Assessing the Accuracy of an Algorithm for the Estimation of Spatial Gait Parameters Using Inertial Measurement Units: Application to Healthy Subject and Hemiparetic Stroke Survivor

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ABSTRACT

We have reviewed and assessed the reliability of a dead reckoning and drift correction algorithm for the estimation of spatial gait parameters using Inertial Measurement Units (IMUs). In particular, we are interested in obtaining accurate stride lengths measurements in order to assess the effects of a wearable haptic cueing device designed to assist people with neurological health conditions during gait rehabilitation. To assess the accuracy of the stride lengths estimates, we compared the output of the algorithm with measurements obtained using a high-end marker-based motion capture system, here adopted as a gold standard. In addition, we introduce an alternative method for detecting initial impact events (i.e. the instants at which one foot contacts the ground, here used for delimiting strides) using accelerometer data. Our method, based on a kinematic feature we named 'jerkage', has proved more robust than detecting peaks on raw accelerometer data. We argue that the resulting measurements of stride lengths are accurate enough to provide trend data needed to support worthwhile gait rehabilitation applications. This approach has potential to assist physiotherapists and patients without access to fully-equipped movement labs. More specifically, it has applications for collecting data to guide and assess gait rehabilitation both outdoors and at home.

CCS CONCEPTS

• Human-centered computing → Mobile devices; **• Applied computing → Health informatics**;

KEYWORDS

Gait Analysis; Inertial Measurement Unit; IMU; Motion Capture; Dead Reckoning; Stroke; Hemiparetic Gait; Gait Rehabilitation

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1 INTRODUCTION

Inertial Measurement Units (IMU) are small, low cost, highly portable devices that incorporate accelerometers and gyroscopes. Some IMUs also include magnetometers, in which case the term Magnetic, Angular Rate and Gravity (MARG) sensor is also used. These sensor arrays allow the tracking of acceleration, rotational velocity and orientation relative to the earth's magnetic field of whatever they are attached to. They are used extensively in aviation, robotics, and Human-Computer Interaction (HCI). Their increasing affordability and small size have made them a common feature of mobile and wearable devices and other consumer electronics. In addition, IMUs have become increasingly employed in gait analysis [8, 12].

1.1 Background Scenario: Haptic Cueing for Gait Rehabilitation

This study is part of a broader project to evaluate the effects of haptic cueing on gait rehabilitation of people with chronic and degenerative neurological health conditions, and develop a wearable device that can deliver flexible, adaptive rhythmic haptic cues to wearers [3, 4]. The purpose of the device is to assist survivors with gait rehabilitation and the restoration of mobility outside of the clinic. The devices currently being developed as part of this project – called the *Haptic Bracelets* (see Fig. 1) – allow wireless capture of motion data in real time using inbuilt IMUs and deliver adaptive haptic cueing through a series of vibrations at a steady rhythm. The frequency of the vibrations is based on the user's uncued average gait cadence estimated using the IMU data. The vibrations – generated by the vibrotactiles of the Haptic Bracelets – help the patient obtaining a more stable and symmetric pace of walking. The Haptic Bracelets are worn on both legs and synced wirelessly

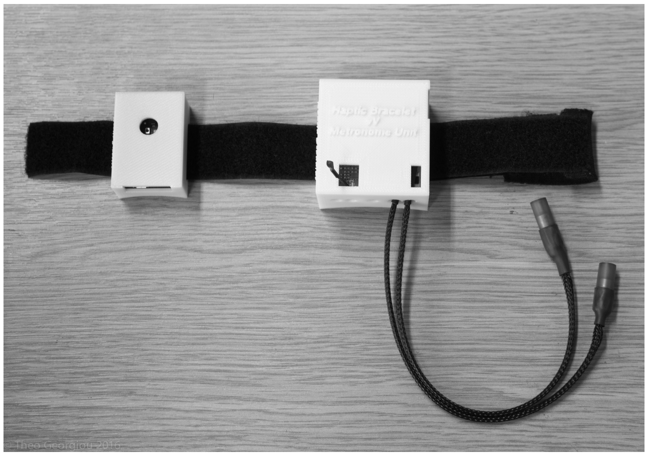

Figure 1: Current prototype of Haptic Bracelet: the smaller module contains the IMU sensor board, while the bigger module contains the board controlling the vibrotactiles.

in order to collect synchronised IMU data and control frequency, intensity, and phase of the haptic cues.

