Inertial-based Gait Analysis Applied to Patients with Parkinson Disease

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Abstract: People with Parkinson's disease have a high incidence of falls due to motor difficulties. Recent studies have shown that PD patients can receive benefit from motor therapy based on cueing and feedback. This study describes a system based on a foot-mounted IMU for the calculation of gait parameters applied to different datasets of healthy elderly people, geriatric patients and patients with PD, in order to integrate it into a real-time acquisition system with application for tactile cueing. This system is divided into different steps: the identification of gait cycles and their events, the estimation of the path of the foot, which includes the estimation of the orientation of the foot, the application of methods to correct the error derived from the double integration of acceleration such as ZUPT, and finally the estimation of the different gait metrics. The results show that the algorithm developed is an accurate method for stride segmentation and is considered adequate to assess the gait metrics for gait evaluation of patients with motor difficulties.

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1 INTRODUCTION

Parkinson's disease (PD) is the second most common neurodegenerative disease and it is increasing with the aging of the world population. However its low incidence, it affects about 1% of the population over 65 years old worldwide (Moore et al., 2005). PD causes a high incidence of falls due to death dopaminergic neurons in the substantia nigra that causes movement disorders (Moore et al., 2005). In fact, "it is estimated that 60.5% of patients with PD have at least one fall and that 39% have recurrent falls" (Kalilani et al., 2016), which consequently contributes to the increased risk of fractures in patients. The symptoms of the disease are gradual and include problems with gait, balance, posture, in addition to tremors, bradykinesia and rigidity. The disease can't be cured, but it is usually treated with medication, such as levodopa, and in some cases with neurosurgery, but the patients benefit from physiotherapy since diagnose to improve physical capacity, gait and balance (Tomlinson et al., 2014).

With the increase in the number of Parkinson's patients, the high incidence of falls and considering the need for physical therapy to improve their quality of life, it is increasingly important to develop solutions that allow patients to improve their motor skills in a common environment, outside the physical therapy environment. In addition, access to physical therapy and the frequency of sessions can often become increasingly limited, which motivates the development of a device that assesses the patient's gait and provides feedback to correct certain positions, or even stimulates a more controlled gait.

In fact, motor impairment of PD leads to specific gait characteristic in PD, such as reduced step length, longer step time and consequently reduced gait speed and less regular gait cycle (Mariani et al., 2013). Stance duration and double support duration were increased for the Parkinson's population, whereas single support duration, mean cadence, and heel-to-heel base of support were markedly reduced (Nelson et al., 2002). Some of these parameters are difficult to assess and vary significantly from patient to patient, so an additional system that can estimate gait metrics is beneficial in helping doctors confirm their observa-

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tions and diagnoses during long-term trails.

Gait analysis is usually performed in a laboratory setting using a motion capture system or a pressure-sensitive walkway. These systems are considered gold standard in terms of accuracy. These systems allow a high degree of accuracy in measurement, however they are very complex to use on a daily basis and are only suitable for laboratory or hospital-like environments such as physiotherapy clinics, due to their high monetary value and little ease of use (Tunca et al., 2017) and adaptation to any environment. Therefore, a portable system of good precision that can estimate the parameters of gait is an added advantage for the evaluation of motor disorders and for monitoring motion performance in PD.

The evolution of wearable sensor technology enabled to obtain an acquisition system with a low cost and size that allows gait dysfunction and motor symptoms to be assessed. The most used wearable sensors are inertial sensors packed into inertial measurement units (IMUs) (Tunca et al., 2020). IMU consists of a unit that integrates tri-axial accelerometer, gyroscope and magnetometer. This unit also allows BLE or Wireless communication with a device, being able to acquire synchronized data in real time from several IMUs, in order to obtain a complete information of the gait (Tunca et al., 2017).

