task, whether it is done with or without help [26]. The Functional Independence Measure includes a set of 18 tasks divided in six different areas: self-care, sphincter control, mobility, locomotion, communication and social cognition. The score for each task goes from one to seven, according to the level of independence [22]. On the other hand, the Modified Rankin Handicap Scale [25] is a more general scale, since it does not assign a score for each task but simply measures the level of handicap of the patient (in a scale from zero to five).

Table 2.1: Functional Ability Ranking Scale (Adapted from [23]).

| | |
|---|---|
| 0 | Does not attempt with the affected arm. |
| 1 | Affected arm does not participate functionally; however, attempt is made to use it. In unilateral tasks the unaffected arm may be used to move the affected one. |
| 2 | Affected arm does participate, but requires assistance of the unaffected arm for minor readjustments or change of position, or requires more than two attempts to complete, or accomplishes very slowly. In bilateral tasks the affected arm may serve only as a helper or stabilizer. |
| 3 | Affected arm does participate, but movement is influenced to some degree by synergy or is performed slowly and/or with effort. |
| 4 | Affected arm does participate; movement is close to normal, but slightly slower; may lack precision, fine coordination or fluidity. |
| 5 | Arm does participate; movement appears to be normal. |

However, these scales are only suitable for a broad assessment of activities of daily living, as they evaluate disability and handicap (if the patient is capable of performing a certain task) but ignore neuromuscular capacity (if the patient is performing the task correctly) [24]. Moreover, sometimes it is also necessary to have measures that are more sensitive to slight changes [27]. The Wolf Motor Function Test [23] and the Arm Motor Ability Test [11] also assess a set of meaningful tasks that are likely to be part of everyday activities, like combing the hair, cutting meat or turning a key in a lock. However, the rating scale goes beyond the level of independence and tries to characterize the movement regarding its coordination, fluidity, and other clinically relevant characteristics [23]. This rating scale is called the Functional Ability Ranking Scale and is presented on Table 2.1. In addition to the score obtained on this scale, the Wolf Motor Function Test also considers a timed score quantifying the speed of performance in seconds.

The Motor Activity Log [28] is similar to the previous two instruments but instead of using the same scale, uses two scores for each task, one for the amount of use and other for the quality of movement of the affected arm. However, the rationale behind these scores is quite comparable to the one used for the Functional Ability Ranking Scale.

The Fugl-Meyer Assessment (FM) [29] has been highly endorsed by the stroke rehabilitation community to be used on clinical trials since it is considered one of the most comprehensive quantitative measures of motor impairment following stroke. As mentioned in the previous section, Bobath gives particular importance to the role of posture (certain body parts stabilized) on the ability to perform movements of the limb [14]. The FM scale was developed taking into account this principle and therefore tries to fill the lack of standardization of the patient's posture of the existing scales. Additionally, it also takes into account the degree of compensatory mechanisms [24, 29]. This is particularly important since this kind of behaviour can go unnoticed as the patient is apparently able to complete the task, but is not promoting the appropriate mechanisms of motor recovery.

The FM scale is divided into 5 domains - motor function, sensory function, balance, joint range of motion, and joint pain. The motor function domain includes items measuring movement, coordination, and reflex action about the shoulder, elbow, forearm, wrist, hand, hip, knee, and ankle and is divided into 66 points for the upper limb and 34 points for the lower limb. Each item is scored on a three-point ordinal scale where zero is the minimum and two is the maximum [24]. The items for the upper limb motor function are represented in Table 2.2. The joint range of motion is compared with the unaffected limb and scored accordingly for each movement (in a scale of zero to five), resulting in a total of 44 points [29]. Details on the other domains will not be addressed here due to their irrelevance to the work.

The application of these scales still requires some of the clinical reasoning described in the previous section since some parameters or scores are open to a range of interpretation and may require subjective judgments [27]. Thus, even though they provide a quantitative score, the rationale behind these assessment scales is always, to some extent, qualitative and subjective.

Hence, there is a need for a more objective way of measuring performance. One alternative is the use of kinematic analysis, which is an objective, discriminative measure that quantifies movement biomechanics. Kinematics describes movements of the body through space and time, namely linear and angular displacements, velocities and accelerations, but without considering the forces involved [30]. Hence, it could be used to measure the extent of deviation from normal movement patterns and help specialists in the process of performance and outcome evaluation. However, even though kinematic analysis has been widely used for gait analysis and its validity has been well established, its clinical use for the assessment of upper limb movement is in its early stages and is still not well established [10].

Table 2.2: Fugl-Meyer items for upper limb motor function assessment (Adapted from [29]).

<table>
<tr><th colspan="4">A) Shoulder/Elbow/Forearm</th></tr>
<tr><td>I</td><td colspan="2">Reflex activity</td><td>Flexors<br>Extensors</td></tr>
<tr><td rowspan="6">II</td><td rowspan="3">a)</td><td>Shoulder</td><td>Retraction<br>Elevation<br>Abduction<br>Outwards rotation</td></tr>
<tr><td>Elbow</td><td>Flexion</td></tr>
<tr><td>Forearm</td><td>Supination</td></tr>
<tr><td rowspan="3">b)</td><td>Shoulder</td><td>Adduction/Inwards rotation</td></tr>
<tr><td>Elbow</td><td>Extension</td></tr>
<tr><td>Forearm</td><td>Pronation</td></tr>
<tr><td rowspan="3">III</td><td colspan="3">Hand to lumbar spine</td></tr>
<tr><td colspan="2">Shoulder</td><td>Flexion 0º-90º</td></tr>
<tr><td colspan="2">Elbow 90º</td><td>Pronation/Supination</td></tr>
<tr><td rowspan="2">IV</td><td colspan="2">Shoulder</td><td>Abduction 0º-90º<br>Flexion 90º-180º</td></tr>
<tr><td colspan="2">Elbow 0º</td><td>Pronation/Supination</td></tr>
<tr><td>V</td><td colspan="3">Normal reflex activity</td></tr>
<tr><th colspan="4">B) Wrist</th></tr>
<tr><td colspan="3">Elbow 90º</td><td>Wrist stability<br>Wrist flexion/extension</td></tr>
<tr><td colspan="3">Elbow 0º</td><td>Wrist stability<br>Wrist flexion/extension</td></tr>
<tr><td colspan="4">Circumduction</td></tr>
<tr><th colspan="4">C) Hand</th></tr>
<tr><td colspan="4">Fingers massflexion<br>Fingers massextension<br>Grasp (6 different types)</td></tr>
<tr><th colspan="4">D) Coordination/Speed</th></tr>
<tr><td colspan="4">Tremor<br>Dysmetria<br>Time</td></tr>
</table>

## 2.3 Upper Limb Biomechanics

One of the fundamental requirements of upper limb rehabilitation is the understanding of which movements the upper limb is capable of executing and which joints are involved in those movements. Thus, this section provides an overview of the upper limb functional anatomy and biomechanics.

The appendicular skeleton includes the bones of the upper and lower limbs and the girdles that attach the limbs to the axial skeleton, namely the pectoral girdle and the pelvic girdle. In particular, the upper limb consists of the bones of the arm (the proximal part of the arm), forearm (the distal part of the arm), wrist and hand [31]. The bone structure of the upper limb and the pectoral girdle, which are involved on upper limb movements, can be found in Figure 2.2.

Besides bones, the upper limb is also composed of joints. A joint, or articulation, is the place where two bones, often referred to as segments, come together [31]. The major joints involved in upper limb movement are generally referred to as shoulder, elbow and wrist.

The shoulder complex is composed of several joints, each contributing to the movement of the arm in a coordinated manner. These include the scapulothoracic, sternoclavicular, acromioclavicular and glenohumeral joints. However, the majority of movement is allowed by the glenohumeral joint [32].

The elbow is composed by three joints that allow motion between the three bones of the arm and forearm (humerus, radius, and ulna). Movement between the forearm and the arm is enabled by the ulnohumeral and radiohumeral joints, and movements between the radius and the ulna take place at the radioulnar joints [32].

The wrist joint, or radiocarpal joint is the articulation that allows the movement of the whole hand and involves the distal end of the radius and two of the carpal bones [32].

There are different types of movement associated with the upper limb joints (Figure 2.3). These movements are described below, always in relation to the anatomic position (Figure 2.4).

Flexion is a bending movement of a joint that causes a decrease on the angle between two adjacent segments. The opposite movement is called extension, which is a straightening movement that conversely causes an increase on the same angle, as the joint returns to the initial anatomic position [32]. An example of a flexion/extension type of movement is shown in Figure 2.3a.

Abduction is the movement away from the sagittal plane while adduction is the movement towards the sagittal plane. Two examples of abduction/adduction are provided on Figures 2.3b and 2.3e. In order to facilitate interpretation, when referring to the wrist joint, the abduction and adduction movements are often referred to as radial flexion and ulnar flexion, respectively [32].

Pronation and supination are specific of the forearm and happen when the radius rotates over and back on the ulna at the radioulnar joints (Figure 2.3c). Supination is the movement of the forearm that causes the palm of the hand to rotate and face forwards from the anatomical position. In contrast, pronation is the movement in which the palm of the hand faces backwards [32].

Rotation is the turning of a segment around its long axis and can be either medial or lateral. A medial rotation refers to the movement of a segment so that the anterior surface of the segment

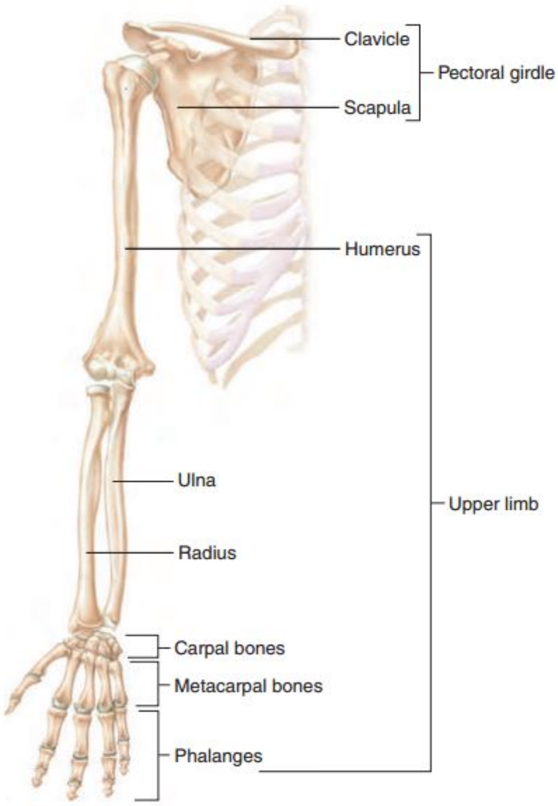
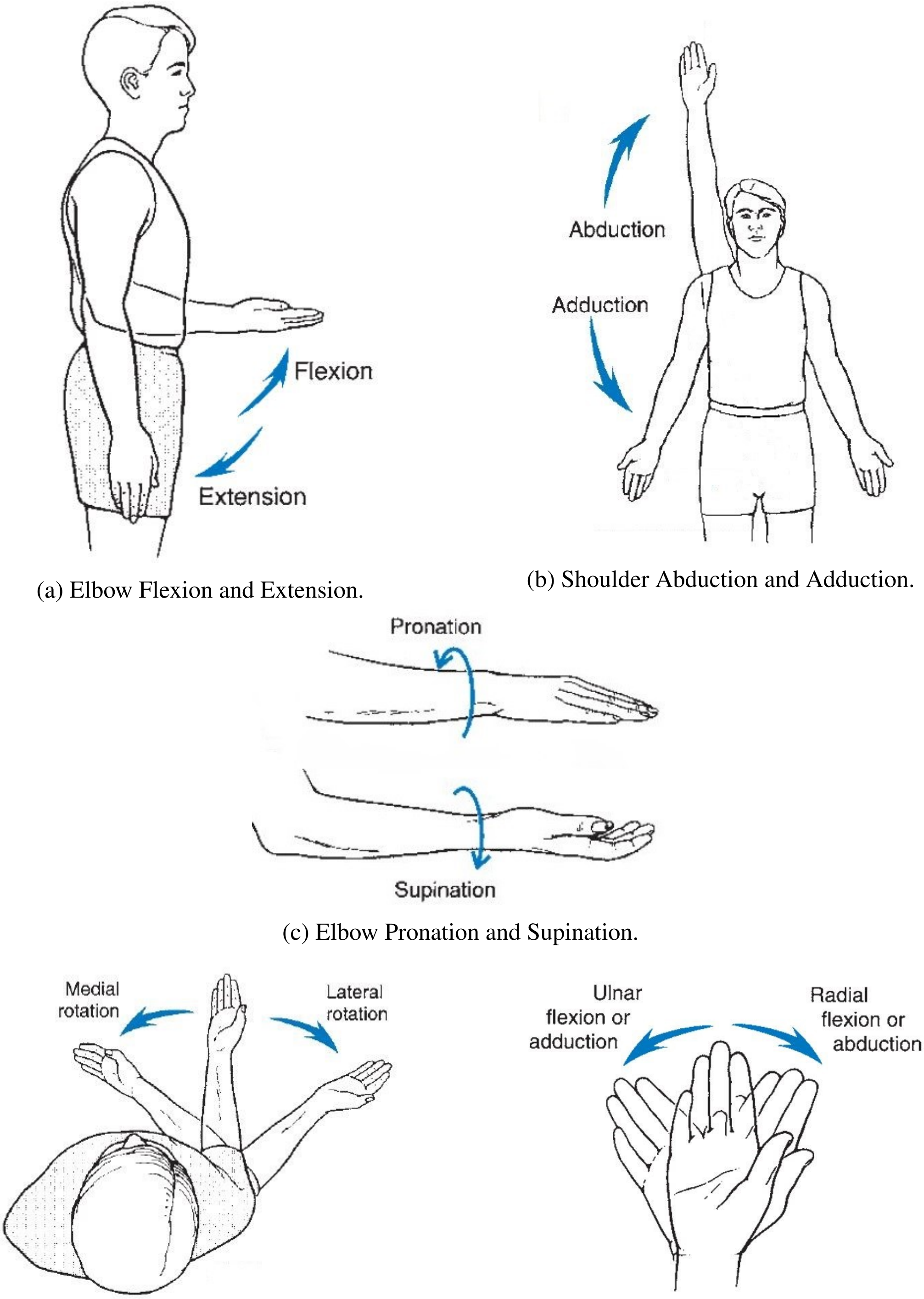



Figure 2.2: Bones of the right pectoral girdle and upper limb (anterior view) [31].

moves towards the sagittal plane while the posterior surface moves away from the same plane. The opposite movement is the lateral rotation, in which the anterior surface of the segment moves away and the posterior surface moves towards the sagittal plane [32]. An example of this type of movement is shown in Figure 2.3d.

In summary, the shoulder joint has three DOFs, allowing movements of flexion/extension, abduction/adduction and medial/lateral rotation; the elbow joint has two DOFs, allowing movements of flexion/extension and pronation/supination; and the wrist joint also has two DOFs, allowing movements of flexion/extension and abduction/adduction [32].




(a) Elbow Flexion and Extension.

(b) Shoulder Abduction and Adduction.

(c) Elbow Pronation and Supination.

(d) Shoulder Rotation.

(e) Wrist Abduction and Adduction.

Figure 2.3: Different types of movement of the upper limb joints (Adapted from [32]).

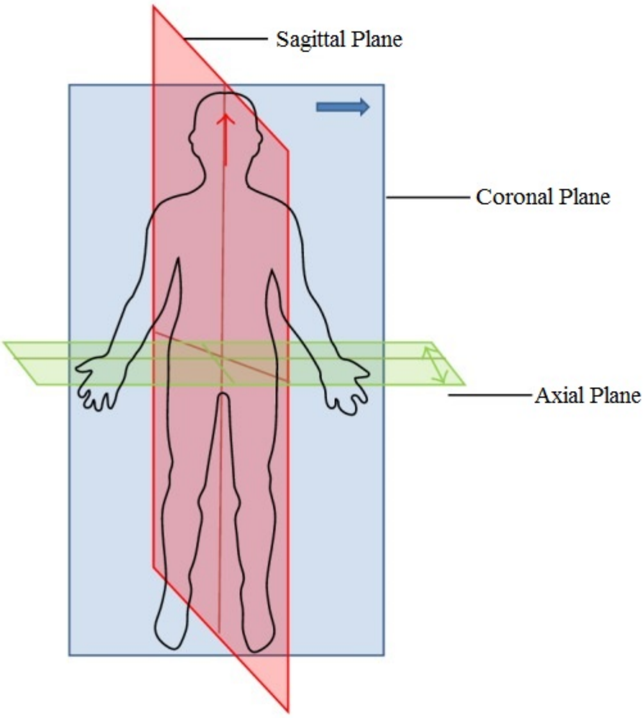



Figure 2.4: Anatomical position and planes [33].