1.2 IMUs and Gait Analysis

Tracking and analysing human body movement reliably is a key issue for research and clinical assessment of pathologies affecting motor skills.

Various technologies are currently employed for tracking human movement. Marker-based optical motion capture is considered one of the most reliable and precise solutions and it is regarded at present as a gold standard. However – even though more affordable motion capture systems have recently become available – high-end motion capture systems suitable for precise gait analysis are expensive. Such systems require a dedicated space of adequate size, are difficult to transport, and cannot be used outdoors.

IMUs, on the other hand, are much more affordable and portable, can be embedded in clothes and shoes, can be used outdoors and at home, and – paired with a data logger – can also be left with the patient for collecting data over a longer period of time. In addition to portability and affordability, one less obvious advantage of using IMUs for gait analysis relative to motion capture is the absence of data loss due to marker occlusion. This can be particularly useful in rehabilitation since physiotherapists sometimes walk closely with a hemiparesis survivor for safety reasons during therapy or data collection. In the case of optical motion capture, this may occlude the reflective markers, creating gaps in the tracking data. On the other hand, a less obvious limitation of IMUs over optical motion capture is that it is difficult to reliably estimate what is known as the 'walking base'. This distance, also known as the 'stride width' or 'base of support', is the side-to-side distance between the line of the two feet [13]. This limitation is due to the lack of a common spatial reference point for the left and right IMUs. Nonetheless, albeit having considerable limitations compared with a full optical motion capture suite, IMUs can be a very effective solution for tracking and analysing specific parameters of human gait, and constitute a useful option in situations where other technologies cannot be readily employed.

The data returned by IMUs is morphologically different from that obtained from marker-based optical motion capture systems. Whereas raw motion capture data consists of three-dimensional vectors describing the position of markers over time using an absolute Cartesian coordinate system[1], the data returned by an IMU/MARG sensor is usually in the form of three three-dimensional vectors, respectively indicating acceleration, rotational velocity, and orientation[2]. Orientation data is provided by the magnetometer (compass), which tracks the orientation of the unit in relation to the earth's magnetic field. However, magnetometers are considerably affected by magnetic distortions typically present in motion labs [2]. Therefore, this comparative study will not employ magnetometer data and will focus on the use of information returned by the inertial sensors – namely acceleration and rotational velocity – to measure specific gait parameters.

1.3 Gait Parameters

The data obtained from the IMUs placed on either leg of a person walking is synced, timestamped, and can be used to compute various spatio-temporal gait parameters, such as cadence, walking speed, stride length, step length, and timing of the different stages of the gait cycle. More complex configurations – including multiple IMUs per limb – can also be used for joint angle measurements [11].

In the case of our project on haptic cueing for gait rehabilitation, gait parameters have several uses. Initially, these parameters are used, before applying any cueing, to calculate the mean cadence (averaged across both legs). This is used as an initial haptic cueing tempo, applied at an even tempo to each leg in turn. Subsequently, the gait parameters are used to assess both the immediate and longer term effects of the haptic cueing on gait stability and symmetry. A study evaluating the effects on the gait of stroke survivors is currently being carried out.

Estimating spatial gait parameters using only IMU data poses some challenges, since, firstly, there is no absolute coordinate system to refer to, unlike with optical motion capture, and secondly, accelerometers are subject to drift. Positional data must be calculated from the acceleration and angular velocity data returned by the IMU. Simple double integration of acceleration data would result in very large amounts of residual error, since drift would accumulate quadratically. Algorithms designed for correcting the residual error by exploiting specific constraints of cyclic motion can be used for estimating spatial gait parameters [14]. In this study, we have adopted the algorithm[3] developed by Madgwick et al. [6]. The algorithm uses dead reckoning and drift correction each time the foot hits the ground. Related algorithms found in the literature include those by Mahony et al. [7] and by Martin & Salaün [9].

[1]Most marker-based systems also allow to capture 6DoF data (six degrees of freedom, consisting of three-dimensional position and Euler angles) by defining rigid bodies. However, this is achieved by processing the positional data of single markers grouped into a rigid body.

[2]IMU/MARG sensors are also known as MIMU (Magnetic and Inertial Measurement Unit) or 9DoF (9 Degrees of Freedom) sensors.