Currently, there are many studies of inertial sensors in the scope of gait assessment and gait monitoring performance, mainly for lower-body gait analysis with foot-located IMUs. In fact, one of the major focuses of research in inertial sensors is to develop a system that extracts gait metrics, both spatial and temporal, over short and long gait paths for accurate assessment of dysfunctions. Methodologies with good precision have been developed that combine step segmentation methods by identifying different walking moments and the calculation of spatial metrics (Mariani et al., 2013; Tunca et al., 2017). These studies vary by the segmentation method of the gait, (Rampp et al., 2015) use multi-dimensional subsequence dynamic time warping (msDTW) for geriatric patients and some patients with PD, (Ferrari et al., 2016; Tunca et al., 2017) used algorithms that involve the identification of the angular velocity peaks for Parkinson's patients and healthy.

This study describes a foot-mounted IMU system for the calculation of gait parameters applied to different datasets of healthy people, geriatric patients and patients with PD, in order to integrate it into a real-time acquisition system and application of biofeedback. This system is divided into different steps: the identification of gait cycles and their events, the estimation of the path of the foot, which includes the estimation of the orientation of the foot, the application of methods to correct the error derived from the double integration of acceleration such as zero-velocity updates algorithms (ZUPT), and finally the estimation of the different gait metrics.

2 METHODS

2.1 Acquisition Protocol and Datasets

The requirements of development of this system had the partnership of the Portuguese Parkinson Disease Patient Association (APDPk). However, due to the pandemic situation that was established, the cooperation was no longer possible. The pandemic prevented the involvement of patients in the association, as they are a group of potential risk. Patient participation would undermine safety measures and increase risk of contagion. For this reason, this section describes the datasets used, which are mostly public.

In that sense, it was used 2 datasets and all have certain requirements. The datasets include samples of triaxial inertial data from sensors placed on both feet of the patient while walking and data from an accurate reference system to validate the methods. In the initial phase of familiarization with the data and for the definition of different gait metrics (such as number of steps, speed, stride length), the subjects did not need to have a neurodegenerative disease.

The public eGaIT database (embedded Gait analysis using Intelligent Technologies) contains two datasets which was used in this study, the *Validation Stride Segmentation* and the *Validation of Gait Parameters*. These datasets were provided by Professor Ph.D Bjoern Eskofier of the Machine Learning and Data Analytics laboratory at Friedrich-Alexander University Erlangen-Nuernberg and they are accessible for collaborative research (FAU, 2015). The inertial data of the both datasets were acquired using the same material and set-up system (Barth et al., 2015; Rampp et al., 2015).

The eGaIT database for *Validating Stride Segmentation* consists of data from 30 individuals. Of the total participants, 10 are elderly controls, 5 male and 5 female, 10 individuals are patients with Parkinson's disease, 5 male and 5 female, and 10 are geriatric patients, 4 male and 6 female (Barth et al., 2015). The mean age for the elderly controls is 64.0 ± 8.4 years, the mean age for patients with PD is 63.8 ± 9.3 years and for geriatric patients is 81.0 ± 4.1 years (mean $\pm$ standard deviation). The patients with PD were evaluated to assess symptoms, severity and degree of disease. The ground truth of the start and end points of each stride was provided with the inertial data.

The eGaIT database for *Validating Gait Parameters* consists of data from 101 inpatient geriatric patients, where 55 are female and 46 are male, the mean age is 82.1 ± 6.5 years and the mean height is 164.0 ± 10.0 cm (mean $\pm$ standard deviation) (Rampp et al., 2015). The ground truth of the stride time, stride length, swing time and stance time was also provided with the inertial data. This data set does not contain data from patients with Parkinson's, but does contain data from participants with motor difficulties. It contains the ground truth of the start and end points of the stride and the validation of different spatial and temporal metrics (stride length, stride time, swing time and stance time) from a GAITRite system, which is useful to validate the algorithm of spatial gait parameters (Barth et al., 2015; Rampp et al., 2015).

