2017 International Conference on Rehabilitation Robotics (ICORR)
QEII Centre, London, UK, July 17-20, 2017.

Assessment of Lower Arm Movements Using One Inertial Sensor

Fokke B. van Meulen[1*], Bert-Jan F. van Beijnum[1,2], Jaap H. Buurke[1,3] and Peter H. Veltink[1]

***Abstract*— Reduction of the number of sensors needed to evaluate arm movements, makes a system for the assessment of human body movements more suitable for clinical practice and daily life assessments. In this study, we propose an algorithm to reconstruct lower arm orientation, velocity and position, based on a sensing system which consists of only one inertial measurement unit (IMU) to the forearm. Lower arm movements were reconstructed using a single IMU and assuming that within a measurement there are moments without arm movements. The proposed algorithm, together with a single IMU attached to the forearm, may be used to evaluate lower arm movements during clinical assessments or functional tasks. In this pilot study, reconstructed quantities were compared with an optical reference system. The limits of agreement in the magnitude of the orientation vector and the norm of the velocity vectors are respectively 4.2 deg (normalized, 5.2 percent) and 7.1 cm/s (normalized, 5.8 percent). The limit of agreement of the difference between the reconstructed positions of both sensing systems were relatively greater 7.7 cm (normalized, 16.8 percent).**

I. INTRODUCTION

Proper arm function is essential for many activities of daily living. When arm function is reduced, performance of these activities will be limited. In particular, stroke survivors may have a reduced ability to coordinate their arm movements and experience difficulties while performing daily life activities. Intensive rehabilitation therapy is usually given to restore arm function or to compensate a lack of arm function. For the optimal guidance of this rehabilitation process, arm movements should be objectively assessed during clinical assessments and functional tasks [1], [2]. A patient-specific, objective, and qualitative assessment of arm movements during functional tasks provides information on impairment level during the functional task and/or assessment, and may demonstrate recovery of arm functioning by restoration or compensation [3].

The use of an inertial measurement unit (IMU) is a feasible method for the assessment of body movements in a daily life setting [1], [4]–[6]. IMUs combine accelerometers, gyroscopes, and often also magnetometers. This type of sensor can be used to evaluate quantities such as orientation, change of orientation or change of position. In contrast to the use of an optical reference systems for the evaluation of body movements, IMUs do not require an external physical reference system to estimate these quantities. This in particular makes the use of IMUs suitable for measurements in a daily life setting. For example, multiple IMUs can be used for the assessment of daily life reaching performance [7]. Methods described in this example resulted in qualitative metrics to evaluate arm movements during daily life. However, the total number of IMUs needed to estimate the described metrics (at least eight sensors) makes the system less suitable for clinical assessments and daily life practice [8]. Reducing the number of IMUs to one can make these sensing systems more suitable for the evaluation of daily life movements. Although this would make the system no longer able to evaluate interactions between body parts or movements of multiple body parts, it can still be used to evaluate movements of a body part the IMU is attached to. Systems using only one IMU, attached to the lower arm or somewher else on the body, are already commonly used in rehabilitation practice. Examples include: step counters, activity monitors, the evaluation of the smoothness of movements, the assessment of overall activity, sleep cycles, amd the evaluation of body posture [5], [9]–[12]. However, using a single IMU and additional algorithms, other clinically valuable information may be derived for instance, the quality of arm movements. Quantities such as arm velocity, arm orientation and change of arm position could be useful to estimate metrics (e.g. reaching distance and working area) for the assessment of arm movements during functional tasks and clinical assessments [1], [7].

A major drawback of using only a single IMU is the presence of signal drift when estimating velocity or the change of position of the IMU. This is inherent to using IMUs for velocity and position estimation, in which errors increase rapidly after a few seconds of measuring [13]. This study aimed to develop and evaluate a data processing method for estimation of lower arm velocity and position using a single IMU. This method could potentially be used for the assessment of arm movements during a functional task or to perform instrumented versions of already existing clinical assessments of arm function. The new method presented in this paper was developed by analogy to methods used for the reconstruction of feet movements using IMUs [2], [14], [15]. Within the methods used to reconstruct foot movements, episodes without foot movement were detected and acceleration and velocity signals of these episodes were updated. In this paper it is assumed that during a measurement of arm movements, stroke survivors are seated and there are detectable episodes without movements. The potential limitations of these assumptions are discussed.

This study was part of the INTERACTION project, which was partially funded by the European Commission under the 7th Framework Programme (FP7-ICT-2011-7-287351).