[3]The original script is freely available at https://github.com/xioTechnologies/Gait-Tracking-With-x-IMU

In our case, the algorithm is used to estimate the stride lengths of a person walking straight for trials each of about 8 metres. Stride length and step length are different yet closely related gait parameters, distinguished as follows. Step length refers to the distance by which one foot moves forward in front of the other, whereas stride length is the distance between two successive placements of the same foot. Consequently, one stride length is composed of two step lengths, left and right respectively [13]. In order to assess the accuracy of the algorithm, the stride lengths obtained using the data from the IMUs worn on each shank were compared with those measured using a high quality marker-based motion capture system. Other approaches to spatial gait estimation using IMUs include the method by Köse et al. [5], which used a single IMU attached to the pelvis to estimate step lengths using a combination of Kalman filtering and direct and reverse integration. Similarly, Mariani et al. [8] used foot-worn IMUs and de-drifted integration of inertial signals.

2 METHOD

This section describes how IMU and motion capture data were collected and analysed to establish the accuracy of the dead reckoning algorithm for estimating stride length.

2.1 Participants

The IMU data comprised 42 stride length measurements for the healthy subject (age 33, male) and 49 for the stroke survivor (age 57, female, hemiparetic stroke affecting her right side), totalling 91 stride length estimations. This data was compared against the step length measurements obtained using reference motion capture data.

2.2 Apparatus

The IMU/MARG sensors (gyroscope, accelerometer, and magnetometer) on x-OSC[4] boards were placed in the middle of a rigid plate (Qualisys Large Cluster) with four reflective markers (Fig. 2). The plates were then strapped on the shanks of the subjects as shown in Fig. 3. The same pair of IMUs was used for both subjects, with the same left-right configuration. Sampling frequency for the IMUs was set at 256 Hz; the gyroscope range was $\pm 2000°/s$; and the accelerometer range was $\pm 16g$. Finally, an optical motion capture system featuring eight Qualisys Oqus cameras was used to track the position of the reflective markers at a sampling rate of 100 Hz.

2.3 Procedure

Two subjects, a hemiparetic stroke survivor and a healthy person, were asked to walk straight in the motion capture lab for about 8 metres with the IMUs and marker plates strapped on both shanks. The walking trial was repeated six times for each subject. During each trial, the motion capture data was recorded on a Windows PC running Qualisys Track Manager (QTM). A second computer, a MacBook Pro, was used to record the IMU data and was synchronised to the Windows PC via wireless network, receiving start and stop commands, frame numbers, and other metadata via Open Sound Control (OSC) from QTM.

[4]http://x-io.co.uk/x-osc/

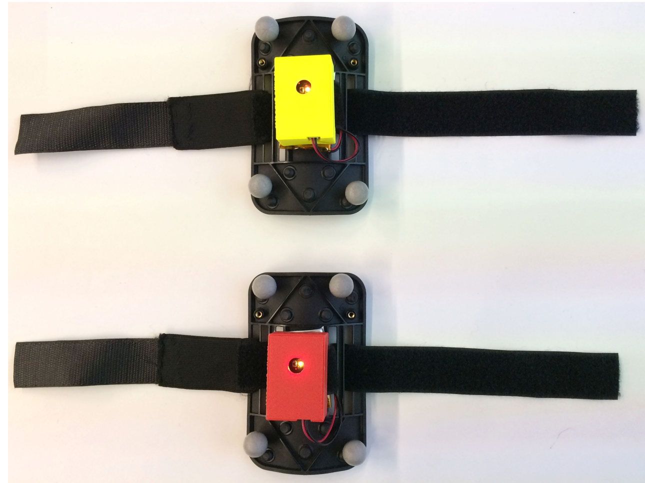

Figure 2: Rigid plates with retroreflective markers and custom boxes (coloured) containing the IMU units.

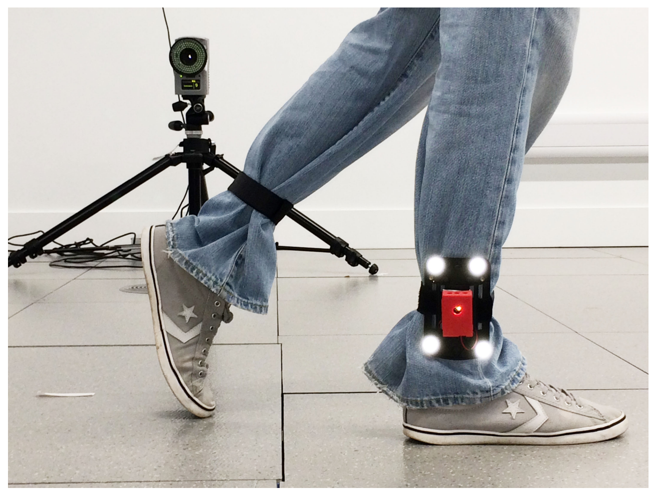

Figure 3: Rigid plates with retroreflective markers and IMU units worn in the motion capture lab.