## 2.4 Upper Limb Motion Analysis

In order to perform a more objective assessment of performance on stroke rehabilitation, it is necessary to quantify movement. This can be done through human motion tracking systems, whose main goal is to retrieve real-time data that represents the pose changes of a human body, or part of it [34].

Therefore, the aim of this section is to present an overview of the existing human motion analysis technologies and then to give special attention to the particular technology that will be used in this work, going deeper into how it can be applied to upper limb motion analysis.

### 2.4.1 Existing Technologies

Human motion tracking systems can be based on a wide variety of motion-sensor technologies and often include algorithms to process the measured data and estimate body kinematics [35]. All the approaches have advantages and disadvantages so the ideal option will ultimately depend on the specific application [36].

In general, human motion tracking systems can be visual-based or non-visual. Visual-based systems rely on optical sensors and can be further divided into marker-based and marker-free, depending on whether or not there is a need to put markers on the subject's body [34]. An advantage of using optical sensors is their ability to provide data at relatively high speed and low latency since light is a fast medium [36].

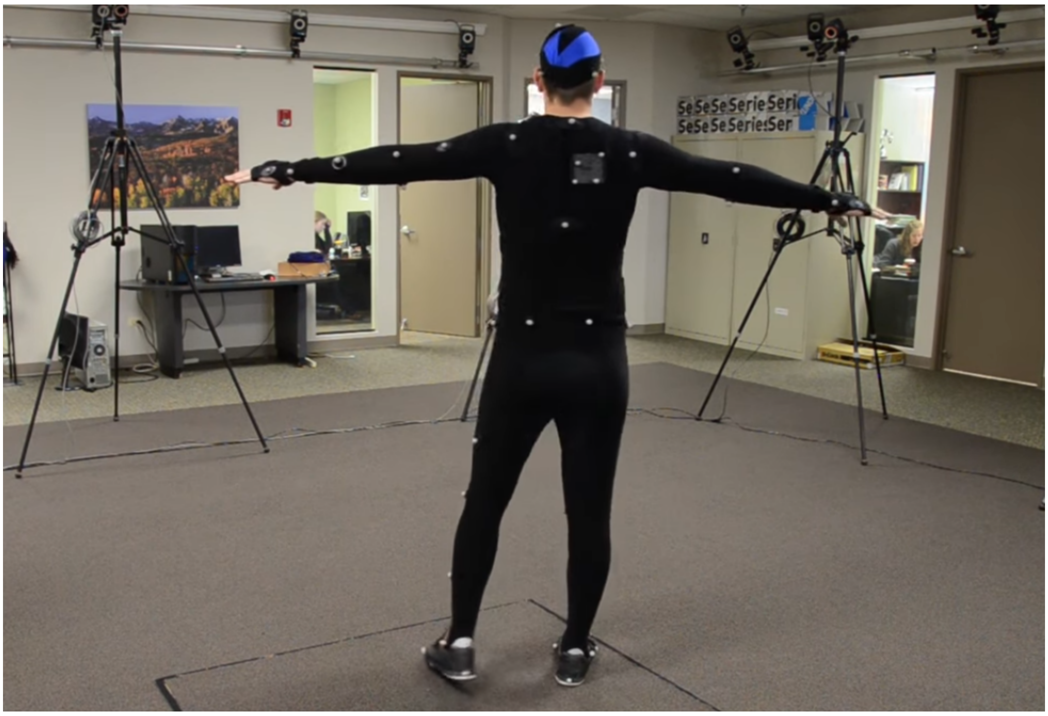


Figure 2.5: The VICON motion capture system [38].

Visual marker based systems rely on measurements of emitted or reflected light, depending on the type of markers used (active or passive) [36]. The optical sensors normally used are cameras that capture the markers' positions. Then, different algorithms are used to compute the position and orientation of the body [35]. These systems are considered the most accurate in retrieving position information and are often used as a golden-standard in human motion tracking and analysis [34]. However, they are highly costly and require a clean laboratory environment since there must be a clear line of sight between the cameras and the markers [35]. The presence of something blocking this path, often referred as an occlusion, causes obscuration difficulties [37]. Other disadvantages include the system's susceptibility to skin movement artifact and the fact that rotated joints or overlapped body parts are impossible to detect [34, 35]. VICON (Vicon Motion Systems Ltd) [38] is an example of a system of this kind and an illustration of its usage can be seen in Figure 2.5.

Marker-free visual based tracking systems also rely on optical sensors but, as the name implies, do not require the use of markers. Instead, they make use of the boundaries and features of human bodies to be able to capture motion in a less restrictive manner [34]. The advent of this type of cameras for video-game applications, as it is the case of Microsoft® Kinect, has substantially lowered their price, making them an affordable and portable solution [39]. Even though they overcome a lot of the problems that come from the use of markers, they are not able to provide the same level of accuracy as marker-based systems and they also require a clean line of sight between the camera and the subject [34].

Non-visual motion tracking systems rely on different kinds of non-optical sensors that can be either mechanical, acoustic, magnetic or inertial [35].

Mechanical systems typically involve an articulated series of metal or plastic pieces linked together with electromechanical transducers such as potentiometers [35]. This is attached to the subject usually in the form of an exoskeleton and as the subject moves, the articulated mechanical parts change shape and cause the transducers to move [36, 37]. These sensors do not have problems of occlusion and are very precise and accurate. On the other hand, the exoskeleton is rigid and heavy which limits the freedom of movements [35]. Additionally, the structure needs to be designed according to the anthropometric measurements of the subject and the pose estimation is limited to a small range of motion and few DOFs [36, 37].

Acoustic systems use emitters and receivers of sound waves to transmit and sense an ultrasonic pulse whose flight duration is calculated. Knowing the time of flight and speed of sound, it is possible to calculate the distance. With three transmitters and one receiver or three receivers and one transmitter it is possible to estimate 3D position. On the other hand, three transmitters and three receivers are required to calculate position and orientation [37]. These systems allow a greater range of motion than mechanical trackers and even though they also require a clean line of sight, sound waves are more capable of deviating from obstacles [36]. The accuracy of these systems can be affected by wind and also by other factors like temperature and humidity that change the speed of sound [35]. Also, as the efficiency of an acoustic transducer is proportional to the active surface area, there is a need for large devices [34].

Magnetic systems rely on measurements of the local magnetic field vector at sensor units placed on the body. This can be done through the use of either magnetometers or current induced in an electromagnetic coil. Using three orthogonally oriented magnetometers in a single sensor unit, it is possible to get a 3D vector indicating the unit's orientation with respect to the excitation. This can be done using the earth's magnetic field as a DC source. Another alternative is to induce excitations with a multicoil source unit. In that case, three excitations are required to estimate the position and orientation of the sensor unit with respect to the source unit. A single source unit is capable of simultaneously exciting multiple sensor units, which represents an advantage for this type of systems. Additionally, as magnetic fields can pass through the human body and other objects, there are no line-of-sight problems. The biggest limitation of magnetic systems is the presence of ferromagnetic and conductive materials in the environment, which can compromise the magnetic field's shape and strength, causing distortions on the signal [36].

Inertial sensors, such as accelerometers and gyroscopes, seem to overcome the limitations of the systems described so far. As they do not rely on emitters and receivers, these sensors are completely self-contained and have no line-of-sight problems. Moreover, they also have very low latency and jitter and can be measured at high sampling rates [36]. With the advent of microelectronic mechanical systems (MEMS), the size and cost of inertial sensors has been substantially reduced, making them suitable for wearable applications with minor discomfort to the subject [40]. The sensors can simply be attached to body segments of interest and there is no need for a laboratory environment [35]. However, accumulated errors (or drifts) are usually found on measurements by gyroscopes. In order to overcome this and other issues, inertial sensors are often combined with magnetometers [41]. Even though magnetometers are not considered inertial sensors and their inclusion is optional, the combination of accelerometers, gyroscopes and magnetometers is often referred to as Inertial Measurement Unit (IMU).

### 2.4.2 Inertial Measurement Unit

Inertial Measurement Units (IMUs) are able to provide an accurate estimation of their own orientation with respect to a fixed reference frame through the use of a combination of different sensor technologies and sensor fusion algorithms [42].

Gyroscopes provide a measurement of the angular velocity applied to the object. Integrating that velocity over time, it is possible to know the sensor's orientation with respect to an initially known reference angle. However, measurements by gyroscopes suffer from bias or drift, which is a low frequency noise component. Thus, with integration, these errors quickly accumulate in the final estimation [41].

Therefore, gyroscopes alone cannot provide an absolute measurement of orientation and there is a need to add accelerometers and magnetometers to the system [43]. Accelerometers provide the direction of the gravity vector by sensing acceleration due to gravity while magnetometers measure the direction of the Earth's magnetic field. With this information, it is possible to have an absolute reference frame of orientation, which is formed by gravity and the Earth's magnetic North vectors [42, 44]. Normally, the sensors are placed in orthogonal triples for 3D position and orientation in X, Y and Z axis [37].

Besides gyroscopes, accelerometers and magnetometers also have sources of error: the measured direction of gravity can be corrupted by accelerations due to motion and the magnetic field can be disturbed by magnetic interference in the surrounding environment. Through the use of sensor fusion algorithms, it is possible to combine the best data from all sensors, resulting in a more accurate measurement [43].

The great majority of sensor fusion algorithms are based on the Kalman Filter (KF) due to its accuracy and effectiveness [43]. In a few words, the KF is basically a set of mathematical equations that provides an efficient computational (recursive) solution of the least-squares method [45]. But, as the relationships describing rotational kinematics in three-dimensions typically require large vectors, an Extended Kalman Filter (EKF) implementation is normally used to linearize the problem [43].

An example of a sensor fusion approach based on the EKF theory is the XKF3$^{TM}$ [46] algorithm, which optimally estimates 3D orientation with respect to a local Earth fixed frame (Figure 2.6). Besides orientation, the algorithm is also capable of retrieving acceleration without the gravitational component, auto-calibrated angular velocity and local magnetic field [46].

The main role of a sensor fusion algorithm is to stabilize drift. XKF3$^{TM}$ does this by applying some carefully chosen and precisely formulated assumptions about the sensor dynamics and characteristics. For example, it deals with commonly occurring distortions, like transient accelerations or magnetic field distortions, among others [46].

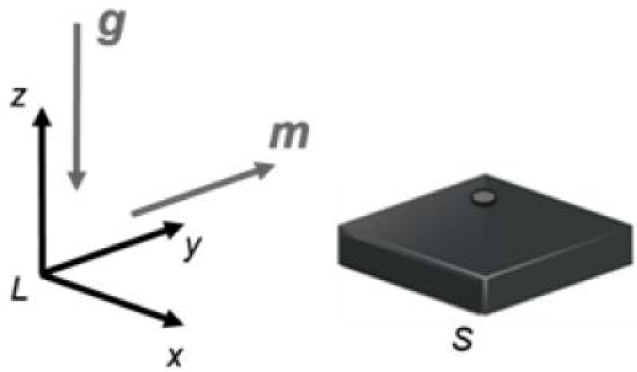



Figure 2.6: Local coordinate frame (L). The orientation of the sensor (S) is identified by the grey dot. The vertical axis of the reference frame is defined by gravity (g) and horizontal axes are defined by the magnetic field (m) [46].

The output of XKF3™ is a normalized unit quaternion expressing the orientation of the sensor with respect to the local coordinates [46].

In conclusion, IMUs are a powerful tool for motion tracking and could be useful for upper limb motion analysis. By attaching sensor units to anatomical segments of interest, it is possible to ascertain the orientation and position of the arm, as well as its trajectories.

### 2.4.3 Orientation Representation

When it comes to orientation representation, the most widely used notations are quaternions and Euler angles. A quaternion is a four-dimensional complex number that can be used to represent the orientation of a rigid body or coordinate frame in three-dimensional space. A quaternion describing the orientation of frame B relative to frame A can be defined by the notation of Equation 2.1, where $q_0$ represents the real component and $q_1$, $q_2$ and $q_3$ the imaginary parts. It is conventional to use unit length quaternions for orientation representation [43].

$$ {}^{A}_{B}\hat{q} = [q_0 \quad q_1 \quad q_2 \quad q_3] \tag{2.1} $$

In order to facilitate interpretation, it is possible to convert quaternions into Euler angles. Euler angles describe the rotation of a rigid body from one coordinate system to another by means of three successive angular rotations: rotation $\gamma$ around local Z-axis (yaw angle), rotation $\beta$ around local Y-axis (pitch angle) and rotation $\alpha$ around local X-axis (roll angle) (Figure 2.7) [46].

The main reason for preferring quaternions over Euler angles is the fact that the latter suffer from gimbal lock, which is the loss of rotational DOFs due to singularities [48].

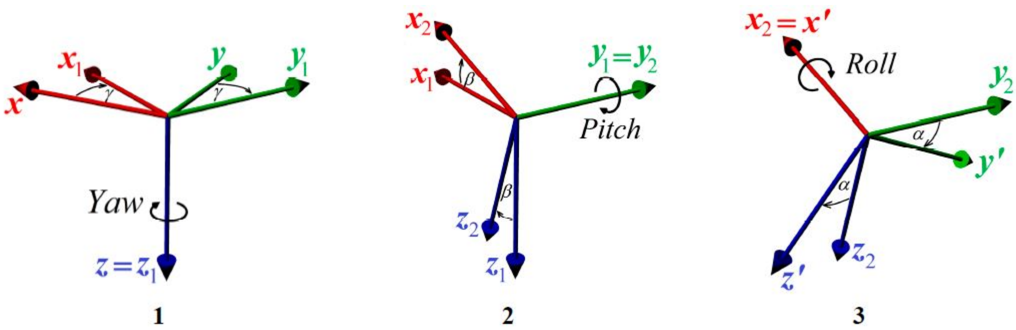



Figure 2.7: Z-Y-X sequence for Euler angles: $\gamma$ represents yaw, $\beta$ represents pitch and $\alpha$ represents roll [47].

## 2.5 Use of Technology for Functional Rehabilitation Purposes

In the previous section, it was shown how technology can be used to accurately track human motion. Hence, it should come as no surprise that this kind of technology has already been used for rehabilitation purposes, namely to track movement and quantitatively assess its quality, while performing rehabilitation exercises or tasks.

This section starts by giving an overview of several studies that used different kinematic measures to assess movement quality and differentiate between healthy subjects and stroke patients. Then, some examples of commercially available systems for real-time feedback on rehabilitation are also provided.

### 2.5.1 Quantitative Assessment of Functional Impairments using Kinematic Measures

Using the motion tracking technologies described on 2.4.1, it is possible to measure several kinematic variables that describe the upper limb movement during a task. These variables, or the metrics that can be calculated with them, can be used to quantitatively assess movement quality. Thus, they can be helpful to evaluate the patients' performance and progress during the course of rehabilitation [49].

There are several studies on the literature that propose a set of normative values for upper limb movement during several ADLs [50, 51, 52, 53]. They used marker-based visual tracking systems [50] and magnetic tracking systems [51, 52, 53] to extract values of joint angles and joint range of motion for several healthy subjects. These values could then be used as a reference for the assessment of movements performed by stroke patients.

Other studies propose several different metrics based on kinematic measurements and demonstrate their effectiveness on distinguishing between healthy and stroke patients. Drinking is the most commonly analysed ADL [30, 54, 55], along with the reaching movement, namely reach to target, pointing and reach to grasp [10, 56]. Except for [55], which used an inertial sensor, all of these studies made use of visual marker-based systems to extract the kinematic variables.

Murphy et al. [30] divided the drinking task into five phases: reaching for the glass, forward transport of the glass to the mouth, drinking, back transport of the glass to the table, and returning the hand to the initial position. The kinematic variables used in this study were divided in four categories: (i) velocity and movement time; (ii) movement strategy; (iii) smoothness and coordination of movement and (iv) compensatory trunk displacement and maximal angular joint motions. The first category includes the total movement time, which is the total amount of time required to complete the task, the peak tangential velocity of the hand and the peak angular velocity of the elbow joint, both for the reaching phase. The second category contains the time, and percentage of time, to reach the first peak tangential velocity of the hand and the peak angular velocity of the elbow joint. The third category uses the total number of movement units during the reaching and forward transport phases to quantify smoothness. To define a movement unit, the tangential velocity profile of the hand is searched for local minima and maxima and a difference bigger than 20 mm/s between a minimum and next maximum velocity is considered a velocity peak and consequently a new movement unit. Movement coordination is defined by interjoint coordination between the shoulder and elbow joint angles through a correlation coefficient. The fourth and final category includes the maximal displacement of the trunk from the initial position and the joint angles for maximal elbow extension and shoulder flexion during reaching as well as for maximal shoulder abduction and flexion during drinking.