[1]Biomedical Signals and Systems, MIRA - Institute for Biomedical Technology and Technical Medicine, University of Twente, Enschede, The Netherlands

[2]Centre for Telematics and Information Technology, University of Twente, Enschede, The Netherlands

[3]Roessingh Research and Development, Roessingh Rehabilitation Hospital, Enschede, The Netherlands

*Corresponding author: f.b.vanmeulen@utwente.nl

II. MATERIALS AND METHODS

A. System setup

In this study, one Xsens MTw Awinda IMU sensor was used (Xsens Technologies B.V., Enschede, The Netherlands). The sensor is attached using an elastic strap to the posterior side of the right forearm, just proximal of the wrist joint. The sensor is positioned along the forearm, the x-axis of the sensor frame (ϕ^s) parallel to the forearm and pointing towards the elbow, the y-axis pointing towards the medial side of the forearm and the z-axis perpendicular to the x- and y-axis in a right-handed fashion (Fig. 1). Sensor acceleration, sensor angular velocity and magnetic field are internally measured at 1000 Hz. Xsens' sensor fusion algorithms estimate the sensor orientation of the sensor frame relative to the global frame (R^{gs}) [16]. All sensor data (including accelerations, angular velocity and sensor orientation) is transmitted wirelessly to a computer and collected with a sample frequency of 100 Hz.

B. Sensor orientation, velocity and position estimation

The position, velocity and orientation data of the IMU in a global frame (ϕ^g, explained in more detail in Fig. 4), were estimated offline. All data were processed and analyzed using MATLAB® (MathWorks Inc., Natick, MA). To reduce noise, measured sensor accelerations and angular velocities were filtered using an eighth order Butterworth low-pass filter with a cut-off frequency of 20 Hz. Sensor velocity and sensor position were estimated using sensor acceleration and sensor orientation signals (Fig. 2). Noise reduction and integration methods are based on Schepers et al. [14].

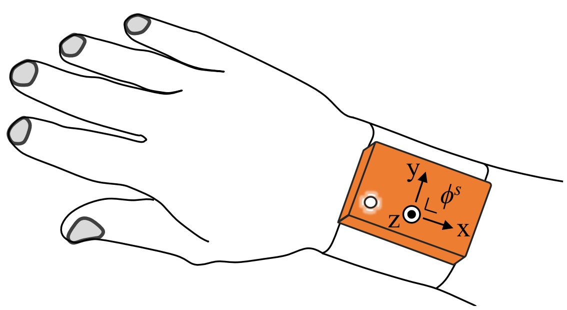


Fig. 1. Overview of system setup. Xsens MTw Awinda attached to the posterior side of the right forearm, close to the wrist. ϕ^s is the sensor coordinate frame.

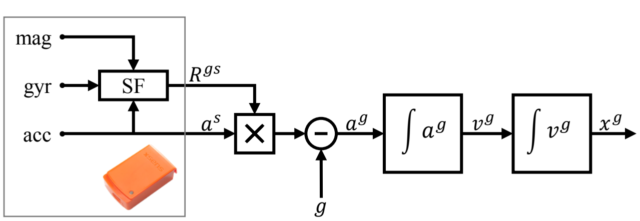


Fig. 2. Schematic overview of data processing method to estimate sensor acceleration (a^g), sensor velocity (v^g) and sensor position (x^g) in the global frame. Signals measured by the IMU (inside grey frame) are: mag (magnetometer), gyr (gyroscope) and acc (accelerometer). SF = Sensor Fusion algorithms. R^{gs} = sensor orientation in global frame. g = gravitational acceleration. a^s = sensor acceleration in sensor frame.

First, measured accelerations were converted from accelerations in a sensor frame (a^s), towards sensor accelerations in a global frame (a^g), by rotating the measured accelerations using the orientation of the sensor and subtracting the gravitational acceleration (g) from the z-component of the acceleration signal:

$$\begin{bmatrix} a_x^g(t) \\ a_y^g(t) \\ a_z^g(t) \end{bmatrix} = R^{gs}(t) * \begin{bmatrix} a_x^s(t) \\ a_y^s(t) \\ a_z^s(t) \end{bmatrix} - \begin{bmatrix} 0 \\ 0 \\ g \end{bmatrix} \tag{1}$$

By integrating the sensor acceleration in a global frame, the sensor velocity in the global frame (v^g) could be estimated using:

$$v^g(t) = v^g(t-1) + a^g(t) * T_s \tag{2}$$

The estimated sensor velocity is equal to the velocity of the previous sample plus the instantaneous acceleration multiplied by the sample time (T_s, the inverse sample frequency). It was assumed that the sensor velocity was zero at the first sample, $v(0) = 0$.