2.2 Algorithm Architecture

The algorithm architecture is represented in Fig.1 and is based on two approaches. The first is the foot-mounted complementary filter (CF) aided IMU approach for pedestrian tracking in indoor environment (Fourati, 2015). However, the system proposed in this study is not for estimating the trajectory, but for estimating gait parameters. The second is the identification of gait events to estimate the position for each stride to calculate gait metrics (Rampp et al., 2015).

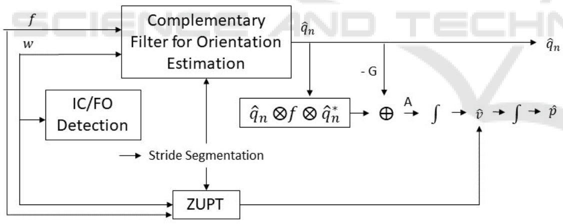

Figure 1: System Architecture (Barth et al., 2015).

In this sense, the complementary filter is used to estimate the orientation of the foot along the gait, represented by the quaternion, $\hat{q}_n(t)$. The complementary filter has as inputs the raw acceleration (f) and raw angular velocity given by the sensors (w). This quaternion will be used to transform the acceleration into the body's reference, which is the raw acceleration given by the sensor (f), in the Earth's coordinate system, $a = \begin{bmatrix} 0 & a_e^T \end{bmatrix}^T$.

$$a = \hat{q}_n(t) \otimes f \otimes \hat{q}_n^*(t) \quad (1)$$

Gravitational acceleration G is also calculated with the use of a quaternion, $G' = q_n(t) \otimes \begin{bmatrix} 0 & 0 & -1 & 0 \end{bmatrix} \otimes q_n^*(t)$, $G = \frac{G'}{\|G'\|_2}$. Next, it is necessary to remove the contribution of G from the acceleration vector $a_e = \begin{bmatrix} a_{ex} & a_{ey} & a_{ez} \end{bmatrix}^T$, to obtain the acceleration of movement of the foot in the earth frame,

$$A(t) = a_e(t) - G \quad (2)$$

and thus it is possible to integrate the calculated acceleration by obtaining the 3-D vector in the Earth coordinate system. Theoretically, the resulting velocity vector can be immediately integrated again to obtain position. However, due to the presence of noise in the inertial signal, which leads to changes and drifts in the measured acceleration and errors in the orientation estimation by the quaternion, the immediate integration of the acceleration would result in an estimation of the wrong position, due to the referred accumulation of errors. One method to reduce the error is the application of the Zero Velocity Update (ZUPT) method, which will be referred to in section 2.2.2. This method is based on the correction of linear speed during gait. Gait is a cyclic movement that results in the transfer of weight from one foot to another alternately. When a foot is in contact with the ground, its linear speed is theoretically zero (Fourati, 2015). Due to the accumulation of error during the referred process, the linear speed during these support phases may not be zero, and thus the ZUPT method identifies the moments of zero speed and corrects the speed initially calculated. The corrected speed is integrated to obtain position.

Previous studies (Ferrari et al., 2016; Tunca et al., 2017) showed that this approach was not as accurate as the Pedestrian Dead-Reckoning (PDR) system using the Kalman Filter. However, this method will be used to calculate the position step by step, and in each step the position will return to zero and a new orientation will be calculated by not increasing the accumulation of the error throughout the acquisition period. Thus, through position and speed it is possible to calculate the spatial metrics of the gait. Also, it was used the CF due to its easy implementation, understanding and because it requires little computational power.

2.2.1 IC/FO Events Detection

As mentioned in the introduction, there are many literature that have studied and developed stride segmentation methods and some which are based on the identification of the initial contacts of the foot on the floor (IC) and the foot-off (FO), the lifting of the foot from the floor (Ferrari et al., 2016; Tunca et al., 2017), but few are capable of running in closed loop for real time acquisition or for real time gait events. The identification of these events is important because from them it is possible to estimate all temporal metrics of the gait, such as stride time, swing time, stance time, cadence and double support. The evaluation of the angular velocity signal according to the medio-lateral axis is a method with good accuracy, ideal for automatic detection of gait events. The method developed is based in (Ferrari et al., 2016).