After analyzing the contribution of each of these variables to discriminate between healthy subjects and stroke patients, the authors concluded that the most important ones could be grouped into two major factors. The first factor included total movement time, number of movement units and peak angular velocity of the elbow, while the second consisted of compensatory movement patterns and interjoint coordination [30].

Kim et al. [54] similarly divided the drinking task into the same phases described for the Murphy et al. study [30]. The variables they used to define quality of movement were the movement time, i.e. the time required to complete each phase, and phase ratio, which is the amount of time required to complete each phase, over the total duration of the drinking task. The joint angles and angular velocities of the upper limb joints were also calculated for each phase.

Besides drinking, which is a unilateral task, Thies et al. [55] also studied a bilateral task, namely the simple manipulation of a plate. It consisted of a small lift of the plate in front of the trunk, followed by a sideways translation of the plate towards the side where the plate is then lowered onto the table. Moreover, their kinematic analysis is quite different from other existing approaches, since they focus on movement variability, inspired by its application on gait analysis. So, in order to quantify movement variability between different executions of the same task (trials), dynamic programming for curve-registration is applied to the linear acceleration signals. These signals are collected by an inertial sensor placed on the forearm of the subject.

The main consideration of this study is that signal variability must be divided in two parts, namely timing and magnitude, that are quantified separately. So first, for each trial-to-trial comparison, the signal from one trial is time-warped to the signal from another trial (defined as a reference). The variability in timing can then be quantified by the amount of warping (warping cost) necessary to align the two signals. Moreover, the variability in signal magnitude is defined by the root mean square error between the signal from the reference trial and the warped signal. Finally, the average of the variability metrics (warping cost and root mean square error) computed for the acceleration signals from all three axes is calculated for each trial-to-trial comparison [55].

The authors investigated the effectiveness of these variability metrics in differentiating a group of six control subjects from a group of six stroke patients. The main conclusions were that the warping cost for the glass task was significantly higher in stroke patients than controls. However, these differences were not so significant for the plate task, which was justified by the bilaterality of the task and consequent help of the unimpared arm [55].

Patterson et al. [10] analyzed the reliability of a set of metrics to assess movement strategy and performance during two different tasks: reach to target and reach to grasp. These metrics included: (i) movement time, which corresponded to the time elapsed from the point where velocity exceeded 5% of peak velocity to the point where it went below 5% of peak velocity; (ii) peak velocity, which is the maximum velocity reached during the task; (iii) index of curvature, that corresponds to the length ratio between the actual hand path and the straight path between the starting and ending hand positions and (iv) trunk displacement (from the initial position). Two additional variables related with the grasping part of the task, namely maximum aperture of the hand and percentage of the movement where it occurs, were also considered due to the possibility of placing small markers on the fingers.

After using these variables to assess performance on a group of nine controls and 19 stroke patients, the main conclusions were that the intraclass correlation coefficient was very high on the stroke group and not so significant in the control group. This lack of consistency may be explained by the possibility for healthy subjects to have more flexible movement pattern selections, leading to a larger heterogeneity in the group. Nevertheless, the high intraclass correlation coefficient in the stroke group shows that the metrics used on this study are stable enough to assess performance of upper limb tasks in stroke survivors [10].

Subramanian et al. [56] also studied the reach to grasp task. The other task they analysed was not reach to target but pointing instead, which is similar but does not require actually touching the target. It was a retrospective study with 86 stroke patients that aimed at estimating which values for kinematic variables delimit the level of upper limb impairment. Specifically, the kinematic variables used in this study were: (i) trunk displacement; (ii) shoulder flexion; (iii) shoulder horizontal adduction and (iv) elbow extension. Trunk displacement was measured as the travelled distance of the trunk marker on the sagital plane between the begining and end of the task. These events were determined in a simillar way to the previously described study [10], but with a threshold of 10% of peak velocity. The other variables correspond to particular joint angles that are defined according to the placement of the markers.

The study results showed that trunk displacement and shoulder flexion were the kinematic variables that contributed the most to differentiate between impairment levels. As for the reach to grasp task, trunk displacement alone was enough. This was further corroborated by the high autocorrelation values between the remaining variables [56].

Table 2.3: Summary and classification of the previously studied kinematic measures to quantitatively assess movement quality (Adapted from [49]).

| **Movement Speed** | **Movement Accuracy** | **Movement Efficiency** |
|---|---|---|
| Movement Time [10, 30, 54]<br>Peak Velocity [10, 30]<br>Phase Ratio [54] | Movement Variability [55] | Index of Curvature [10] |
| **Movement Smoothness** | **Movement Coordination** | **Movement Control Strategy** |
| No. of Movement Units [30] | Interjoint Coordination [30, 59] | Time to Peak Velocity [30]<br>% Time to Peak Velocity [30] |
| **Neuromuscular Capability** | **Torque Production** | **Compensatory Strategies** |
| Joint Range of Motion [30, 50, 51, 52, 53, 54, 56] | Joint Angular Velocity [30, 54] | Trunk Displacement [10, 21, 30, 56, 57, 58] |

As a matter of fact, trunk displacement has also been reported in other simillar studies as being a major indicator of compensatory strategies associated with reaching [21, 57, 58].

A summary of the previously studied kinematic measures to quantitatively assess movement quality is provided in Table 2.3. Each measure was given a category according to the classification proposed by [49]. By simply looking at the table, it is possible to conclude that joint range of motion and trunk displacement are the most widely used measures.

In conclusion, it is noteworthy that the study of kinematic measures has been limited to the drinking task and reaching movements (only one study investigated the task of moving a plate). As movement patterns normally differ according to each task requirements, the effectiveness of a certain metric for the assessment of performance of one task may or may not be suitable for another [10]. Moreover, in order to get the best possible accuracy, the great majority of these studies used expensive equipment that requires a laboratory environment. Hence, to incorporate this kind of measures into a complete rehabilitation system with feedback on performance, it would be necessary to implement them with low-cost technology, such as inertial sensors [55]. Finally, as motion tracking systems are only capable of providing raw kinematic data, it is important to translate that data into more meaningful metrics, that should be easier to interpret [12].

### 2.5.2 Available Systems for Real-Time Feedback on Functional Rehabilitation

Recently, there has been an increasing number of commercially available systems for rehabilitation purposes. These systems make use of human motion tracking technologies to provide an alternative to the classical face-to-face therapy, allowing therapists to remotely monitor and evaluate the progress of their patients. As such, patients can perform rehabilitation exercises in an

Figure 2.8: The Bimeo PRO System [64].

autonomous way, and even at home. Thus, one of the fundamental requirements of these systems is the ability to provide feedback on patient performance, not only to the therapist, but also to the patient in real-time.

Commercially available systems are mostly based on either inertial or marker-free visual based motion tracking technologies. Starting with the ones based on inertial systems, the great majority focuses only on the lower limb. It is the case of systems like Mobility LAB (APDM, Inc.) [60], RIABLO (CoRehab, SRL) [61], RehaGait® (Hasomed, GmbH) [62], YouKicker® (YouRehab, Ltd.) and LEGSys™ (BioSensics LLC) [63].

On the other hand, Bimeo PRO (Kinestica d.o.o.) [64] aims at facilitating upper limb rehabilitation, combining the use of inertial sensors with a simple user interface (Figure 2.8). The system is designed for bimanual and unimanual training therapy, with or without arm weight support. The different therapy modes provided by the system allow both the training of individual arm joints and the exercise of ADLs, which is done through two different types of exercise games. The first type of games encourage the patient to perform simple isolated movements, which are accurately assessed by the system's algorithms. The resulting assessment scores for each session are stored into a database for further analysis by the therapist. The second group of games consist of more complex tasks that simulate ADLs. A set of parameters and the points scored in the game are also stored in the database. Feedback for patients is provided in terms of their score in the games.

Simillarly, the 3DTutor™ (MediTouch Ltd.) [65] also uses inertial sensors, that together with a rehabilitation software and a set of games, allow the patient to intensively exercise specific joints (Figure 2.9). The system allows the tracking of almost every joint in the body, including the upper limb joints, since the sensors can be attached to several body parts. Additionally, the rehabilitation software provides instructions about the movement and also feedback that aims at avoiding the development of compensatory strategies and ensure a better performance during the execution of the exercises. The range of motion of the joint that is being exercised is measured before the start of each game, setting the standard for the desired movement. Thus, each joint can only be assessed independently, one DOF at a time.

The SWORD Phoenix (SWORD Health, S.A.) [66] has three main components: a set of sensor units, a web portal and a mobile application. Using the web portal, the therapist can create a

Figure 2.9: The 3DTutor™ System [65].

new patient profile, prescribe and schedule sessions, and adjust the specifications of each exercise of a session. The system provides a great variety of exercises, including simple joint movements (like elbow abduction) and more complex tasks (like the hand-to-mouth exercise). The scheduled sessions are then available on the mobile application, whose interface will guide the patient through the exercises and display the progress on each repetition, providing real-time feedback on performance (Figure 2.10). In the end of each session, the results are provided on the web portal, including information about the accuracy, velocity and smoothness of the movement, and even about posture. This allows the therapist to readjust the parameters of the exercises, if necessary.

An example of a system using a marker-free visual based motion tracking technology is VERA™ (Reflexion Health, Inc.) [67]. Specifically, it uses a Microsoft® Kinect camera to track approximately twenty-two joints in 3D. It is a tele-rehabilitation platform that enables a home-based rehabilitation scheme, providing clinicians with the necessary tools to remotely monitor patient's progress. The system provides a wide variety of exercises and a virtual assistant to guide the patient throughout their execution (Figure 2.11). Additionally, it also counts the number of repetitions and delivers real-time feedback on exercise quality and performance. The recordings and results of each session are available for further analysis.

In conclusion, the presented systems all have similar goals, giving special emphasis to feedback on performance. Another notable aspect is the fact that some of the systems try to engage the patients through the use of motivating and fun games. However, not all of them provide the possibility of exercising functional tasks and ADLs, which has been shown to be the most indicated way of enabling functional recovery (Section 2.2.1). This is probably due to their inability to evaluate performance of complex tasks, involving more than one joint and DOF.

Figure 2.10: The SWORD Phoenix System [66].

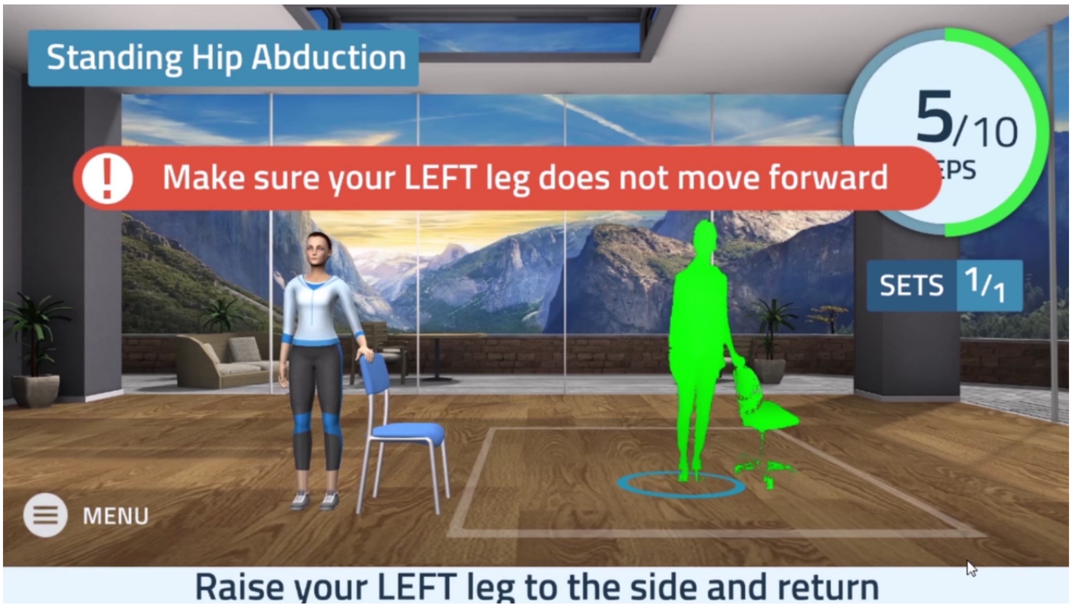



Figure 2.11: The VERA™ System [67].

## 2.6 Conclusions

Regarding the clinical part of the literature review, one of the main conclusions was that functional recovery relies on principles of motor learning and neuroplasticity. Taking in consideration these principles, even though there is not a widely accepted approach, the main recommendations are that stroke rehabilitation should focus on high-intensity, repetitive task-specific practice with feedback on performance.

In terms of the clinical reasoning behind the assessment of quality of movement, the main idea is that it requires understanding the relationships between the requirements for efficient functional movement. These include balance strategies, patterns of movement, speed and accuracy, and strength and endurance, and are all to some extent correlated with postural control. The occurrence of compensatory strategies is also an important factor that should be avoided while performing any kind of task.

The analysis of the existing clinical scales for stroke rehabilitation assessment also allowed for a better understanding of the most important aspects about quality of movement, in a slightly more objective manner. However, these scales are still highly open to a range of interpretation and may require subjective judgments, emphasizing the need for more objective metrics.

As the development of objective metrics requires the quantification of movement and consequent extraction of kinematic variables and signals, an overview of the existing motion tracking technologies was provided. After discussing their advantages and disadvantages, it was possible to justify why Inertial Measurement Units are the most promising technology for rehabilitation purposes.

The last part of the literature review provided a review of the existing studies using kinematic measures to assess quality of movement, as well as some examples of commercially available systems for stroke rehabilitation purposes. The presented studies focused mainly on the drinking task and on reaching movements, and the most widely used metrics were joint range of motion and trunk displacement. Even though the studies showed promising results, none of the proposed metrics is completely established for clinical use. The main conclusions regarding the commercially available systems were that they all give special importance to feedback on performance. However, not all of them allow for the practice of functional tasks and ADLs, probably due to the lack of appropriate assessment metrics.

# Chapter 3

# Quality Assessment of Upper Limb Movement

## 3.1 Overview

This chapter describes the methodology used to achieve the proposed set of metrics for quality assessment of upper limb movement. The first section explains how the inertial sensors provide the input signals for the described algorithms while the second addresses the definition of a frame of reference. The next section describes how position and velocity signals were obtained, followed by a section on the computation of joint angles. In section 3.6, the algorithm developed for detecting the beginning and end of a movement is described. Finally, the last section explains how the proposed performance assessment metrics were calculated.

## 3.2 Input Signals and Upper Limb Kinematic Chain

The input signals for the algorithms developed in this work were acquired through IMU sensors placed on the upper limb segments, as shown in Figure 3.1. Having a sampling frequency of 50Hz, these sensors provide unit quaternions expressing their orientation with respect to a global Earth fixed frame, which is determined by gravity and the Earth's magnetic field.

The sensors have their own local coordinate system, as depicted in Figure 3.2. Thus, the orientation of each segment can be associated with the sensor axis with which it is aligned. For example, the arm segment is aligned with the x-axis, that can be represented by vector $(1,\ 0,\ 0)$. Thus, in order to find the orientation of the arm with respect to the global Earth frame, the output quaternion of the sensor must be applied to that vector. This is done through a quaternion product, as described by equation 3.1, where vector $p$ is represented as a quaternion whose real part equals zero.

$$p' = q \times p \times q^{-1} \tag{3.1}$$

Figure 3.1: Sensor placement on the upper limb of the subject.