By integrating the sensor velocity, the sensor position in the global frame (x^g) could be estimated using:

$$x^g(t) = x^g(t-1) + v^g(t) * T_s \tag{3}$$

This sensor position, relative to the initial position, is equal to the position of the previous sample plus the instantaneous velocity multiplied by the sample time.

C. Reduction of signal drift

By the integration of an acceleration signal to estimate sensor velocity or by double integration of the sensor acceleration signal to estimate sensor position, offset errors and errors caused by signal noise increase during every integration step. These errors ensure that the velocity and position signals start drifting. To make an accurate estimation of sensor velocity and sensor position during the assessment of lower arm movements, the following conditions were assumed to be true:

1) Over time, there are episodes in which the lower arm is not moving.
2) Over time, in particular during long episodes without movements, the lower arm returns to the initial position and heading.

Given the first condition, a distinction between episodes with or without movements was made. Similar to methods used for the reconstruction of feet movements assessed using IMUs [2], [14], [15], a zero-velocity detector was used to detect moments without arm movements. Based on a method of Skog et al. [15] the zero-velocity detector test whether an episode is with or without velocity (respecively with or without arm movements). The detector is a generalized likelihood ratio detector that uses the measured sensor acceleration and sensor angular velocity data and a fixed detection threshold [17]. The minimal duration of an episode with or without detected arm velocity was set to 0.1 s (10 samples). Shorter episodes were appended to the previous episode. Next, zero-velocity updates were performed to avoid offset

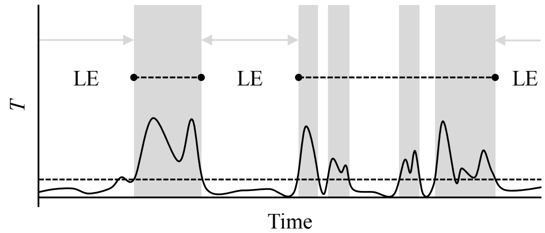


Fig. 3. Artificial result of movement detector, the evaluation signal (T) based on the sensor acceleration and angular velocity signals [15]. As long as the signal is below the threshold (dashed line) the moment is marked as part of an episode without movements (white area), when the signal is above the threshold the moment is marked as part of an episode with movements (grey area). LE = Long episode without movements ($>$ 50 samples). Dashed lines between two dots indicate the selected episode(s) between two long episodes without movements.

errors in the sensor acceleration and sensor velocity signals. Sensor acceleration and sensor velocity signals of episodes without detected movements, were set to zero. Differences in sensor acceleration and sensor velocity before and after an episode with movements, were used to compensate any linear drift over time of respectively the sensor acceleration and sensor velocity signals within these episodes.

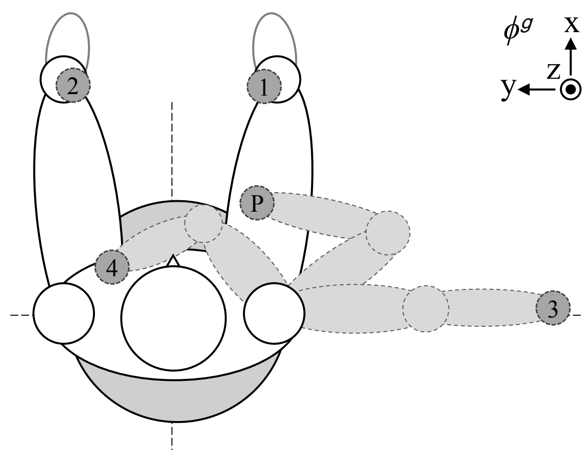
Episodes without movements with a duration of more than 0.5 s (50 samples) were marked as long episodes without movements (see 'LE' in Fig. 3). It was assumed that the arm returns to the initial position and heading before the beginning of each long episode without movements. Previous research on hand movements of stroke survivors, showed a preferred position of the hand along the body during daily life activities [1]. In the current study, the initial position was selected such that it corresponds to the preferred position of the hand while a person is seated (Fig. 4). Given the second condition, the sensor heading (orientation around the z-axis) between two long episodes without movements was linearly compensated such that overall change in reconstructed heading became zero. Furthermore, the average velocity of all movement episodes between the two long episodes without movements (see the dashed lines between the dots in Fig. 3) is subtracted from the reconstructed velocity data of the episodes with movements. As a result, the average velocity between the two long episodes without movements becomes zero as well as the net position change.