Unlike studies of (Ferrari et al., 2016) that calculate in the first instance the positive peaks, which represent the moments that the foot is rotating counterclockwise considering the side view of a person walking to the right. The developed algorithm first identifies the negative peaks that may correspond to the FO / IC events, moments of the gait when the foot is rotating clockwise. Calculating these events first, it is guaranteed that no steps are missed in this processing. Next, the positive peaks, which can represent mid-swing events, are calculated and it is verified if this positive peak is between the first and the second detected peak. If the previous fact occurs then the identified peaks can be considered to correspond in fact to the events of the gait. If not, that is, if a first FO peak has been identified and does not follow a mid swing, the FO is not considered, or if a negative second peak, a possible IC, has not been identified after a positive peak, then it will be looked for a next negative peak following the mid swing found.

The identification of positive and negative peaks is based on the *find_peaks* function of the Python Scipy Signal library (Community, 2020) and takes into account limits and conditions that the peaks must meet in order to be recognized as IC an FO events in all patients. These limits are based on the algorithm used by (Ferrari et al., 2016) and adapted so that events are detected in all datasets for healthy, geriatric and patients with PD. The developed algorithm is executed in soft real-time and has a maximum delay of half a step, since it is necessary to evaluate the gait from step to step to calculate the metrics. However, this delay is compatible for mobile applications, such as feedback tips while walking in loop mode (Ferrari et al., 2016). The result of the algorithm is represented in Figure 2.

With the identification of these events it is possible to segment the stride, calculate the stride time, identify moments such as the stance phase and the swing phase and their respective duration. But for the calculation of the position of each step is important to determine also the mid-stance moments. The mid-stance events were defined has the middle of the stance phase, being the stance phase the period between a IC and a FO moments.

2.2.2 ZUPT Algorithm

The gait can be divided into two important phases, which can be identified through the inertial signal of the IMU fixed on the foot of a person walking. The first is the swing phase which means that the foot and the IMU are in the air. The other is the stance phase, which is the period that the foot is in contact with the floor. According to the studies of (Fourati, 2015), during the stance phase the angular and linear velocity must be very close to zero and the accelerometer should measure only the earth gravitational acceleration, because the foot is on the ground and theoretical it is not moving. However, this phase includes the IC event, the foot-flat period in which the foot is completely resting on the floor and the FO event, when the foot is leaving the ground but is still in contact. Considering that the IMU is fixed only in one part of the foot, it does not present speed only during the foot-flat period (Wang et al., 2015). Thus, Multi-condition ZUPT presented by (Guo et al., 2015) was adapted for this study, aims to identify these moments, the periods when the inertial sensor is not in motion, representing them with a logical function assigning 1 when the linear velocity should be zero and 0 when the velocity does not need correction. This algorithm uses data from the accelerometer and gyroscope and presents several conditions, as follows:

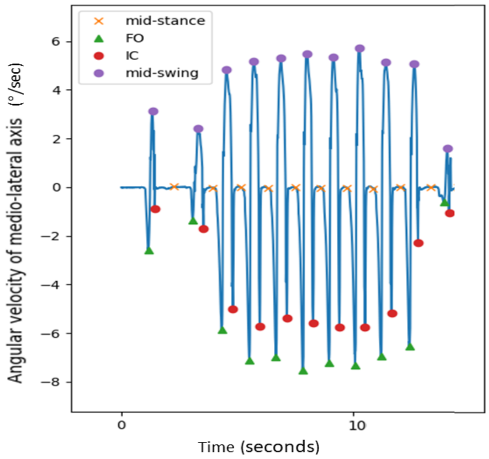

Figure 2: Detection of IC, FO, mid-stance and mid-swing events of a Patient with PD from a eGait dataset.