2.4 Data Processing

The motion capture data was gap-filled in QTM and then imported to MATLAB using MoCap Toolbox 1.5[5] [1]. For each plate, a single secondary marker (also known as 'joint' marker) was defined by averaging the locations of the four markers on plate. Hence, the position of this secondary marker corresponded to the centre of the plate, where the IMU was placed.

The corresponding IMU data was also imported to MATLAB for analysis. Position relative to the starting point of the walk was calculated through double integration of drift-corrected accelerometer data [14]. In principle, accelerometer data can be integrated

[5]https://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/mocaptoolbox

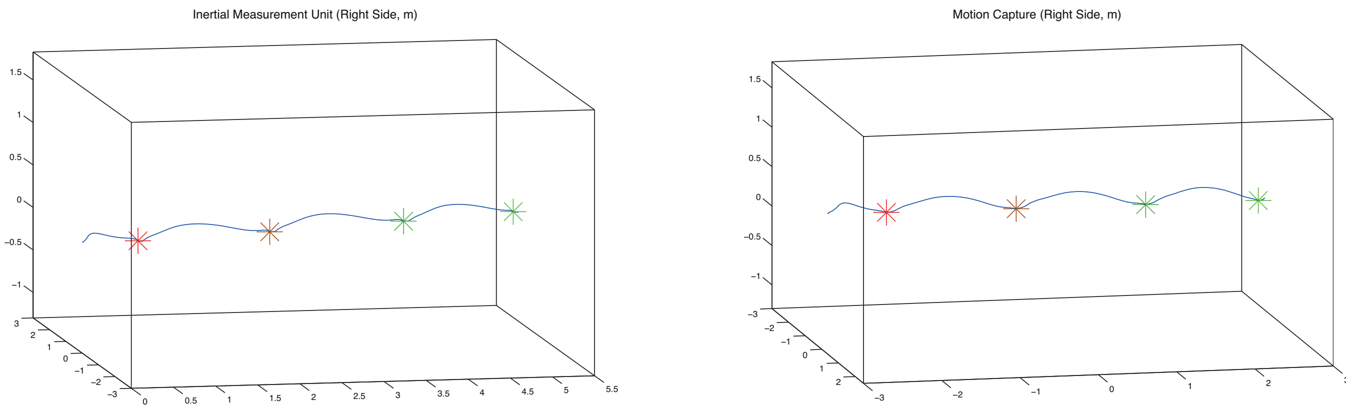

Figure 4: Trajectories of the right leg of the healthy subject obtained using the IMU data (left) and motion capture data (right). The star markers delimit the strides and are obtained using peak detection on the jerkage values as described in section 2.5. By default, the origin of the axes (0,0,0) is placed at the starting point of the trajectory for the IMU data whereas for motion capture it is defined during calibration.

twice to yield position. In practice though, accelerometers are susceptible to drift errors, which then grow quadratically during double integration. To estimate and remove drift, the periodic nature of walking motion can be exploited. This is done by first estimating translational velocity by integrating acceleration. Crucially, during the stance phase of a gait cycle (also called the 'support' or 'contact' phase [13]) the foot contacts the ground. Since velocity and acceleration are assumed to be zero at this point, drift correction can be applied to the calculated velocity. To detect the stationary periods, the algorithm we adopted uses a threshold on low pass filtered accelerometer magnitude. Below that threshold, the leg is considered to be in stance phase. Thus, drift correction is applied by zeroing the velocity during stationary periods and removing any integral drift that may have accumulated during non-stationary periods. In this way, drift-corrected translational velocity can be integrated to yield position.

Fig. 4 shows the trajectories of the right leg position of one of the subjects during a single walk. The trajectory on the left is estimated using the IMU data while the trajectory on the right is obtained from the motion capture data.