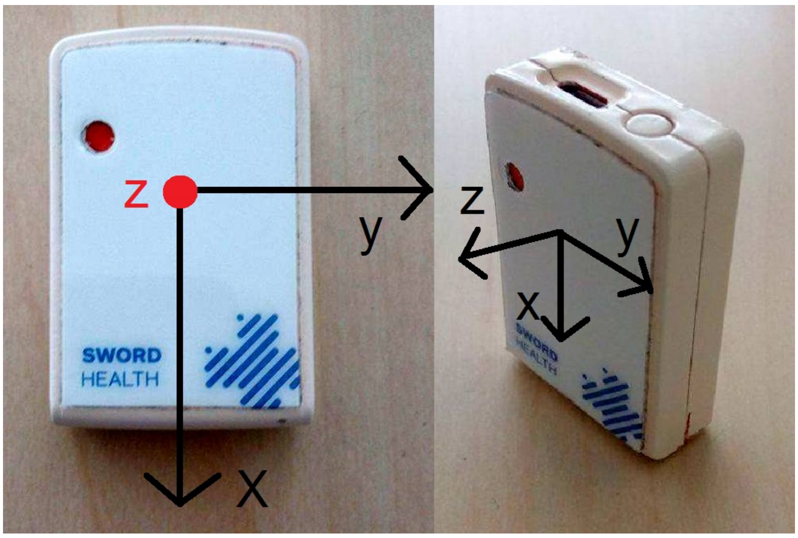



Figure 3.2: Local coordinate system of the sensor.

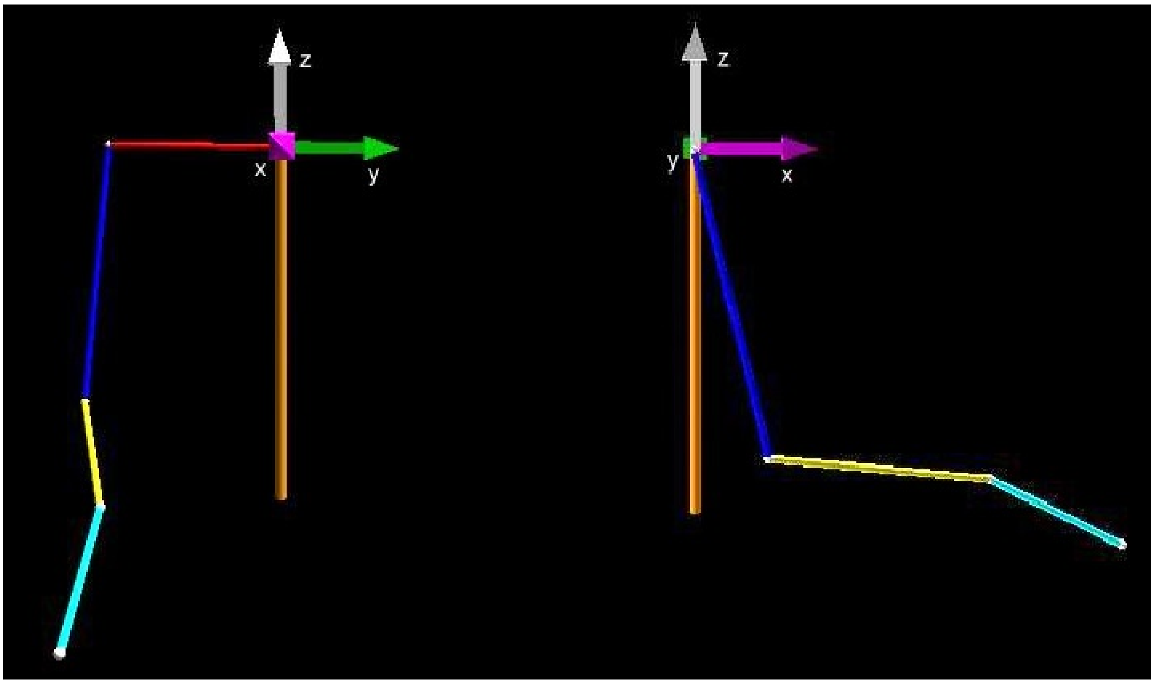



Figure 3.3: Avatar representing the relative positions of the upper limb segments and joints (front view - left; side view - right)[1] .

The upper limb was considered a chain of four rigid bodies (segments) joined by the shoulder, elbow and wrist joints. Therefore, knowing the orientation and length of each segment, it was possible to obtain the relative position of the segments over time and build an avatar, as the one shown in Figure 3.3, where the subject was sitting with the arm resting on the ipsilateral leg. Note that the length of the segments can be estimated from the subject's height through proportionality constants existing in the literature [68].

## 3.3 Frame of Reference Definition

The fact that the orientation of the sensor is given with respect to an Earth fixed frame has some downsides. As the Earth's magnetic field is always pointing in the same direction, the position coordinates obtained for a certain point would be dependent on where the subject is facing. Since the final aim of this work is to apply the algorithms to rehabilitation programs, it is highly likely that the subject will not be on the same place and facing the same side in every rehabilitation session. Consequently, there was a need to define a frame of reference that would be independent of the acquisition conditions. The solution found was to define a frame of reference based on the trunk.

[1]The red segment represents the scapula together with the clavicle, the blue segment is the arm, the yellow one is the forearm and cyan segment corresponds to the hand. The joints, as well as the hand tip, are represented as white spheres and the trunk is represented in orange. The global coordinate system is also presented at the chain origin.

When the subject is in the initial position, it can be assumed that the trunk is aligned with gravity (global z-axis). Thus, the z'-axis coordinates of the new frame of reference $(x',\ y',\ z')$ correspond to the coordinates of global vector $(0,\ 0,\ 1)$ in the trunk sensor local coordinates. Since the quaternion retrieved by the trunk sensor gives the orientation of the trunk with respect to the Earth frame, the inverse rotation should be applied:

$$z'_{\text{axis}} = q_{\text{trunk}}{}^{-1} \times (0,\ 0,\ 0,\ 1) \times q_{\text{trunk}} \tag{3.2}$$

Assuming that the sensor is properly placed on the chest, the y-axis of the local frame of the sensor is already perpendicular to z'-axis. Thus, the y'-axis coordinates correspond to $(0,\ 1,\ 0)$. Finally, the x'-axis corresponds to the cross product of y'-axis and z'-axis (given by Equation 3.2), in that order.

Having defined the frame of reference, it is now possible to represent any vector with respect to it, by simply computing the projection of that vector in each axis. That is, the inner product of the vector with x'-axis gives the new coordinate x of the vector, and similarly for the other components.

Finally, the complete process to obtain the vector representing the orientation of a given segment, with respect to our new frame of reference is depicted in Figure 3.4, using the arm segment as an example.

$$\vec{d}^{\text{ global frame}}_{\text{arm}} = q_{\text{arm}} \times (0,\ 1,\ 0,\ 0) \times q_{\text{arm}}{}^{-1}$$

$$\vec{d}^{\text{ local trunk frame}}_{\text{arm}} = q_{\text{trunk}}{}^{-1} \times \vec{d}^{\text{ global frame}}_{\text{arm}} \times q_{\text{trunk}} \rightarrow \left[\begin{array}{l} \vec{d}_{\text{x}} = \vec{d}^{\text{ local trunk frame}}_{\text{arm}} \cdot x'_{\text{axis}} \\ \vec{d}_{\text{y}} = \vec{d}^{\text{ local trunk frame}}_{\text{arm}} \cdot y'_{\text{axis}} \\ \vec{d}_{\text{z}} = \vec{d}^{\text{ local trunk frame}}_{\text{arm}} \cdot z'_{\text{axis}} \end{array}\right] \rightarrow \vec{d}^{\text{ defined frame}}_{\text{arm}} = (\vec{d}_{\text{x}}, \vec{d}_{\text{y}}, \vec{d}_{\text{z}})$$

Figure 3.4: Steps to obtain the direction of the arm segment.

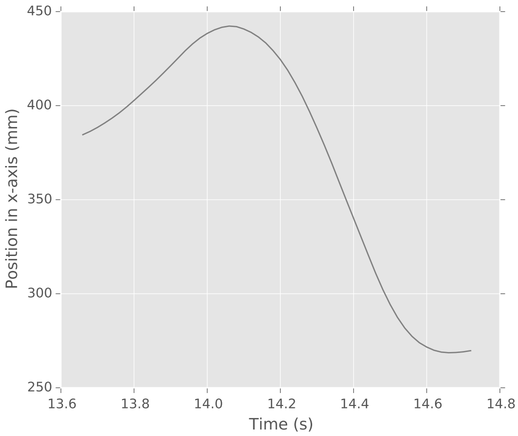
For the forearm and hand segments, the process is identical, since they are also aligned with vector $(1,\ 0,\ 0)$. In the case of the scapula/clavicle segment, the vector with which it is aligned depends on which arm we are considering. For the right arm, the vector is $(0,\ -1,\ 0)$, whereas for the left arm it is $(0,\ 1,\ 0)$.

## 3.4 Position and Velocity Signals

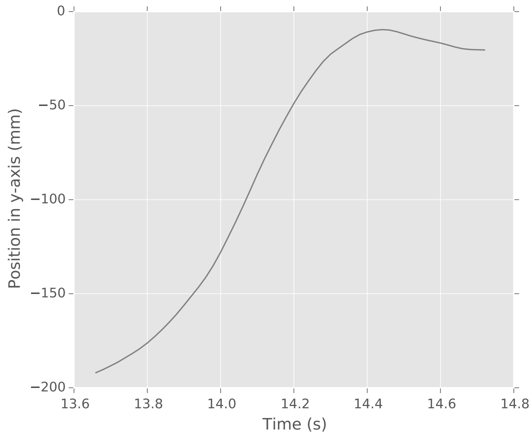
As mentioned before, it is possible to calculate position from the output of the inertial sensors. Consequently, it is also possible to obtain velocity signals. Considering the center of the trunk as the origin and following the kinematic chain, the position of each joint can be calculated with a sum of vectors whose direction ($\vec{d}$) is given by the inertial sensors (Figure 3.4) and magnitude is equivalent to the segment length ($l$). For example, the position of the hand tip ($\mathrm{p}_{\text{hand tip}}$), which is the end-point of the chain, is given by Equation 3.3.

$$p_{\text{hand tip}} = l_{\text{scapula+clavicle}} \times \vec{d}_{\text{scapula+clavicle}} + l_{\text{arm}} \times \vec{d}_{\text{arm}} + l_{\text{forearm}} \times \vec{d}_{\text{forearm}} + l_{\text{hand}} \times \vec{d}_{\text{hand}} \tag{3.3}$$

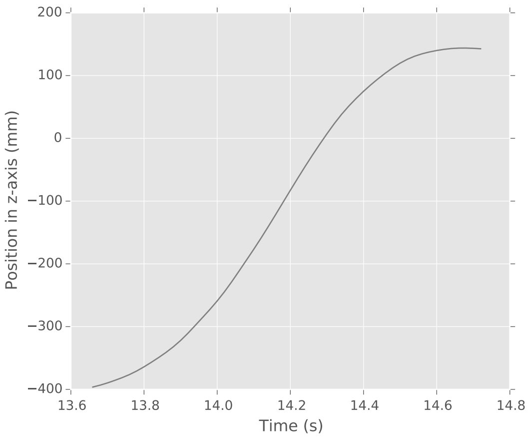
The result of 3.3 is a three dimensional (3D) vector that, if computed over time, can be decomposed in three position signals, one for each axis. An example of a position signal for each axis is depicted in Figure 3.5.




(a) Position in the x-axis.



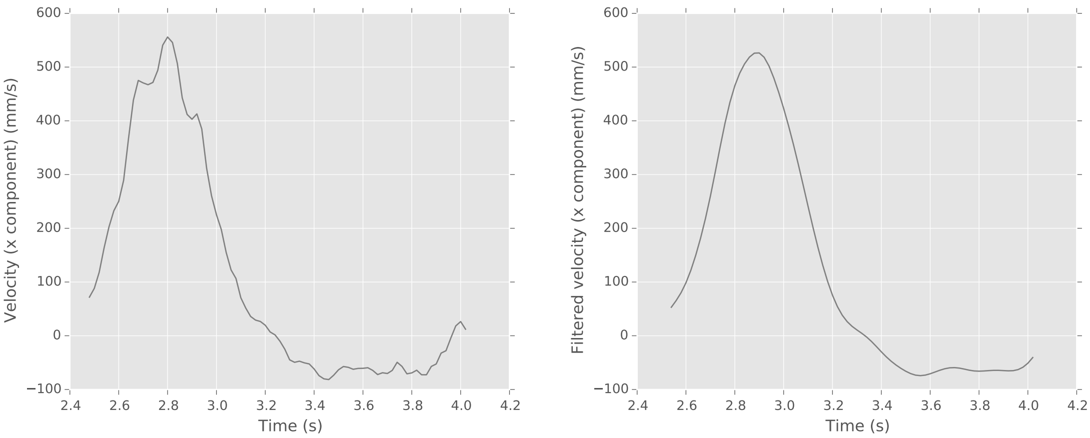

(b) Position in the y-axis.




(c) Position in the z-axis.

Figure 3.5: Position signals for a hand to mouth task.

The velocity signals ($v[t]$) were obtained through the derivatives of position ($p[t]$), which were approximated using the finite differences method described by Equation 3.4, where h is equivalent to the sampling period.




(a) Velocity (x component) before filtering.

(b) Filtered velocity (x component).

Figure 3.6: Velocity component signal before and after filtering.

$$v[t] \approx \frac{p[t+h] - p[t]}{h} \tag{3.4}$$

In order to eliminate some acquisition noise, the signals from each velocity component were low-pass filtered with a 4th order Butterworth filter and a cut-off frequency of 4 Hz, as proposed in [55]. The result of applying this filter to a velocity component is presented in Figure 3.6. After having the filtered signals, the absolute velocity can be calculated through the square root of the quadratic sum of the x, y and z components, resulting in a signal like the one in Figure 3.7.

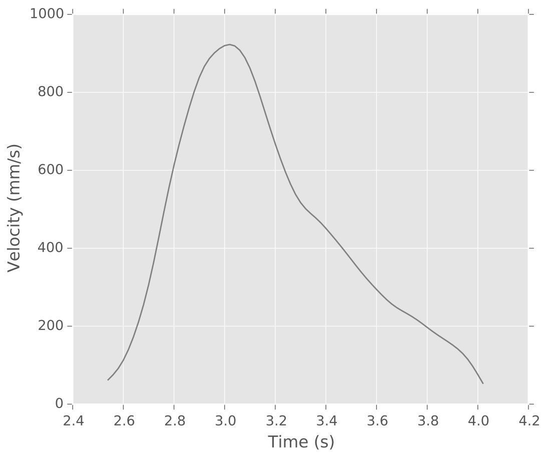



Figure 3.7: Absolute velocity of a hand to mouth task.

## 3.5 Joint Angles

As described in section 2.3, the upper limb joints have several degrees of freedom, allowing a certain range of motion. Thus, besides position and velocity, joint angles should also be taken in consideration for movement analysis and assessment. In particular, shoulder and elbow angles are used in one of the proposed metrics (see section 3.7.3).

Even though shoulder movements are usually discriminated in flexion/extension, abduction/adduction and internal/external rotation, it is often difficult to make that distinction in complex tasks. Thus, in this work, the shoulder angle was considered equivalent to the angle formed between the arm and the trunk. While the trunk can be represented by the vector $\vec{v} = (0,0,-1)$, the vector describing the arm direction ($\vec{u}$) was already deduced in Figure 3.4. The angle between these two vectors can be calculated using Equation 3.5.

$$\theta = \arccos\left(\frac{\vec{u}\cdot\vec{v}}{||\vec{u}||\cdot||\vec{v}||}\right) \tag{3.5}$$

The elbow angle, particularly for flexion and extension, is basically the angle between the arm and forearm. This angle is also computed using Equation 3.5, where vectors $\vec{v}$ and $\vec{u}$ describe the arm and forearm orientation, respectively (see section 3.3).

## 3.6 Movement Onset and End Detection

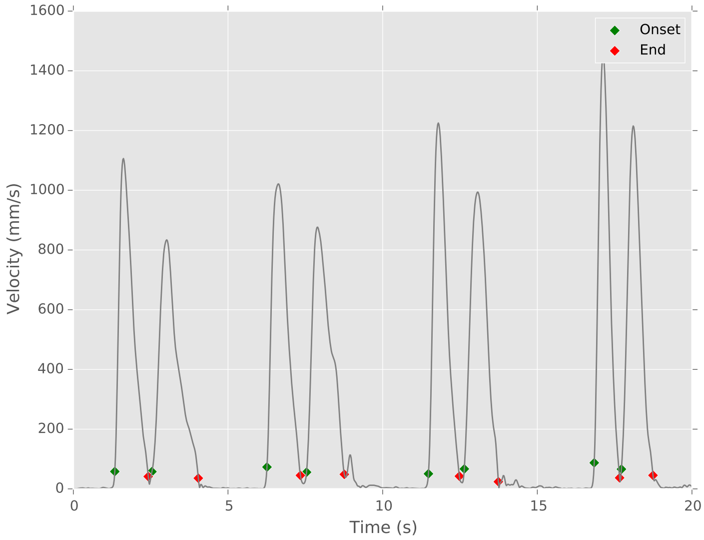
In order to calculate the performance metrics for each task execution separately, there is a need to properly identify its beginning, or onset, and end. Thus, an algorithm was developed for that purpose.