1. Since the acceleration in periods 1 must be just the acceleration of gravity, the magnitude of the acceleration ($|a_k|$) must be between two limits. The limits are defined around the value 9.8 m/s^2.

$$C1 = \begin{cases} 1 & 8 < |a_k| < 11 \\ 0 & \text{otherwise} \end{cases} \quad (3)$$

2. The acceleration variance must be above a given threshold where $\overline{a_k^b}$ is a mean acceleration value at time k, and s is the size of the averaging window (s = 15). The variance is computed by:

$$\sigma\left(a_k^b\right)^2 = \frac{1}{2s+1}\sum_{j=k-8}^{k+8}\left(|a_j| - \overline{a_k^b}\right)^2 \quad (4)$$

The second condition is defined by this way:

$$C2 = \begin{cases} 1 & \sigma\left(a_k^b\right) < 0.5 \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

3. The magnitude of the angular rate ($|\omega_k|$) must be below a given threshold.

$$C3 = \begin{cases} 1 & |\omega_k| < 0.8 \\ 0 & \text{otherwise} \end{cases} \quad (6)$$

The logical result of the ZUPT algorithm is obtained when the 3 conditions are satisfied. The final logical result is filtered out by a median filter with neighboring window of 29 samples. The Figure 3 shows de result of this multi-condition algorithm from data of a patient with parkinson disease.

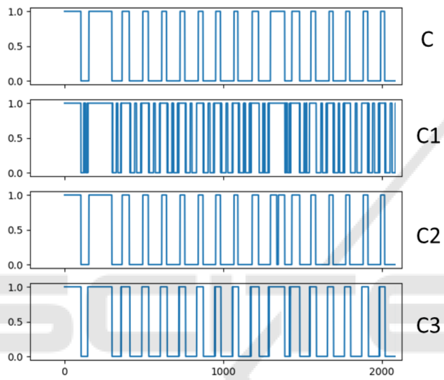

Figure 3: ZUPT algorithm applied to all data acquisition of a patient with PD from the eGait dataset.

This method will work for each stride and if the zero speed zones identified by the ZUPT are outside the IC-FO period, the system does not consider the ZUPT phases and considers the stance phase identified by the event detection algorithm 2.2.1.

2.2.3 Gait Parameters

Temporal gait parameters were calculated based on the gait events identified from each dataset, and were defined from two consecutive strides. The *stance time* is defined in seconds as the duration of stance phase, starting with initial-contact (IC) or heel strike (HS) and ending with foot-off (FO) or toe-off (TO) of the same foot. The *swing time* is the duration of swing phase, starting with FO and ending with IC of the same foot. The stride time is the duration of a gait cycle. Considering the instant when the event occurred of the stride i as $t_{\mathrm{IC}}(i)$ and $t_{\mathrm{FO}}(i)$, it is possible to define each time parameter (Rampp et al., 2015).

$$\textit{Stride Time }(i) = t_{\mathrm{IC}}(i+1) - t_{\mathrm{IC}}(i) \quad (7)$$

$$\textit{Swing Time }(i) = t_{\mathrm{IC}}(i) - t_{\mathrm{FO}}(i) \quad (8)$$

$$\textit{Stance Time }(i) = t_{\mathrm{FO}}(i+1) - t_{\mathrm{IC}}(i) \quad (9)$$

After calculating the 3D position based on the developed system, it is easy to calculate the spatial metrics. The *stride length* is the distance between two successive placements of the same foot, defined as the two norm of a 2-D vector containing the distance in x- (posterior-anterior axis) and z- (medio-lateral axis) direction at the end of the stride, since the position in the start of the stride is zero (Rampp et al., 2015).

$$\textit{Stride length} = \left\| \begin{pmatrix} p_x(n) \\ p_z(n) \end{pmatrix} \right\|_2 = \sqrt{p_x(n)^2 + p_z(n)^2} \quad (10)$$

3 RESULTS

As in this study, different datasets are used with different validation metrics. This section is divided into two parts: stride segmentation results of the two datasets of the eGait database and gait metrics results of the second eGait dataset.