2.5 Initial Contact Detection and Step Length Estimation

In gait analysis, the *initial contact* is the instant at which one foot contacts the ground. This is one of the major events of the gait cycle [13]. In order to calculate the stride lengths from the IMU data, it is necessary to detect when these events occur, since – as noted earlier – two consecutive initial contacts of the same foot delimit a single stride. Raw accelerometer data is one option to use for this purpose, since the impact of the foot with the floor causes a quick change of velocity, hence an acceleration peak. Peak detection algorithms can then be used to detect these events. However, the magnitude of the acceleration detected at initial contact can vary considerably from person to person, especially when working with participants whose gait is affected by diverse pathologies. Other factors that may affect the accelerometer initial contact data include the subject's weight and the softness of the floor — a hard floor usually returns sharper acceleration peaks than surfaces such as carpet. Thus, the detection of peaks in raw accelerometer data is prone to both false positives and false negatives. We found that initial contacts could be detected more reliably by using a different kinematic feature.

In kinematic analysis, 'jerk' (or 'jolt') is the name given to the third order derivative of movement position, namely the change of acceleration over time. We found that the sum of the squares of the jerk on all three axes gave a clean indication of initial contact. Keeping this as a squared quantity helped to ensure a strong signal to noise ratio. Since we need to refer to this quantity several times, and as it does not currently appear to have an accepted name, we will refer to this feature as *'Jerkage'* or *'Joltage'*. Note that while jerk is a vector, jerkage is scalar. It is calculated as follows:

$$Jerkage = \left(\frac{da_x}{dt}\right)^2 + \left(\frac{da_y}{dt}\right)^2 + \left(\frac{da_z}{dt}\right)^2. \qquad (1)$$

In this way, we obtain exclusively positive values and the peaks corresponding to the initial impacts are more clearly defined compared to the raw accelerometer data, as shown in Fig. 5. Using jerkage values instead of raw acceleration data for peak detection resulted in a considerably better performance of the detection algorithm, without the need of adjusting detection parameters for different subjects and walking surfaces.

The indices of the jerkage peaks were used to segment the positional data. The star markers along the trajectories plotted in Fig. 4 show where initial contacts were detected. Stride length values are obtained by computing the Euclidean distance between subsequent initial contact points. All of those strides that were successfully captured in full by both the motion capture system and the inertial measurement units were then considered for analysis.

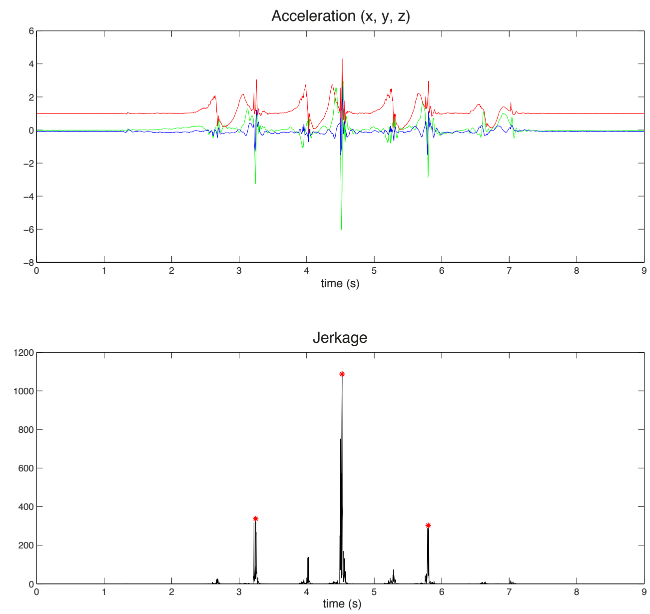

Figure 5: Raw accelerometer data of the three axes in units of g of the left foot of the healthy subject (top) and corresponding jerkage magnitude (bottom). The red stars indicate the detected peaks.

3 RESULTS

Table 1 reports correlations between the stride length values as measured by the IMU compared with values measured by the reference optical motion capture system. Mean discrepancies between the two measurements are given both as distances, and as percentages. The table shows the results for the stroke survivor and healthy participant separately and combined. Similarly, the results are given for left hand steps and right hand steps separately and then merged.

Using the visualisation proposed by Martin Bland [10] and adopted by Mariani [8], Fig. 6 compares the stride length obtained from the two measurement systems for the healthy subject, while Fig. 7 compares the corresponding values for the stroke survivor.