Most of the approaches on the literature use the end-point linear velocity, normally the hand velocity, to detect motion. Specifically, movement onset is defined as the time when the velocity of the hand exceeds a certain percentage of the maximum velocity achieved during the task execution. Similarly, movement end is detected when the velocity of the hand goes below that same percentage. The exact value for that percentage varies between the authors, ranging from 2% to 10% [10, 21, 30, 56, 57].

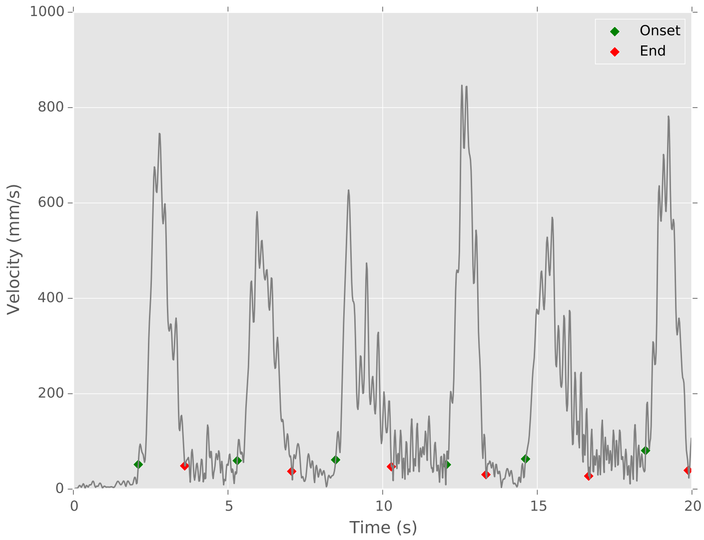
However, these approaches are not suitable for real-time applications, where the peak velocity is not known beforehand. For that reason, instead of using a percentage, a fixed threshold of 50 mm/s for the hand tip velocity was chosen, as it is roughly equivalent to 5% of the average peak velocity of a healthy movement.

After finding a time interval that respects the above mentioned threshold, a second verification was made to ensure that a reasonable distance was traveled during that period of time. This was achieved by calculating the sum of the Euclidean distance between consecutive position coordinates. If the resulting sum was less than 100 mm, the detected onset and end times were discarded.

An example of the result of the application of this algorithm in a set of healthy task executions can be seen on Figure 3.8a. On the other hand, Figure 3.8b shows the result of the algorithm on a less smooth signal, resulting from a patient with tremors.




(a) Set of healthy task executions.




(b) Set of unhealthy task executions.

Figure 3.8: Result of the onset and end detection algorithm.

## 3.7 Performance Metrics

After performing an extensive literature review and consulting with clinical specialists, a selection of the most promising kinematic measures described in section 2.5.1 was made. There was a concern in choosing measures that address different aspects of movement, in order to have a more complete assessment.

In terms of movement speed, the implemented metrics were total movement time and peak velocity [10, 30, 54]. Movement efficiency can be characterized by the end-point error, since it reveals if the subject reached the desired goal [69, 70]. Concerning movement coordination, a measure similar to the one proposed in [30] and [59] was implemented. Finally, it was concluded that the most relevant compensatory strategy is trunk displacement, since it is also related with postural control [10, 21, 30, 56, 57, 58]. In the following sections, a detailed description of the metrics and how they were implemented is presented.

### 3.7.1 Total Movement Time and Peak Velocity

After applying the onset and end detection method described in section 3.6, it is easy to calculate the time taken to complete the task, from now on referred to as Total Movement Time (TMT) and measured in seconds (s).

Additionally, the end-point (hand tip) Peak Velocity (PV) was also considered a measure of performance, being obtained by simply computing the maximum value of the absolute velocity signal during the task execution, in millimeters per second (mm/s). It is noteworthy that the return to the initial position is not considered for any of these metrics.

### 3.7.2 End-Point Error

The End-Point Error (EPE) aims at detecting if the subject succeeded or failed to complete a certain task. For example, in a hand to mouth task, the goal is to get the hand as close as possible to the mouth.

This measure was calculated as the Euclidean distance, in millimeters (mm), between the end-point position coordinates at the end of the task and a previously known reference position. In a rehabilitation program situation, this position should be recorded during a trial session, where the therapist could help the subject reach the desired goal if needed.

### 3.7.3 Interjoint Coordination

Complex tasks normally require moving more than one joint at the same time. This requires a certain coordination, which is associated with how coupled the joints are. Tasks like carrying the hand to the mouth or the back of the head, and reaching for an object in front, imply shoulder flexion/extension and/or abduction/adduction, as well as elbow flexion/extension. Thus, the performance metric proposed for this purpose is the Interjoint Coordination (IJC) and measures the temporal correlation between the shoulder and elbow angles over time.

The correlation between two variables $X$ and $Y$ is dimensionless and can be calculated using the Pearson product moment correlation coefficient ($\rho$), which is obtained by dividing the covariance of the two variables and the product of their standard deviations ($\sigma$):

$$\rho_{X,Y} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{3.6}$$

If the two joints begin and end rotation synchronously and maintain a fixed ratio of angular velocities, the correlation coefficient will be closer to $\pm 1$ [59].

### 3.7.4 Trunk Displacement

The goal of this metric is to detect postural changes during task executions, namely the Trunk Displacement (TD). This is a very common compensatory strategy since it can allow the completion of the task with less effort for the arm.

For the calculation of this metric, unlike the others, the frame of reference described in section 3.3 is not used, since we are interested in analyzing the movement of the trunk. Conversely, it is the orientation with respect to the Earth global frame that should be used.

As mentioned before, it can be assumed that, at the initial position, the subject is sitting straight. Thus, the direction of the trunk at that moment can be considered the reference and is calculated using Equation 3.1, where q is the quaternion retrieved by the trunk sensor and p is the vector $(-1,\ 0,\ 0)$ with a real part equal to zero, since it represents the local sensor axis with which the trunk is aligned.

Using the same method, the direction of the trunk is then computed for every sample from the beginning to the end of the task execution. Also, for each sample, the angle between the direction of the trunk at that time and at the reference position is calculated using Equation 3.5. The TD metric corresponds to the maximum angle achieved during the task execution, in degrees (deg).

## 3.8 Conclusions

This chapter described how the output of the inertial sensors was used to calculate the set of proposed performance metrics. The fact that those metrics were based on the literature, where different motion analysis technologies were used, raised some challenges, like the need to define a new frame of reference. Also, due to the intended real-time application, there were also some adjustments that were necessary, for example in the development of the onset and end detection algorithm.

It is worth noting that, during the development of the algorithms, there was some preliminary testing on healthy individuals to enable the adjustment of parameters and consequent improvement of the methodologies. However, the proper validation of the proposed performance metrics is addressed in the next chapter.

# Chapter 4

# Validation

## 4.1 Overview

As the main goal of this work is to assess quality of movement, the proposed performance metrics must be able to differentiate between healthy movements and movements performed by people who have suffered a stroke. Hence, this chapter presents the validation study that was performed to evaluate the discriminatory ability of said metrics. The first two sections describe the subjects who participated in the study, as well as the followed protocol. In section 4.4, the results for each metric and for the overall classification are presented and also discussed.

## 4.2 Subjects

A total of ten patients with hemiparesis following stroke and nine healthy participants were recruited for this study. All of the participants were undergoing rehabilitation at Clínica Fisiátrica Dr. Paulo Milheiro Maia. However, subjects with pathologies that did not affect the upper limb were considered healthy. Information about the two groups is presented in Table 4.1.

The participants were asked to read and sign an informed consent before entering the study. However, as the subjects were only asked to perform three movements with the upper limb, the study was considered observational and non-interventional, and there was no need for approval from an ethics comittee.

Table 4.1: Information about the subjects who participated on the validation study.

| | **Controls** | **Patients** |
|---|---|---|
| **Number** | 9 | 10 |
| **Gender (%)** | 3 female (33%) | 4 female (40%) |
| **Age (years)** | 62±12 | 68±12 |
| **Height (cm)** | 162±10 | 162±5 |
| **Evaluated Sides** | 6 right; 3 left | 4 right; 6 left |

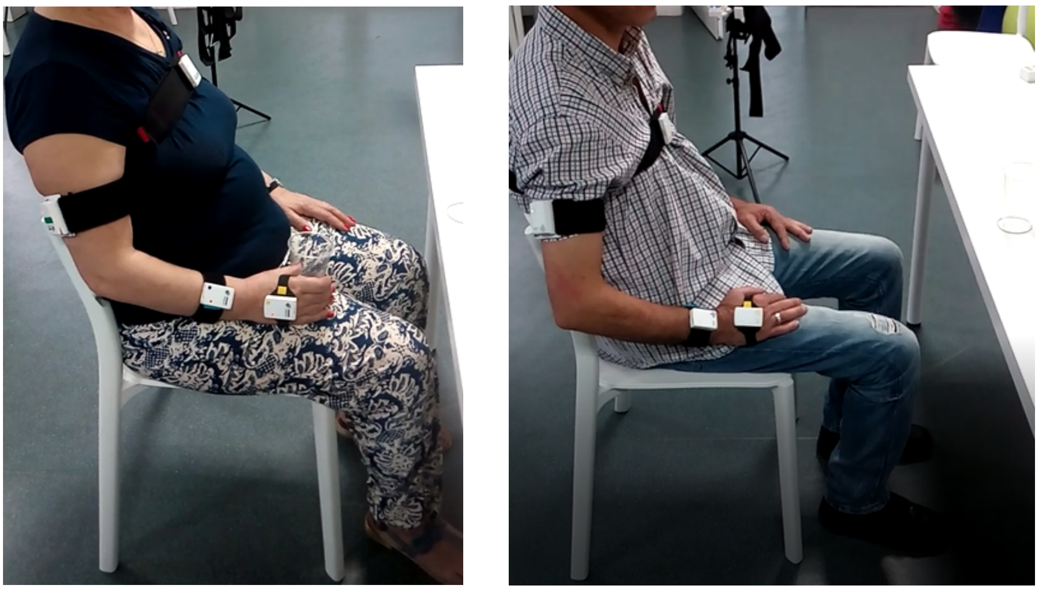
## 4.3 Acquisition Protocol

Participants were asked to perform three tasks: bring a glass to the mouth, bring the hand to the back of the head and reach for a glass placed on a table in front of them. These tasks were chosen as representative of activities of daily living such as drinking, combing or washing the hair, and reaching for objects.

All tasks were performed while sitting on a chair in front of a table, as shown in Figure 4.1. Regarding the initial position, in the hand to mouth task the participant was holding the glass and had both arms resting on the lap in a neutral adducted position and with approximately 90° of elbow flexion (Figure 4.1a). For the hand to the back of the head and reaching tasks, the initial position was identical but without the glass (Figure 4.1b). Note that for the reaching task, the glass was placed on the table at a distance equivalent to the arm length, so as to be reachable without the need to move the trunk. However, compensatory strategies were allowed if needed.

Each task was initially performed twice for a trial session, in order to record the position of the desired goal. If needed, the subject performed the task with help from a therapist. Then, for the evaluation itself, each task was performed at least five times. The participants were instructed to perform the tasks at their own pace and as naturally as possible.

The sensors were placed on the upper limb of the subjects according to Figure 3.1 and the signals were acquired using the SWORD Phoenix mobile application at a sampling rate of 50Hz. Additionally, every task execution was also recorded on video.



(a) Hand to mouth. (b) Hand to back of the head and reaching.

Figure 4.1: Initial positions for task execution.

## 4.4 Results and Discussion

For each subject, three executions of each type of task were considered. The final number of executions for the hand to mouth and hand to the back of the head tasks was 54, while the reaching task had a total of 48 executions. Some of the executions had to be discarded due to problems in video recording, detachment of a sensor (forcing a new calibration) and also due to a change in the acquisition protocol after the first acquisitions.

The video recordings of each execution were analyzed by clinical experts from the SWORD Health team, without knowing if the subject belonged to the control or patient group. The experts were asked to give a score from 0 to 2 to each video, where 0 corresponded to a healthy movement, 1 to a partially unhealthy movement and 2 to an unhealthy movement. Each video was evaluated by two different experts separately. In case of discordance, which happened in 28 out of 156 executions, the evaluation of a third expert was used as a tie breaker.

This classification was used to separate the task executions (from now on referred to as movements) in groups. Additionally, the movements classified with 0 were separated based on whether they were from a subject of the control group or patient group. Thus, there was a total of 4 groups, whose composition is described in Table 4.2.

The performance metrics described in section 3.7 were computed for every movement in each group and the results are presented in the following sections. The mean values for each group, as well as the 95% confidence intervals (CIs), are depicted in the form of bar charts. Additionally, in order to allow the visualization of data distribution, scatter plots are also presented.

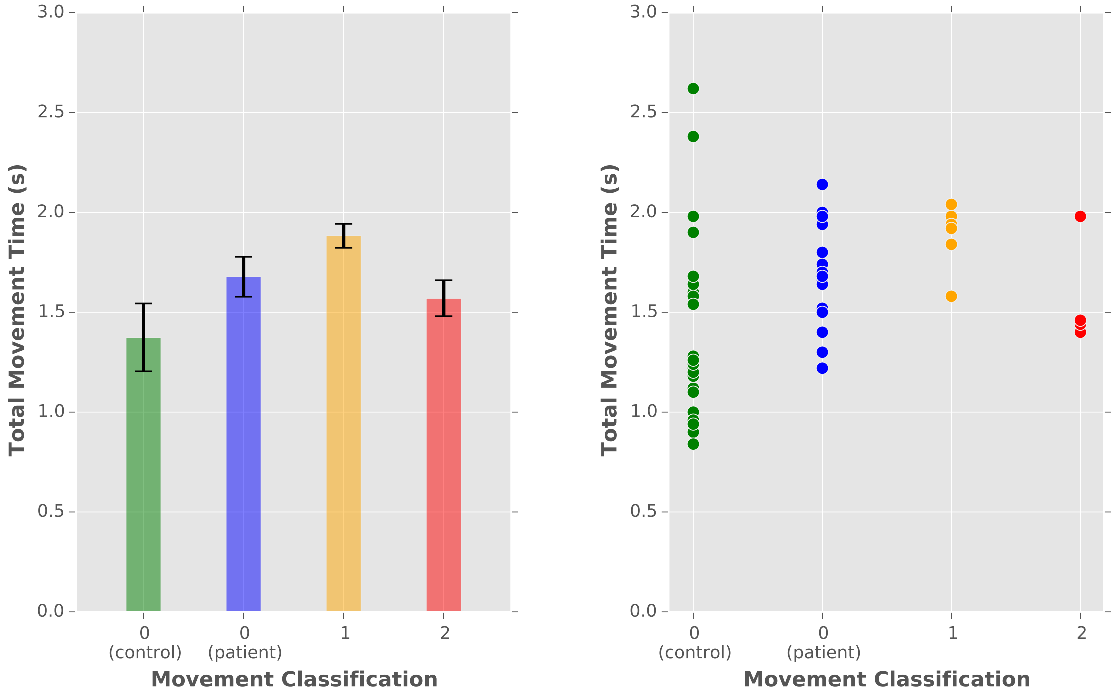
Table 4.2: Sample size of each group of movements.

| | **Hand to mouth** | **Hand to the back of the head** | **Reaching** |
|---|---|---|---|
| **0 (control group)** | 27 | 25 | 24 |
| **0 (patient group)** | 17 | 14 | 17 |
| **1** | 6 | 9 | 1 |
| **2** | 4 | 6 | 6 |

### 4.4.1 Total Movement Time

The TMT metric turned out to be very variable, specially for the hand to mouth task (Figure 4.2), where the healthy movements ranged from 0.84 to 2.62 seconds. Even though participants were instructed to perform the movement naturally and had a glass to make it more realistic, some of them tended to be too slow and others too fast. This was probably due to their awareness of being evaluated.