D. Validation protocol

To demonstrate the accuracy of the proposed methods, a first validation experiment was performed. One healthy participant performed multiple arm movements while wearing the IMU (Fig. 1). Reconstructed sensor orientation, sensor velocity and sensor position were compared with data of an optical reference system (Visualeyez, Phoenix Technologies Inc., Vancouver, BC, Canada). Four active markers of the optical reference system were attached directly to the IMU. These marker positions were traced at a sample frequency of 100 Hz and sensor orientations were reconstructed based on the different marker positions.

Five prescribed movement sequences were performed during the experiment (Fig. 4). These movements vary from simple back and forth movements, towards multiple consecutive movements that are comparable with daily life movements. Each movement sequence was repeated three times within a single measurement, at a participant selected pace. Within measurements that include movement sequence #5, the participant was asked to simulate daily life movements using both hands for a period of three minutes. The participant was instructed to repeat the previous movement sequences and to simulate other activities of daily living, such as preparing meals, opening a jar or washing hands. The participant was free to decide which activities he performed. Each measurement was performed three times, except for the measurements in which movement sequence #5 was performed, which were only repeated twice.

Using both sensing systems, the following time dependent quantities were estimated for describing movement quality: magnitude of the orientation vector (rotation angle of the quaternion), norm of the sensor velocity vector, and the distance between the reconstructed sensor position and the initial position (position 'P' in Fig. 4), expressed in the global coordinate frame (ϕ^g). The norms of the velocity vector reconstructed with both sensing systems were correlated to each other, to synchronize both sensing systems. Of each quantity reconstructed with both systems, the average of the first second (100 samples) was used for the alignment of both quantities. After synchronization and alignment, estimated quantities were compared with each other. Samples in which



MSeq:	Prescribed Movements:
#1	(P) → (1) → (P)
#2	(P) → (2) → (P)
#3	(P) → (1) → (2) → (P)
#4	(P) → (1) → (2) → (P) → (3) → (4) → (P)
#5	(P) → (daily life tasks) → (P)

Fig. 4. Movements performed during the validation experiment. Schematic top-down view of a participant seated on a stool. The participant is instructed to reach with his right hand towards the positions 1 to 4 and P as described in the table with the prescribed movement sequences (MSeq). Positions are: (P) initial position of a measurement, on the lap of the right upper leg, (1) on the right knee, (2) on the left knee, (3) lateral of the right shoulder, with a complete extension of the elbow and a shoulder abduction of 90 degrees and (4) on the left shoulder. The positions were not physically marked. The grey circle represents the stool. The center of the stool is the origin of the global coordinate frame (ϕ^g), with the x-axis pointing forwards, the z-axis pointing upwards and the y-axis sideways, perpendicular to the x and z-axis in a right-handed fashion.

not all active markers of the optical reference system were recorded were excluded from comparison.

To compare the differences between a quantity measured with both sensing systems (d), the mean difference ($\bar{d}$) as well as the limits of agreement (i.e., $\bar{d} \pm 1.96 \times std(d)$) were calculated [18]. Next, the limits of agreement were normalized by dividing the limits of agreement of an quantity by the range of the quantity as it was reconstructed with the reference system. This makes the limits of agreement a percentage of the total range and the parameter comparable for the different quantities.

III. RESULTS

A total of 14 measurements were performed including five different movement sequences. Fig. 5 shows an example movement reconstruction of one measurement while performing movement sequence #3, moving the hand from the initial position to the right knee, the left knee and back again (repeated three times). Fig. 6 shows the different quantities of this measurement, estimated using both sensing systems. The blue line in Figs. 5 and 6 show the IMU movement reconstruction when applying the zero velocity updates, as frequently used in other studies, but without considering the conditions as suggested in the current study.

Differences between the optical reference system and the IMU sensing system of all quantities are included in Table I. Moments of incomplete marker reconstruction of the optical reference system (indicated with blue dots in the upper graph of Fig. 6) were excluded from analysis. The limits of agreement in the magnitude of orientation vector and the norm of the velocity vectors are respectively 4.2 deg (normalized, 5.2 percent) and 7.1 cm/s (normalized, 5.8 percent). The limit of agreement of the difference between