4 DISCUSSION AND FUTURE WORK

In all of the cases reported in Table 1, the mean relative measurement discrepancies relative to the reference system were between 0.4 % and 5.7 %. While this is not ideal accuracy, it is workable for our purposes of estimating baseline mean spatial gait performance, and tracking trends in these parameters over time. Considering the figures in Table 1 in more detail, it is clear that the IMU used on the left hand side of the body seems to be more accurate, with mean absolute differences consistently less than a half of those of the IMU used on the right. In fact, it is important to emphasise that high correlation coefficients should not be taken as indicators of agreement [10]. Rather, they measure the strength of the linear relation between two variables. The relationship between highly

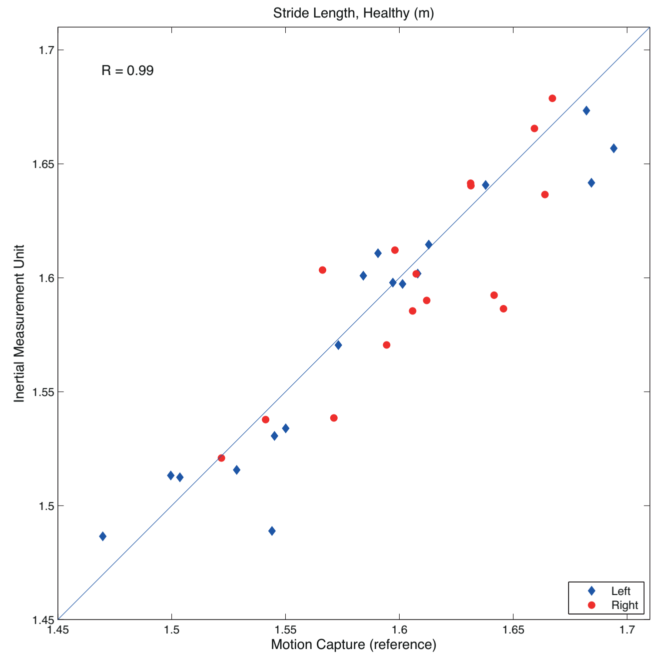

Figure 6: Comparison of stride length values estimated using the inertial measurement units and marker-based motion capture for the healthy subject.

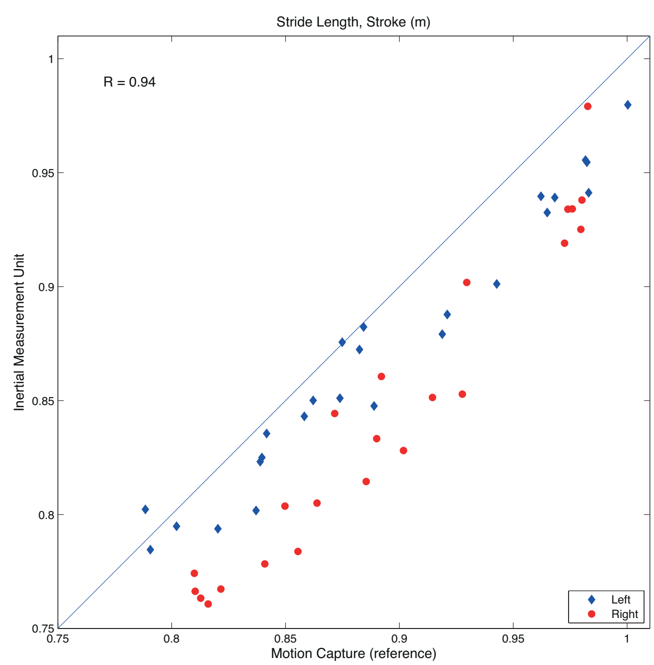

Figure 7: Comparison of stride length values estimated using the inertial measurement units and marker-based motion capture for the hemiparetic stroke survivor (paretic side: right).

Table 1: Correlations between stride length values estimated in two different ways: using inertial measurement units vs. marker-based motion capture (reference). Mean discrepancies (ε) between the two measurements are given as millimetres, and as percentages.