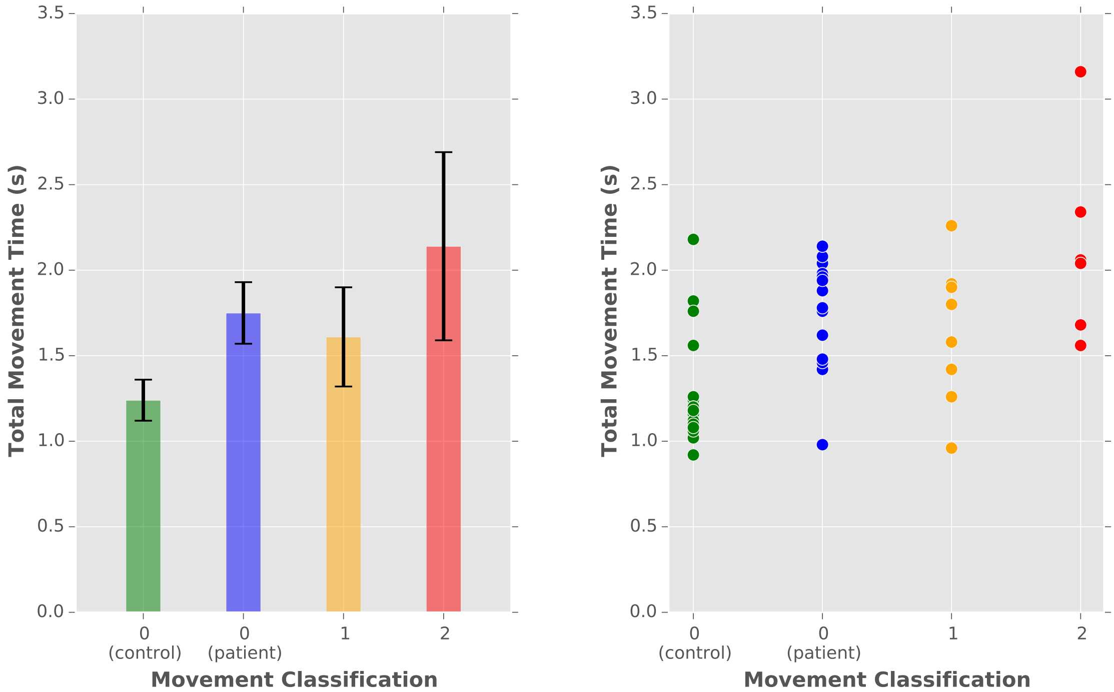
However, this was not so evident for the other two types of task. For the hand to the back of the head task, one of the type 2 movements took clearly more time than all others (Figure 4.3b), causing the CI to be quite large (Figure 4.3a). Indeed, after conducting an unpaired-samples t-test, the two groups proved to be significantly different ($t(6) = -2.96; p = 0.01$).




(a) Mean values and 95% CIs.

(b) Distribution of values.

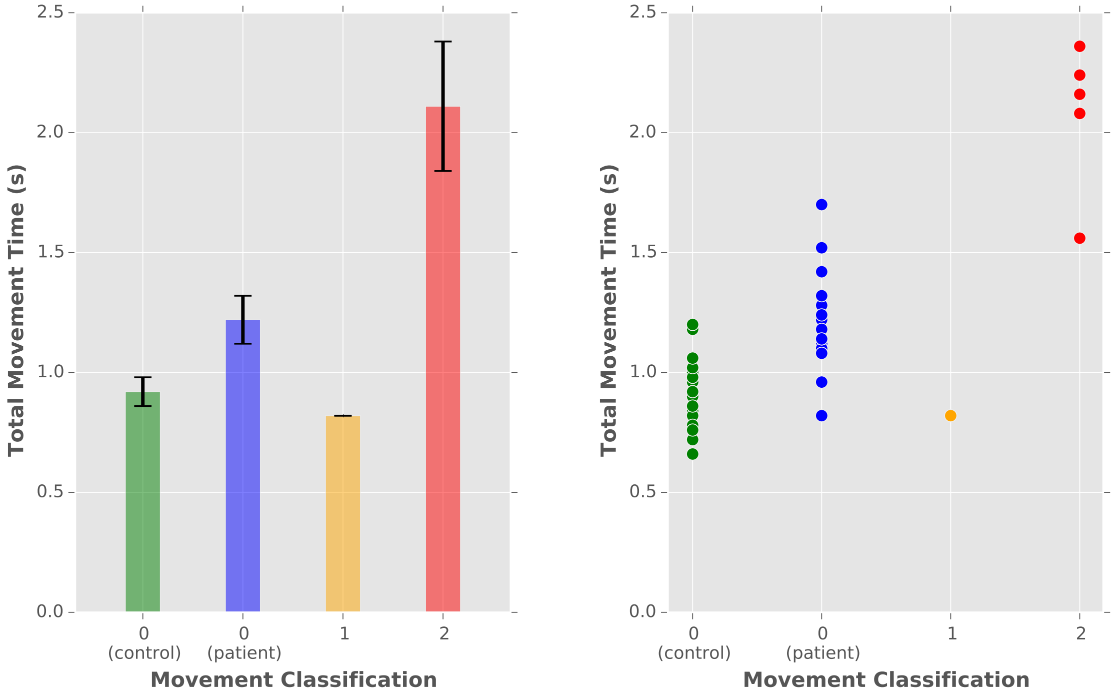
Figure 4.2: Total Movement Time results for the hand to mouth task.




(a) Mean values and 95% CIs.

(b) Distribution of values.

Figure 4.3: Total Movement Time results for the hand to the back of the head task.




(a) Mean values and 95% CIs.

(b) Distribution of values.

Figure 4.4: Total Movement Time results for the reaching task.

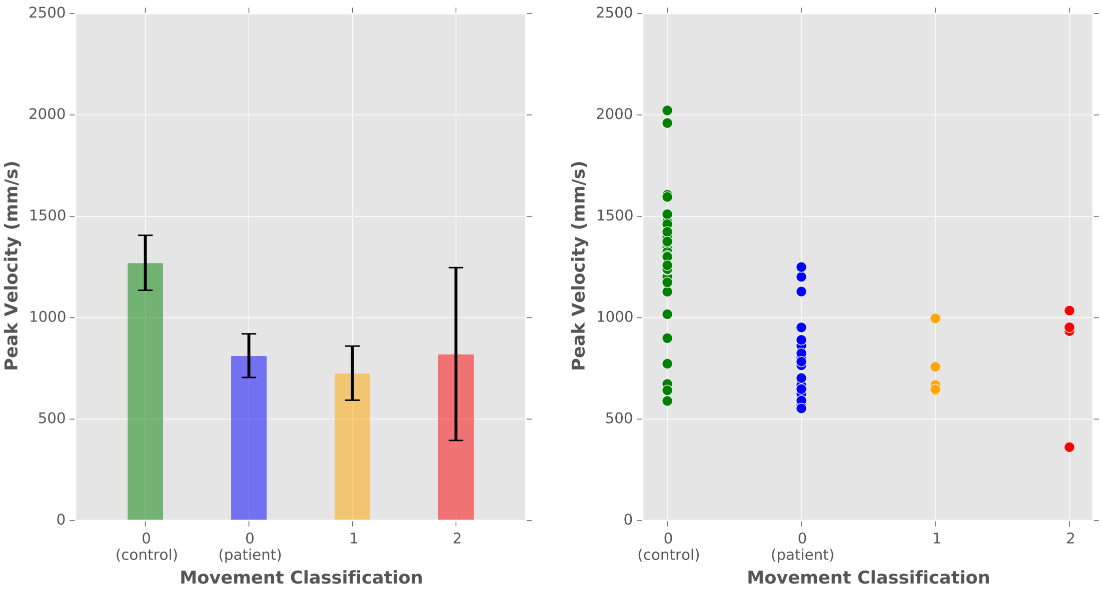
Regarding the reaching task, the difference between type 2 and type 0 movements is quite apparent ($t(6) = -8.77; p = 6.1 \times 10^{-5}$), specially the ones from the control group (Figure 4.4a). Also, there is only one unhealthy movement that overlaps with the healthy ones, as can be seen in Figure 4.4b.

### 4.4.2 Peak Velocity

In the hand to mouth task, there is only one type 2 case that has a much lower PV than others (Figure 4.5b), making it possible to draw a threshold at around 300-500mm/s. The mean difference between type 2 and type 0 movements is not significant ($t(4) = 1.66; p = 0.09$), probably due to the wide CI of the red group (Figure 4.5a). These results can be explained by the same reasons presented for the TMT metric. Additionally, the PV for unhealthy movements might be slightly higher than expected due to brisk movements that might happen in stroke patients [71].

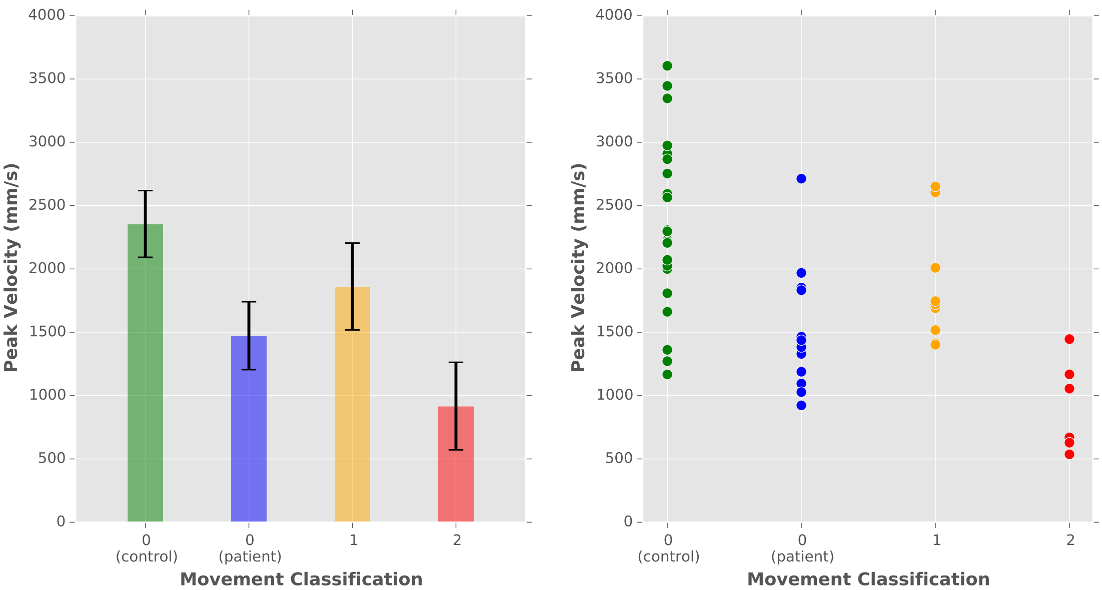
For the hand to the back of the head task, the situation is slightly better. As can be seen in Figure 4.6b, by setting a threshold at around 900mm/s, it is possible to identify three of the six type 2 cases. Also, the mean values of the type 2 and type 0 movements are significantly different ($t(13) = 5.97; p = 2.3 \times 10^{-5}$) and the CI is not so large (Figure 4.6a).

Last, concerning the reaching task, the PV values for the type 2 movements are very variable and similar to the values from the type 0 ones (Figure 4.7b), making it impossible to discriminate



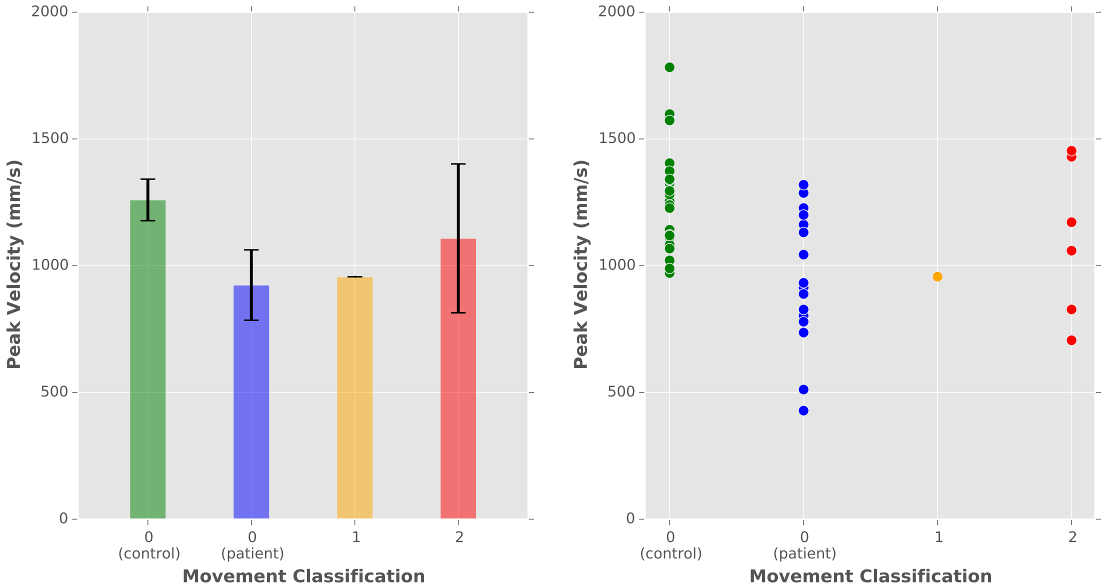

(a) Mean values and 95% CIs. (b) Distribution of values.

Figure 4.5: Peak Velocity results for the hand to mouth task.




(a) Mean values and 95% CIs. (b) Distribution of values.

Figure 4.6: Peak Velocity results for the hand to the back of the head task.




(a) Mean values and 95% CIs.

(b) Distribution of values.

Figure 4.7: Peak Velocity results for the reaching task.

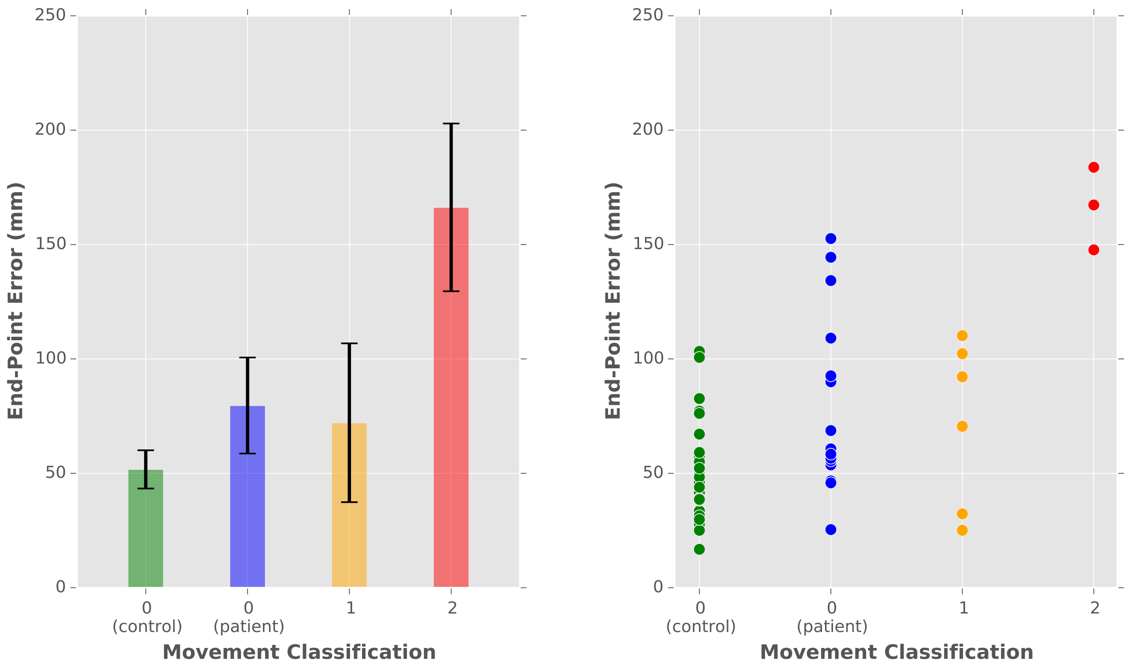
between them. The mean value for the red group is actually higher than the blue one, as can be seen in Figure 4.7a. Once again, this might be due to trembling.

### 4.4.3 End-Point Error

For the hand to mouth task, the red movements have clearly higher EPE values (Figure 4.8b). However, there are three blue cases (classified as healthy) that stand out from the rest of the group and hamper the establishment of a threshold. The three cases belong to the same patient and, after visualizing the corresponding videos, it was verified that the patient was facing slightly to the side. This was probably due to the position of the camera, which was not present on the trial session, during which the patient was probably facing forward. However, there are still significant differences between the type 2 and type 0 mean values ($t(3) = -9.08; p = 0.001$), as shown in Figure 4.8a.

Concerning the hand to the back of the head task, the EPE metric was successful in distinguishing the type 2 movements from all others since it is possible to draw a separation line at around 120mm in Figure 4.9b. As can be seen in Figure 4.9a, there is also a significant difference between the type 2 and type 0 mean values ($t(5) = -4.61; p = 0.003$).