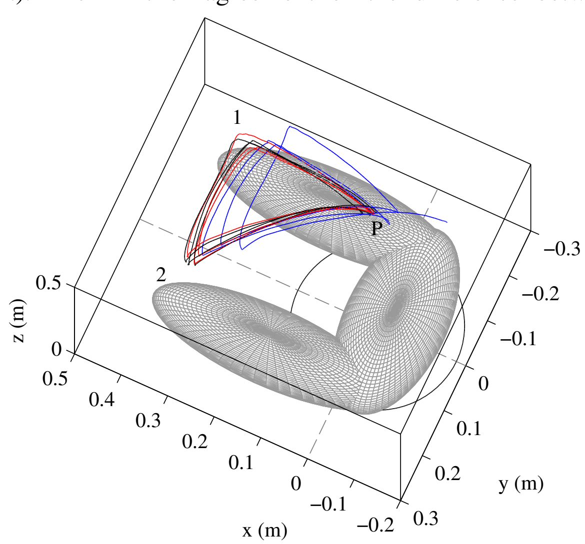


Fig. 5. An example reconstruction of sensor positions in the global frame (ϕ^g), while performing movement sequence #3. Black = Reference, Red = IMU, Blue = IMU, reconstruction without considering the conditions as suggested in the current study. Ellipsoids represents pelvis as well as left and right upper leg. The circle represents the stool. Movements were from: (P) → (1) → (2) → (P) (MSeq: #3 in Fig. 4). Note: the participant did not return to the exact same positions between movement repetitions, as the positions were not physically marked.

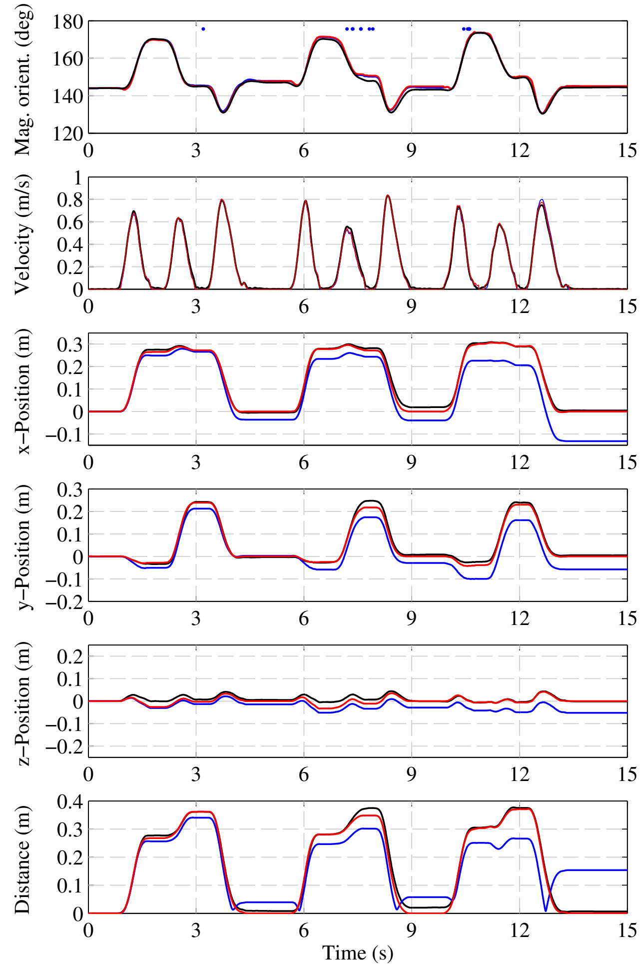


Fig. 6. Quantities reconstructed of one measurement in which movement sequence #3 was performed three times. Black = Reference, Red = IMU, Blue = IMU, reconstruction without considering the conditions as suggested in the current study. From top to bottom: 1) Magnitude of sensor orientation vector (deg), 2) reconstruction of the norm of the sensor velocity vector (m/s), 3), 4), 5) reconstruction of sensor position relative to the initial position, on respectively the x- y- and z-axis of the global frame (m) and 6) Euclidean distance to the initial position (m). Movements were from (P) → (1) → (2) → (P). Blue dots in the upper graph indicate moments of incomplete marker reconstruction of the optical reference system. Note, in 1) and 2) the red and blue lines overlap each other.

the reconstructed positions of both sensing systems were relatively greater 7.7 cm (normalized, 16.8 percent).

The limits of agreement for the reconstructed sensor velocity and sensor position are large for the measurements in which movement sequence #4 was performed. Within these measurements, the large differences between both sensing systems specifically arise when reconstructing the movements towards positions 3 and 4 (Fig. 4). The participant was keeping his arm still for longer periods at these positions, compared to the other positions. Therefore, these episodes were marked as long episodes without movement. As a consequence, the methods used to reconstruct movements of the IMU wrongly assumed that the arm was back at the initial position. When excluding measurements of movement sequence #4, the overall limits of agreement for the reconstructed velocity are 4.7 cm/s (normalized, 4.8 percent) and for the reconstructed position they are 3.9 cm (normalized, 10.4 percent).