LEFT	N of strides	R	ε mean (mm)	(%)	ε std (mm)	(%)
Healthy	18	0.946	6.6	0.4	21.0	1.3
Stroke	25	0.979	20.6	2.3	14.8	1.7
Overall	43	0.999	14.8	1.2	18.8	1.6

RIGHT	N of strides	R	ε mean (mm)	(%)	ε std (mm)	(%)
Healthy	24	0.997	12.4	0.9	30.0	2.2
Stroke	24	0.970	50.5	5.7	17.6	2.0
Overall	48	0.997	31.5	2.8	31.0	2.7

LEFT & RIGHT	N of strides	R	ε mean (mm)	(%)	ε std (mm)	(%)
Healthy	42	0.996	9.9	0.7	26.4	1.8
Stroke	49	0.942	35.3	4.0	22.0	2.5
Overall	91	0.998	23.6	2.0	27.2	2.3

correlated variables could, in principle, be complicated by a multiplicative factor (i.e. the slope of the line is not equal to 1) or a constant offset (i.e. the vertical intercept is not equal to 0). In Figs. 6 and 7, the systems perfectly agree when the data points lie along the line of equality. This graphical representation effectively gives an overview of the degree of agreement between the two systems for each leg of the participants. This shows that the right IMU has a tendency – especially for the stroke survivor – of slightly underestimating step lengths compared to the left one. Even though, as previously noted, the existing performance of the right IMU is workable for purposes of tracking overall improvements in gait, accuracy could be improved by correcting this systematic bias. This could be achieved by exploiting known constraints. For example, we can assume that each walking trial ends with both legs approximately at the same distance from the starting point. Consequently, a correction factor could be applied to the IMU trajectory for the right leg to uniformly rescale it to yield the same overall trajectory length as the IMU for the left leg. Corrections of this kind have not been calculated for the present paper, but we will validate this method in a future study. A simple, if more expensive, alternative might be to use a 'matched' pair of high-end calibrated IMUs.

A different, but related, tendency suggested by the results is that the measurement differences between the IMUs and the reference system appear to be more pronounced in the case of the stroke survivor, particularly in the right (paretic) side (see Fig. 7). This could be due to differences in kinematic patterns between paretic and non-paretic sides of the body. Such differences might require different bilateral parameter settings for accurate stride length estimation. For example, paretic and non-paretic legs might ideally require different thresholds for the detection of periods when the foot is stationary.

More specifically, there are two crucial settings in our IMU algorithm, one currently set manually, and one currently set by assumption. The manual setting is an acceleration magnitude threshold for the detection of periods when the foot is stationary. At present, a single value for this parameter is used for both legs. The other crucial parameter, currently set by assumption, is the nominal sampling rate of the IMUs. In fact, the achieved sampling rate may differ slightly from the set rate. Both of these parameters affect the stride length estimates. In both cases, the data already available to the system could be used to assess these values more accurately using an optimisation algorithm. This would also make the system simpler to use.

Additional tests involving a higher number of subjects and more IMU devices will be carried out in order to verify if different kinematic patterns in the paretic side affect stride length estimation. Moreover, the actual sampling rate of various IMU devices will be measured in order to understand if a specific device or model is more prone to sampling rate shifts that may affect stride length estimation.

5 SUMMARY AND CONCLUSION

We have presented a simple adaption of a dead reckoning and drift correction algorithm for IMUs and assessed its reliability for estimating spatial gait parameters for use in gait rehabilitation. Our target application is measuring trends in comparative left vs right mean stride lengths (using one IMU per leg) for survivors of neurological health conditions such as hemiparetic stroke. In order to determine the extent to which this data could be measured reliably using IMUs (for example, away from the lab – outdoors or in the home) we compared data with measurements obtained using a reference optical motion capture system. In order to gain insights into possible differences in approach that might be needed, we took data for both a healthy subject and a hemiparetic stroke survivor. We employed a method for detecting foot impacts based on the kinematic feature 'jerkage'. This proved substantially more robust than considering peaks in acceleration. We identified a potential correction, important for left vs right comparisons, that could be applied to address drift in one foot relative to another. We noted that in the case of hemiparetic users, important for our application, different parameter settings may be required for the two sides of the body in order to ensure accurate stride length estimation. This issue will be studied further by means of additional tests involving more participants wearing different IMUs.

While use of IMUs to measure gait parameters outdoor and in the home for presents challenges, this study has given us a basis for concluding that trends in comparative left vs right mean stride lengths could be measured sufficiently accurately for useful applications in gait rehabilitation. We conclude that IMUs have the potential to allow haptic cueing to be guided and assessed in a self managed way outside the lab. This promises new approaches for wearable systems for gait rehabilitation.

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