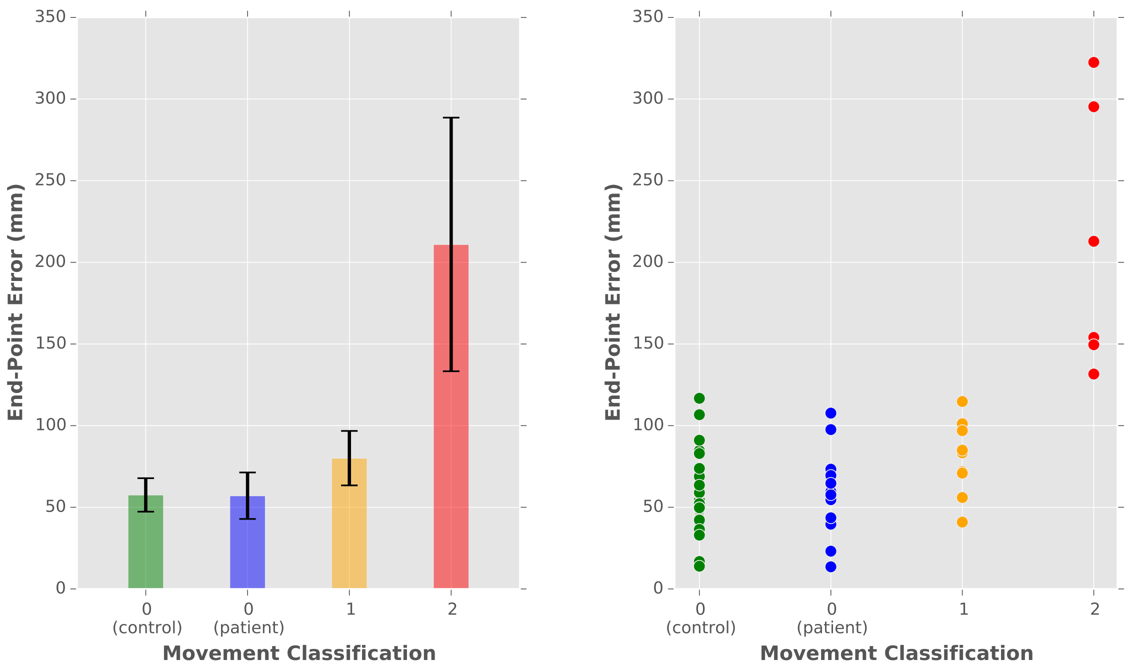
Finally, regarding the reaching task, even though the mean value for the type 2 movements is higher than the rest (Figure 4.10a), it is not possible to look at Figure 4.10b and define a threshold that clearly separates the healthy movements from the unhealthy ones. This can be explained by the fact that, even though there was an effort on marking the site of the glass from the trial session to the evaluation, there were probably slight changes in some cases.




(a) Mean values and 95% CIs.

(b) Distribution of values.

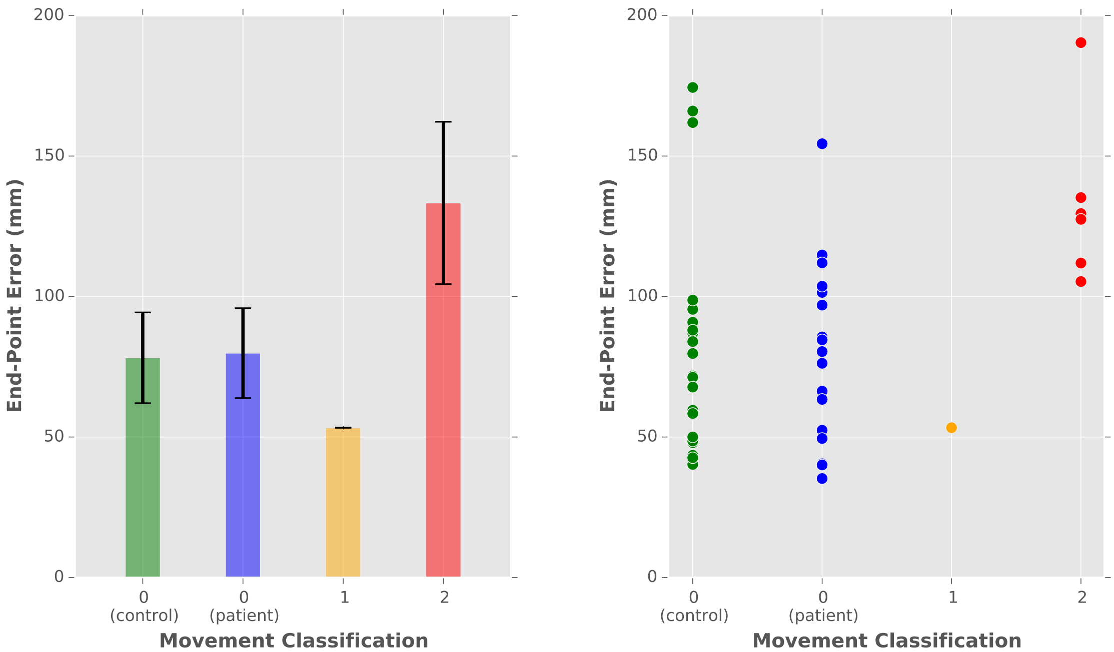
Figure 4.8: End-Point Error results for the hand to mouth task.




(a) Mean values and 95% CIs.

(b) Distribution of values.

Figure 4.9: End-Point Error results for the hand to the back of the head task.




(a) Mean values and 95% CIs.

(b) Distribution of values.

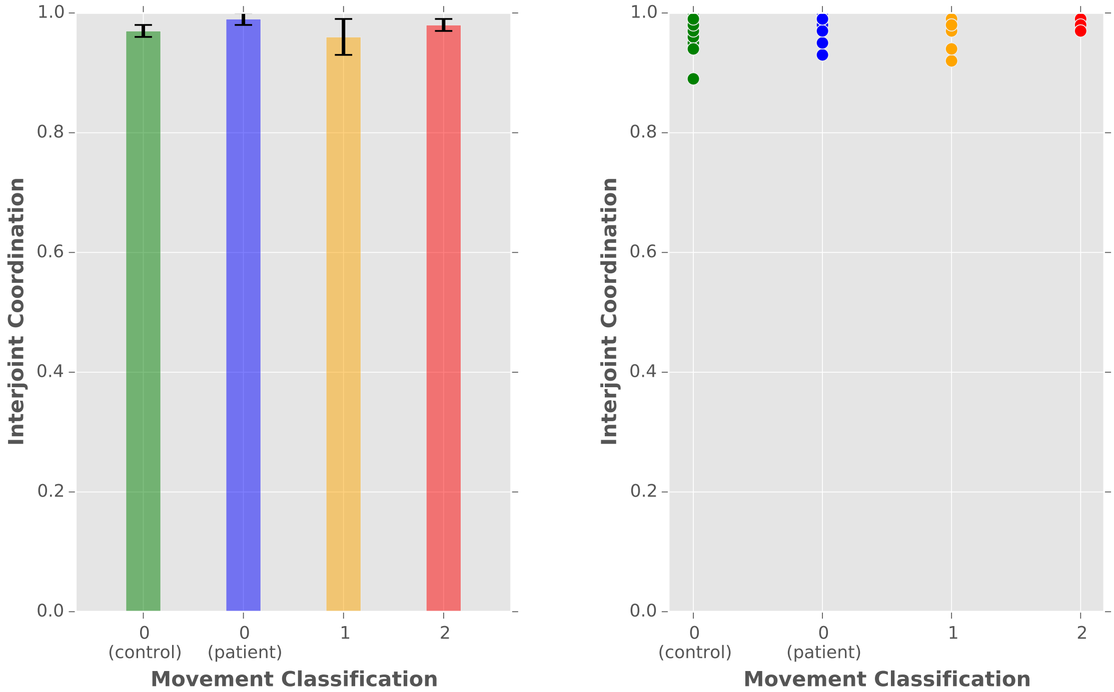
Figure 4.10: End-Point Error results for the reaching task.

### 4.4.4 Interjoint Coordination

The IJC values for the hand to mouth task are pratically the same for every movement (Figure 4.11), which means that this metric is not suitable for this kind of task. After analyzing the angle/angle diagrams for the unhealthy movements, it could be seen that, even though sometimes the shoulder and/or the elbow did not move much (having a small range of motion), they still moved in coordination with each other. An example of a case like this is depicted in Figure 4.12a, next to a case of an actually healthy movement (Figure 4.12b).

For the hand to the back of the head task, the differences are clearer, at least for three of the six type 2 movements, and it is possible to set a threshold at 0.8 (Figure 4.13b). However, the differences between the mean values are not statistically significant ($t(5) = 1.48; p = 0.1$). Note that the CI for the red group was truncated at 1 since that is the maximum value allowed for IJC (Figure 4.13a).

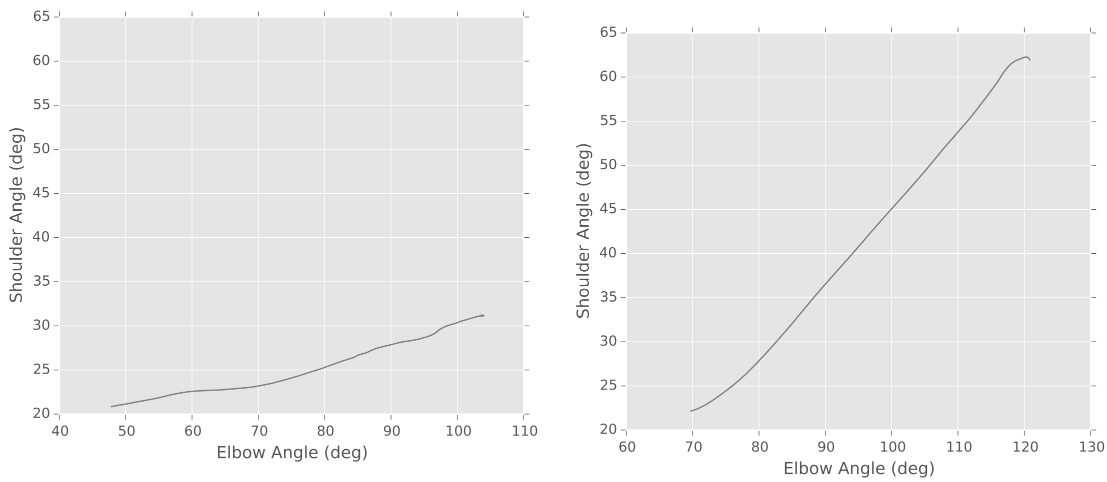
With regard to the reaching task, it can be seen in Figure 4.14a that type 1 and 2 movements present lower mean values than the type 0 ones ($t(40) = 8.26; p = 3.5 \times 10^{-8}$). In spite of that, if a threshold of 0.75 is applied, there are still six blue cases that would be considered unhealthy (Figure 4.14b).




(a) Mean values and 95% CIs.

(b) Distribution of values.

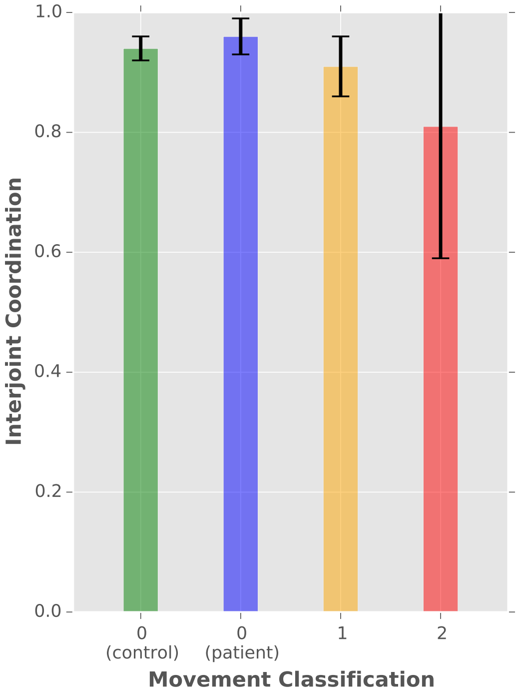
Figure 4.11: Interjoint Coordination results for the hand to mouth task.



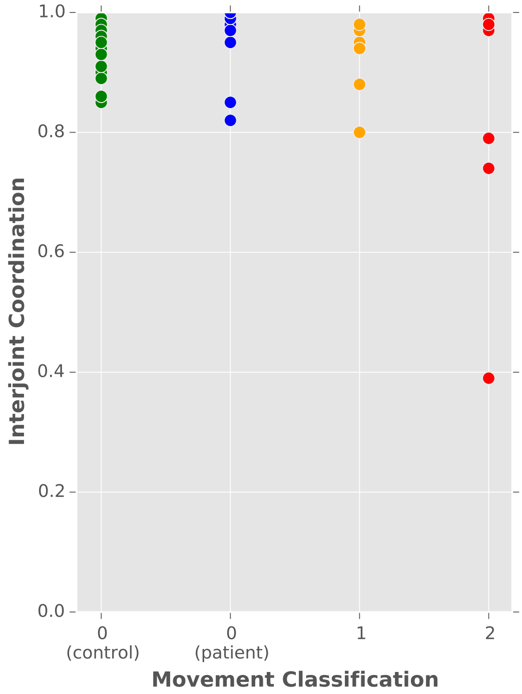

(a) Unhealthy hand to mouth task execution (with good IJC but small shoulder range of motion).

(b) Healthy hand to mouth task execution.

Figure 4.12: Examples of angle/angle diagrams for good IJC values.

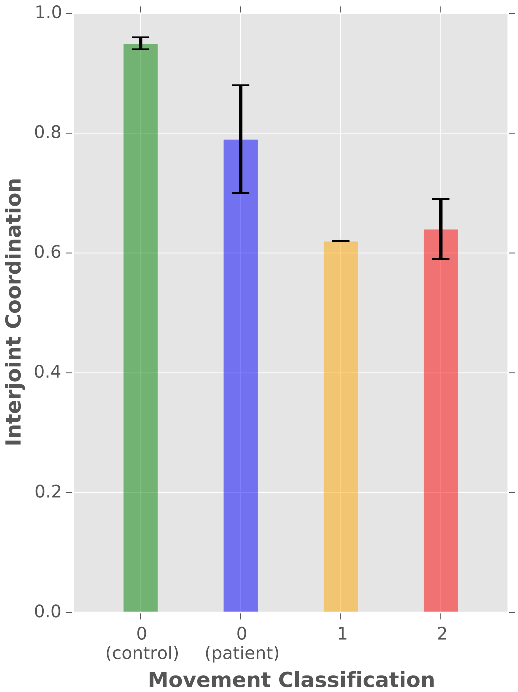



(a) Mean values and 95% CIs.

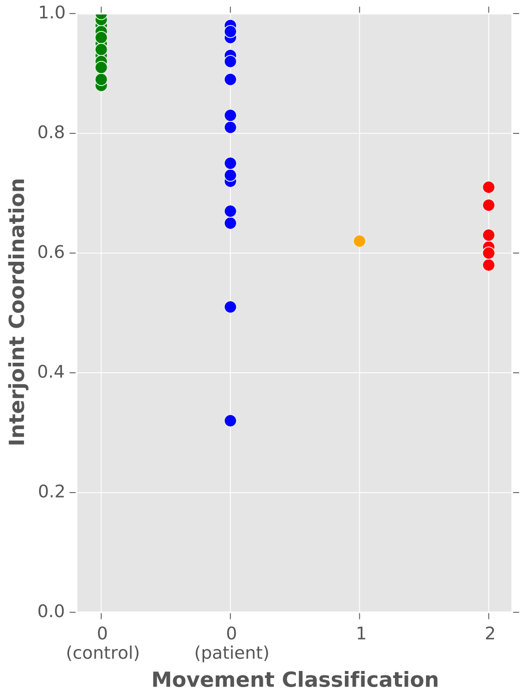



(b) Distribution of values.

Figure 4.13: Interjoint Coordination results for the hand to the back of the head task.