TABLE I
DIFFERENCES BETWEEN THE QUANTITIES ESTIMATED WITH THE OPTICAL REFERENCE SYSTEM AND IMU SENSING SYSTEM.

Mag. of orientation vector (deg)			
MSeq:	Mean(d)	LoA†	nLoA‡
#1	0.4	1.7	4.8 %
#2	0.4	1.3	8.0 %
#3	-0.1	1.7	4.0 %
#4	2.8	8.4	4.1 %
#5	0.7	11.0	5.3 %
A*	0.8	4.2	5.2 %
Norm of velocity vector (cm/s)			
MSeq:	Mean(d)	LoA†	nLoA‡
#1	-0.8	4.1	4.8 %
#2	-0.7	3.6	3.7 %
#3	0.0	4.0	4.7 %
#4	0.4	16.9	9.6 %
#5	0.2	8.5	6.5 %
A*	-0.3	7.1	5.8 %
Distance to initial position (cm)			
MSeq:	Mean(d)	LoA†	nLoA‡
#1	0.8	4.7	16.1 %
#2	0.3	2.0	5.1 %
#3	0.1	2.3	6.1 %
#4	-0.7	23.1	42.4 %
#5	1.0	7.5	13.4 %
A*	0.2	7.7	16.8 %

Presented values are for each quantity the average of all measurements per movement sequence (MSeq). * average over all measurements. † Limits of agreement (i.e., $1.96 \times std(d)$). ‡ Normalized limits of agreement, as a percentage of the quantity range as reconstructed with the reference system.

IV. DISCUSSION

In this paper, a method is presented to reconstruct lower arm orientation, arm velocity and arm position, by using a single IMU. The presented method is evaluated in a first validation experiment in which one participant performed multiple structured and unstructured movement sequences, while wearing a single IMU on the forearm. Quantities reconstructed with the presented algorithm were compared with those estimated with an optical reference system. Reconstructed arm orientation shows a normalized difference of 5 percent, arm velocity shows a normalized difference of 6 percent and arm position a normalized difference of 17 percent. These differences in position estimates were comparable with errors of a multiple IMU sensing system that was used in a different study [7]. While performing circular arm movements the multiple IMU sensing system of the other study had an average error of 3.5 cm (SD $\pm$ 3.4 cm), versus the 7.7 cm limits of agreement in distance estimation of the current study. In this other study, these errors were acceptable for the evaluation of hand positions of stroke survivors who are ambulating in a daily life setting and these errors were acceptable to assess metrics such as hand reaching distances and hand working area. The algorithm presented in the current paper, may be used to estimate quantities describing lower arm movements using a single IMU. These include clinically relevant quantities such as reaching distance, hand speed and forearm orientation [1]. Finally, the short set-up time for this single sensor system, lower monetary costs, and no need for the use of an external camera system make this sensing system suitable for instrumented clinical assessments of arm movements as part of rehabilitation practice (e.g., Fugl-Meyer Test, Action Research Arm Test or Box and Block Test [19]) and performance evaluation during activities of daily living.

In the presented algorithm two specific conditions are assumed to be true: 1) there are detectable episodes without sensor movements and 2) over time, the sensor returns to the initial position and heading. Although these conditions allow an estimation of the different quantities, the applicability of these conditions is limited. Considering the first condition, sensor drift might still be present when movement duration is longer than a few seconds. Therefore, movement reconstructions of continuous arm movements still starts drifting. Further research should be performed to define the maximum duration of a movement episode in which movements can be reconstructed accurately enough. Furthermore, a fixed threshold is used in the zero-velocity detection algorithm and a fixed threshold is used to discriminate between longer and shorter periods without movements (i.e., to discriminate between periods without or with movements in which the arm is returned to the initial position or not). These thresholds may cause falsely detected 'long episodes without movements', as was the case in the measurements of movement sequence #4. This could be prevented by making more dynamic thresholds, based on information of the reconstructed movements. In addition to the evaluation of gyroscope and accelerometer data, sensor orientation (i.e., lower arm posture) may also be used to distinguish between long and short episodes without movements.

The second condition is applicable only in those situations in which the participants initial arm position is not changing. This is true in cases where the participant is lying down or is seated and performing, for instance, a clinical test. However, when, during a measurement, the participant rises up from a chair, starts turning or walking around, the second assumption is no longer true and therefore reliable reconstructions of arm movements can no longer be made. To prevent unreliable evaluation of arm movements, an activity classifier could be used to detect and analyze only those episodes in which a participant is seated or is lying down. An activity classifier based on data of a single IMU is, for instance, proposed by Weenk et al. [20]. Another solution might be the use of an additional IMU positioned on the sternum or pelvis. This allows the evaluation of trunk movements (i.e., walking or turning) and might allow the evaluation of arm movements relative to the sternum or pelvis by evaluating the differential accelerations between both sensors.

It should be noted that the proposed algorithm is tested under controlled conditions that may not be comparable with daily life. Furthermore, the algorithm is tested in only one healthy participant. Results may change for different participants with different levels of arm function, in particular of those who survived a stroke. Stroke survivors may experience reduced motor performance and muscle spasticity that may result in the inability to hold their arm. More research is needed in order to check how often the assumed conditions are met during daily life, while evaluating arm movements of stroke survivors. Another limitation of this study is the way in which the reference system was used to validate sensor orientations. The active markers were directly attached to the IMU, therefore all markers were assumed to be positioned in a single plane. This may result in reconstruction errors in the reconstructed orientation by the optical reference system, by misalignment, or small measurement errors. Although orientation differences between both measurement systems were relatively smaller than the differences in reconstructed velocity and position, the differences were larger than expected as IMUs are primarily used for the estimation of sensor orientations [21].

Nowadays, IMUs are small and are already frequently integrated in many electronic devices, such as smartphones and smartwatches. Future research could focus on the use of this data to qualitatively assess arm movements using the proposed algorithm. Furthermore, the addition of a second IMU, in any form, on the other forearm may result in additional clinical relevant information on arm usage [22].

REFERENCES

[1] F. B. van Meulen, B. Klaassen, J. Held, J. Reenalda, J. Buurke, B.-J. F. van Beijnum, A. Luft, and P. H. Veltink, "Objective evaluation of the quality of movement in daily-life after stroke," *Frontiers in Bioengineering and Biotechnology*, vol. 3, no. 210, pp. 1–11, 2016. [Online]. Available: https://doi.org/10.3389/fbioe.2015.00210

[2] J. Y. Xu, Y. Wang, M. Barrett, B. Dobkin, G. J. Pottie, and W. J. Kaiser, "Personalized multilayer daily life profiling through context enabled activity classification and motion reconstruction: An integrated system approach," *IEEE Journal of Biomedical and Health Informatics*, vol. 20, no. 1, pp. 177–188, jan 2016. [Online]. Available: https://doi.org/10.1109/jbhi.2014.2385694

[3] G. Kwakkel, B. Kollen, and E. Lindeman, "Understanding the pattern of functional recovery after stroke: facts and theories," *Restorative neurology and neuroscience*, vol. 22, no. 3-5, p. 281299, 2004. [Online]. Available: http://europepmc.org/abstract/MED/15502272

[4] P. H. Veltink, F. B. van Meulen, B.-J. F. van Beijnum, B. Klaassen, H. Hermens, E. Droog, M. Weusthof, F. Lorussi, A. Tognetti, J. Reenalda, C. Nikamp, C. Baten, J. Buurke, J. Held, A. Luft, H. Luinge, G. D. Toma, C. Mancusso, and R. Paradiso, "Daily-life tele-monitoring of motor performance in stroke survivors," in *13th International Symposium on 3D Analysis of Human Movement (3D-AHM 2014), Lausanne, Switserland*, 2014, pp. 159–162. [Online]. Available: http://doc.utwente.nl/91439/

[5] J. B. Bussmann, U. W. Ebner-Priemer, and J. Fahrenberg, "Ambulatory activity monitoring: progress in measurement of activity, posture, and specific motion patterns in daily life," *European Psychologist*, vol. 14, no. 2, pp. 142–152, 2009. [Online]. Available: https://doi.org/10.1027/1016-9040.14.2.142

[6] A. Salarian, H. Russmann, F. J. Vingerhoets, C. Dehollain, Y. Blanc, P. R. Burkhard, and K. Aminian, "Gait assessment in parkinson's disease: toward an ambulatory system for long-term monitoring," *IEEE Transactions on Biomedical Engineering*, vol. 51, no. 8, pp. 1434–1443, 2004. [Online]. Available: https://doi.org/10.1109/tbme.2004.827933

[7] F. B. van Meulen, J. Reenalda, J. H. Buurke, and P. H. Veltink, "Assessment of daily-life reaching performance after stroke," *Annals of Biomedical Engineering*, vol. 43, no. 2, pp. 478–486, 2015. [Online]. Available: https://doi.org/10.1007/s10439-014-1198-y

[8] J. H. M. Bergmann and A. H. McGregor, "Body-worn sensor design: What do patients and clinicians want?" *Annals of Biomedical Engineering*, vol. 39, no. 9, pp. 2299–2312, 2011. [Online]. Available: https://doi.org/10.1007/s10439-011-0339-9