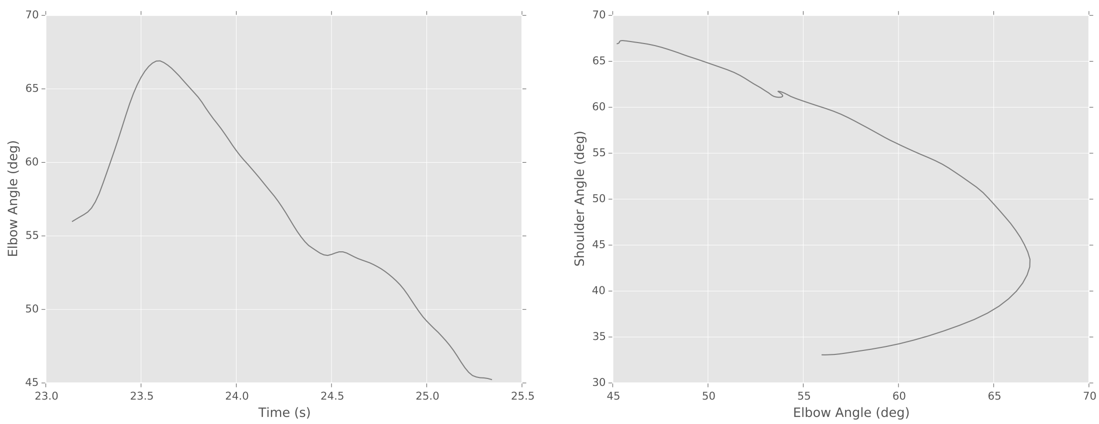

(a) Mean values and 95% CIs.




(b) Distribution of values.

Figure 4.14: Interjoint Coordination results for the reaching task.

These cases were inspected and it was concluded that some of these people did a slight flexion of the elbow before extending it to reach for the glass, which caused the elbow angle signal to look like the one in Figure 4.15a and led to a decrease in the IJC value, as visible in the angle/angle diagram of Figure 4.15b. Moreover, the two cases with the lower IJC value were subject of disagreement between clinical specialists, which means that at least one of them classified them with 1. Also, the third execution of that same subject was classified with 1.




(a) Elbow angle signal.

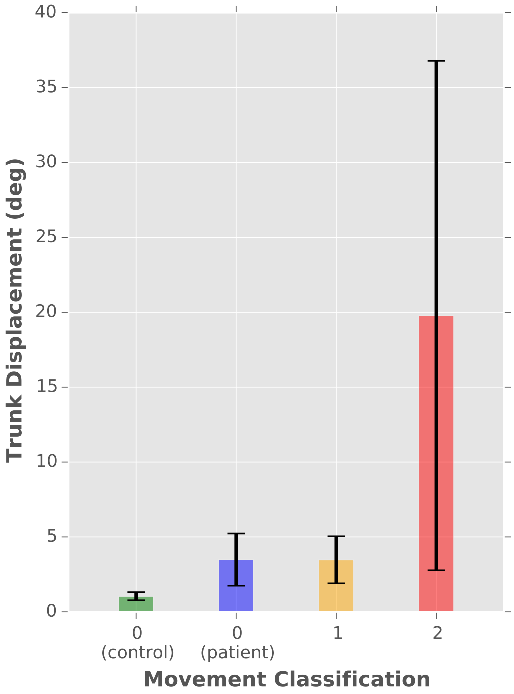
(b) Resulting angle/angle diagram.

Figure 4.15: Example of a case in which the subject does a slight flexion of the elbow before extending it.

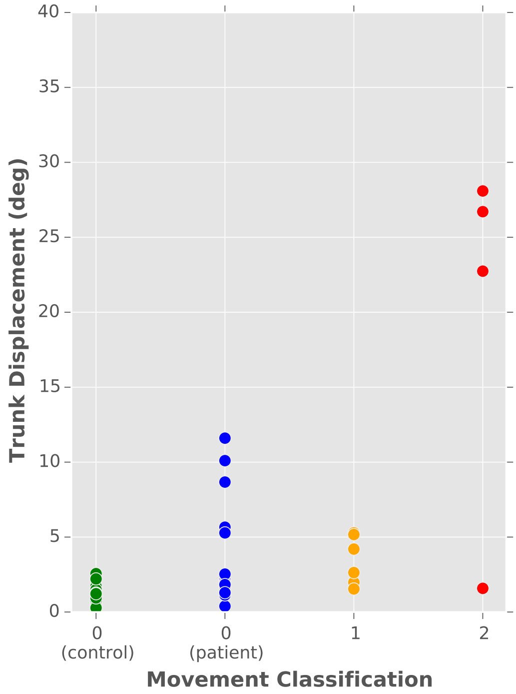
### 4.4.5 Trunk Displacement

Even though it does not happen in all unhealthy movements, the TD metric is substantially higher in some of them, for all three types of task. This causes the CIs for the type 2 movements to be extremely wide, despite the differences in the mean values when compared to the type 0 movements (Figures 4.16a, 4.17a and 4.18a).

These differences are statistically significant for the hand to mouth task ($t(3) = -2.88; p = 0.03$), the hand to the back of the head task ($t(5) = -2.62; p = 0.02$), and also for the reaching task ($t(5) = -2.33; p = 0.03$). Additionally, looking at Figures 4.16b, 4.17b and 4.18b, it is possible to imagine a threshold line at about 20, 30 and 12 degrees, respectively.

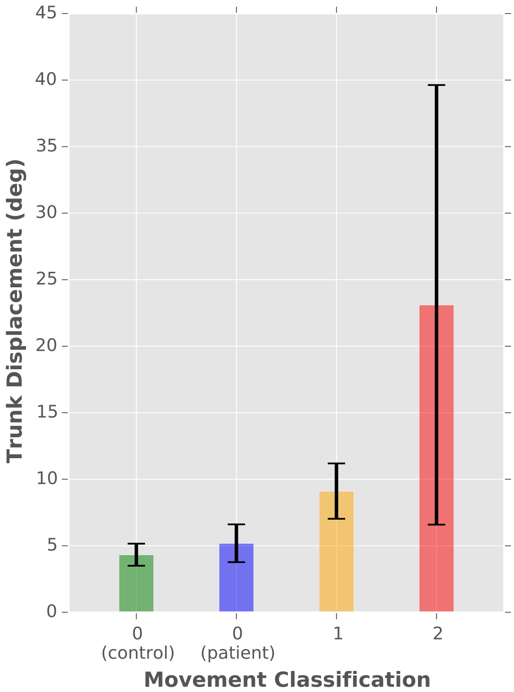



(a) Mean values and 95% CIs.

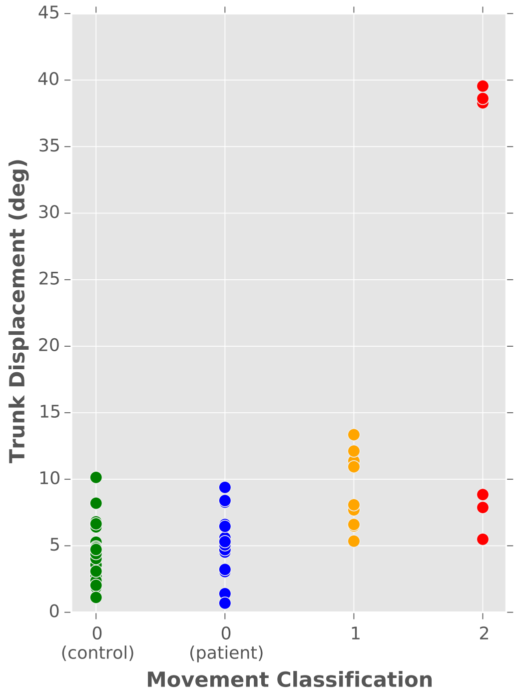



(b) Distribution of values.

Figure 4.16: Trunk Displacement results for the hand to mouth task.

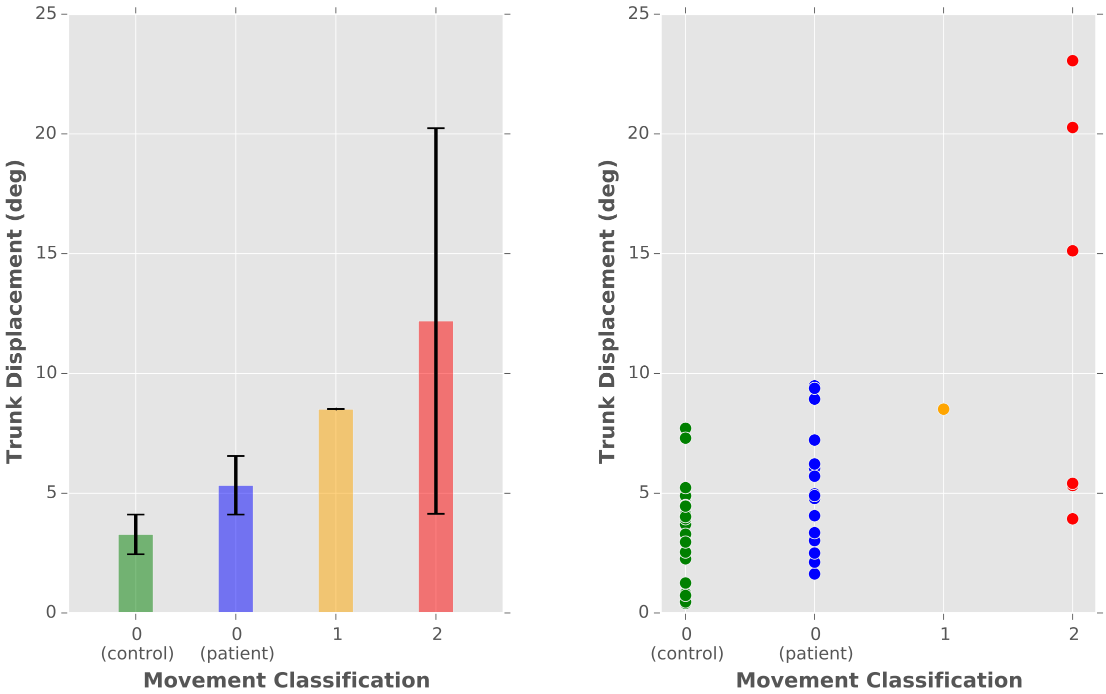



(a) Mean values and 95% CIs.




(b) Distribution of values.

Figure 4.17: Trunk Displacement results for the hand to the back of the head task.




(a) Mean values and 95% CIs. (b) Distribution of values.

Figure 4.18: Trunk Displacement results for the reaching task.

### 4.4.6 Overall Classification

After analyzing the results for each metric, it was possible to define separation thresholds for some of them, at least between type 2 and type 0 movements, since it was not possible to get satisfactory results regarding type 1 movements.

Having those thresholds, it is possible to combine the most promising metrics in a simple "OR"-like algorithm. That is, if a certain movement falls in the region defined as unhealthy (above or below the defined threshold) for at least one metric, that movement is automatically classified as unhealthy.

The set of chosen metrics for each type of task, as well as the defined thresholds to classify a movement as unhealthy, are presented in Table 4.3. For this purpose, only the metrics in which it was possible to isolate some of the type 2 cases were included, so as to see if they were enough to identify all the cases.

Table 4.3: Thresholds defined for each metric and each type of task (NI-Not Included).

| | TMT (s) | PV (mm/s) | EPE (mm) | IJC | TD (deg) |
|---|---|---|---|---|---|
| **Hand to mouth** | NI | <400 | NI | NI | >20 |
| **Hand to the back of the head** | >2.5 | <900 | >120 | <0.8 | >30 |
| **Reaching** | >1.8 | NI | NI | NI | >12 |

Having the classification from the clinical specialists as ground truth, it was possible to calculate the performance of this simple classification (excluding the type 1 movements). The results are presented in Table 4.4 and the performance metrics calculated were the following[1]:

$$Accuracy(\%) = \frac{TP+TN}{TP+TN+FP+FN} \times 100 \tag{4.1}$$

$$Recall(\%) = \frac{TP}{TP+FN} \times 100 \tag{4.2}$$

$$Precision(\%) = \frac{TP}{TP+FP} \times 100 \tag{4.3}$$

Table 4.4: Results for the identification of unhealthy movements.

| | **Accuracy (%)** | **Precision (%)** | **Recall (%)** |
|---|---|---|---|
| **Hand to mouth** | 100 | 100 | 100 |
| **Hand to the back of the head** | 100 | 100 | 100 |
| **Reaching** | 100 | 100 | 100 |

Even though the thresholds were chosen taking only in consideration this particular dataset, these preliminary results show that the chosen metrics, when combined, were enough to identify all the existing unhealthy cases without any false positives. This results need to be further confirmed with datasets that include more type 2 movements. However, it is safe to say that the proposed metrics show potential in assessing the quality of these three tasks.

[1] TP - True Positive; TN - True Negative; FP - False Positive; FN - False Negative; In this case, positive corresponds to unhealthy.

## 4.5 Conclusions

First of all, even though there was an effort to have approximately the same number of controls and patients in the study, the great majority of patients was already at a late stage of their rehabilitation. This resulted in a large number of movements classified as healthy and not enough unhealthy cases to draw considerable conclusions from.

Moreover, the fact that the clinical specialists disagreed in 18% of movements confirms the difficulty level associated with quality assessment of complex movements. This happened mainly between the 0 and 1 scores, which explains the inability of the performance metrics to discriminate this particular group of movements.

Another important point is the fact that the proposed metrics evaluate different aspects of movement, meaning that a single unhealthy movement is not necessarily bad at all of them. This means that the metrics ultimately need to be combined, as demonstrated in section 4.4.6. The fusion method might, however, need to be more complex.

Finally, the implemented metrics were based on the literature, particularly on studies performed in a laboratory environment and using mainly marker based systems. This kind of systems have greater accuracy than inertial sensors, which might be crucial for metrics such as the end-point error, for example. Additionally, they were studied just for the reaching task, whereas in this study they were also applied to two other tasks.

Nevertheless, the results presented in this chapter demonstrated the potential of the proposed metrics, specially the peak velocity and trunk displacement for the hand to mouth task and the total movement time and trunk displacement for the reaching task. When it comes to the hand to the back of the head task, all of the proposed metrics showed promising results.

# Chapter 5

# Conclusions and Future Work

The main goal of this dissertation was to develop algorithms capable of converting raw kinematic data into meaningful metrics that allowed the quality assessment of upper limb movement during functional rehabilitation exercises. In fact, the proposed metrics, namely total movement time, peak velocity, end-point error, interjoint coordination and trunk displacement, showed promising results in discriminating between healthy and unhealthy task executions, when tested with actual stroke patients undergoing rehabilitation. A simple combination of the metrics, through an "OR"-like algorithm, was able to identify the existing unhealthy movements. Nevertheless, there is a need for further validation with a larger dataset, with more unhealthy movements. A larger dataset would also make it possible to use machine learning techniques, as long as all movements were classified by clinical experts. This would allow a more complex combination of data, avoiding the need to manually define thresholds.

An important aspect about the proposed algorithms and metrics, is that they were based on an extensive literature research, not only in terms of state of the art methodologies, but also regarding the clinical basis behind quality assessment of movement. There was a concern in developing algorithms that had clinical meaning and that, in some way, reflected the evaluation of an actual clinical expert. Needless to say that it is not an easy task, since the experts themselves find it difficult to express how they assess a movement.

Moreover, even though the developed metrics were based on the literature, some of them were never implemented using inertial sensors, which are more suitable for real rehabilitation settings. The results presented in this work therefore demonstrate the potential of such metrics for rehabilitation purposes, specially for scenarios where the therapist does not need to be present. The fact that the metrics were tested with different types of task was also important, since rehabilitation programs usually consist of several different exercises.

Another desired goal for this work was that the algorithms should be able to give real-time feedback to the patient on his/her performance and progress. In fact, the proposed metrics provide important information that can be used to give feedback to the patient when combined with an appropriate interface. For example, the trunk displacement metric can be employed to alert the patients that they are using compensatory strategies to reach the goal, which can happen without them realizing it. The end-point error can be combined with games to encourage the patient to actually reach the goal. Additionally, if the patient is able to reach the goal faster than the last time, which can be known through the total movement time metric, he/she can be rewarded with a badge, for example.

On the other hand, the metrics can also be useful to the therapist, namely to keep track of the patient's evolution. For example, it can be seen if the patient is taking less time to complete the tasks, if he/she can reach higher velocities and if he/she is more close to be able to achieve the goal (end-point error). The interjoint coordination metric, together with the angle/angle diagrams, can also be used by the therapist to detect certain situations. For example, if the diagram shows a very steep or very smooth slope, it means that one of the joints has a smaller range of motion than the other, which would indicate that the rehabilitation efforts should be more driven towards one of the joints.

Therefore, the next steps, after further validation and possible adjustments and improvements, would be to incorporate these algorithms and metrics into an interface like, for example, the SWORD Phoenix mobile application [66].

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