[9] K. Leuenberger and R. Gassert, "Low-power sensor module for long-term activity monitoring," in *2011 Annual International Conference of the IEEE Engineering in Medicine and Biology Society*. Institute of Electrical and Electronics Engineers (IEEE), aug 2011. [Online]. Available: https://doi.org/10.1109/iembs.2011.6090424

[10] H. J. Luinge, P. H. Veltink, and C. T. M. Baten, "Ambulatory measurement of arm orientation," *Journal of Biomechanics*, vol. 40, no. 1, pp. 78–85, jan 2007. [Online]. Available: https://doi.org/10.1016/j.jbiomech.2005.11.011

[11] M. Noorkõiv, H. Rodgers, and C. I. Price, "Accelerometer measurement of upper extremity movement after stroke: a systematic review of clinical studies," *Journal of NeuroEngineering and Rehabilitation*, vol. 11, no. 1, p. 144, 2014. [Online]. Available: https://doi.org/10.1186/1743-0003-11-144

[12] G. Plasqui, A. G. Bonomi, and K. R. Westerterp, "Daily physical activity assessment with accelerometers: new insights and validation studies," *Obesity Reviews*, vol. 14, no. 6, pp. 451–462, 2013. [Online]. Available: https://doi.org/10.1111/obr.12021

[13] D. Giansanti, G. Maccioni, and V. Macellari, "The development and test of a device for the reconstruction of 3-d position and orientation by means of a kinematic sensor assembly with rate gyroscopes and accelerometers," *IEEE Transactions on Biomedical Engineering*, vol. 52, no. 7, pp. 1271–1277, 2005. [Online]. Available: https://doi.org/10.1109/tbme.2005.847404

[14] H. M. Schepers, E. H. van Asseldonk, C. T. Baten, and P. H. Veltink, "Ambulatory estimation of foot placement during walking using inertial sensors," *Journal of Biomechanics*, vol. 43, no. 16, pp. 3138–3143, dec 2010. [Online]. Available: https://doi.org/10.1016/j.jbiomech.2010.07.039

[15] I. Skog, P. Handel, J.-O. Nilsson, and J. Rantakokko, "Zero-velocity detection – an algorithm evaluation," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 11, pp. 2657–2666, 2010. [Online]. Available: https://doi.org/10.1109/tbme.2010.2060723

[16] H. M. Schepers, H. J. Luinge, G. Bellusci, and P. J. Slycke. (2015) XKF3 - low-power, optimal estimation of 3d orientation using inertial and magnetic sensing. Fairchild. [Online]. Available: https://www.fairchildsemi.co.jp/application-notes/AN/AN-5084.pdf

[17] I. Skog, J.-O. Nilsson, and P. Handel, "Evaluation of zero-velocity detectors for foot-mounted inertial navigation systems," in *2010 International Conference on Indoor Positioning and Indoor Navigation*. IEEE, 2010. [Online]. Available: https://doi.org/10.1109/ipin.2010.5646936

[18] J. M. Bland and D. Altman, "Statistical methods for assessing agreement between two methods of clinical measurement," *The Lancet*, vol. 327, no. 8476, pp. 307–310, feb 1986. [Online]. Available: https://doi.org/10.1016/S0140-6736(86)90837-8

[19] T. Platz, C. Pinkowski, F. van Wijck, I.-H. Kim, P. di Bella, and G. Johnson, "Reliability and validity of arm function assessment with standardized guidelines for the fugl-meyer test, action research arm test and box and block test: a multicentre study," *Clinical Rehabilitation*, vol. 19, no. 4, pp. 404–411, jun 2005. [Online]. Available: https://doi.org/10.1191/0269215505cr832oa

[20] D. Weenk, "Click-on-and-play human motion capture using wearable sensors," Ph.D. dissertation, University of Twente, 2015. [Online]. Available: https://doi.org/10.3990/1.9789036539722

[21] D. Roetenberg, H. Luinge, C. Baten, and P. Veltink, "Compensation of magnetic disturbances improves inertial and magnetic sensing of human body segment orientation," *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 13, no. 3, pp. 395–405, sep 2005. [Online]. Available: https://doi.org/10.1109/tnsre.2005.847353

[22] J. P. Held, B. Klaassen, B.-J. F. van Beijnum, A. R. Luft, and P. H. Veltink, "Usability evaluation of a VibroTactile feedback system in stroke subjects," *Frontiers in Bioengineering and Biotechnology*, vol. 4, jan 2017. [Online]. Available: https://doi.org/10.3389/fbioe.2016.00098