3.1 Stride Segmentation Results

The IC / FO event detection algorithm, described in 2.2.1, is the method used in this study to segment the stride. The accuracy of this algorithm was tested in the eGait datasets. Validation of this algorithm was achieved using the annotated strides of the dataset. The annotation of the samples referring to the beginning and to the end of each stride, for each subject, was performed by manual identification an labeling of gyroscope peaks. In these studies, the stride was considered from the moment when the foot leave the ground (FO) of one cycle to the FO of the next cycle.

In Table 1 the results related to gait segmentation for the different patients in the *Validation of Stride Segmentation* dataset of the eGait database are provided. The table quantifies the number of strides, more specifically, the number of strides annotated in the study (*Annotated Strides*), the number of strides detected by the developed algorithm (*Detected Strides*) and the number of strides that were detected by the developed algorithm and that coincide with the annotated strides (*True Detected Strides*). In the study, patients walked in a straight line for 10 meters, four times, and at the end of each straight line the subject rotates 180 degrees to walk in the opposite direction. The strides annotated in the dataset do not refer of the moments when the patient is changing direction. With this information it is possible to verify that all the annotated strides are correctly identified

Table 1: Results of Stride Segmentation of the eGait Dataset - *Validation of Stride Segmentation*. Mean of the *stride period annotated*, the mean of the *stride period calculated*, the *mean error of the start of each stride* and *end of each stride* are given as mean ± standard deviation.

Patients	**Foot**	**Annotated Nr. Strides**	**Detected Nr. Strides**	**True Detected Nr. Strides**	**Mean Strides per Patient**	**Annotated Stride Period (sec.)**	**Detected Stride Period (sec.)**	**Mean Error Start Stride (samples)**	**Mean Error End Stride (samples)**
PD	Right	248	248	312	24.8 ± 1.8	0.94 ± 0.01	0.94 ± 0.04	-0.98 ± 0.04	0.98 ± 0.04
	Left	248	248	313	24.8 ± 1.6	1.04 ± 0.02	1.04 ± 0.02	-1.01 ± 0.02	1.01 ± 0.02
Geriatric	Right	384	384	491	38.4 ±n11.0	1.35 ± 0.09	1.35 ± 0.09	-0.99 ± 0.02	0.99 ± 0.02
	Left	381	381	490	38.1 ± 10.9	1.34 ± 0.08	1,34 ± 0,08	-0,99 ± 0.00	0,993 ± 0.00
Control	Right	242	242	306	24.2 ± 2.7	1.09 ± 0.03	1.09 ± 0.03	-0.99 ± 0.01	1.00 ± 0.01
	Left	220	220	310	24.4 ± 2.2	1.10 ± 0.03	1.10 ± 0,03	-1.00 ± 0.00	1.00 ± 0.00

by the algorithm for all patients. However, the algorithm has identified more strides, that are those that correspond to moments of changing of direction.

The results table 1 also shows the *average number of strides* taken by the patients during walking in straight line, that is, over a distance of 40 meters, the *average period*, in seconds, of the *stride annotated* in the study, and the *average period* of the *true detected strides*. This period was obtained by dividing the duration of the strides (in samples) by the sampling rate, which is 102.4 Hz. The average number of steps taken by geriatric patients is much higher than the average number of other patients (PD or controls). This group also has a much higher average age, as can be seen in 2.1, which implies more limited mobility, leading to a slower walking cycle (*Stride Period*) and since all groups walked exactly 40 meters, it is possible to deduce that they have a shorter gait length. Patients with Parkinson have in average the same number of steps and a relatively longer gait period than the control group, composed by elderly people. The difference is also not very clear, since the staging of Hoehn and Yahr is on average 1.7 ± 0.9, which is a not very advanced stage in the disease where changes in gait begin to exist (Keus et al., 2009).

To evaluate the quality of the segmentation, the average of the differences between the samples at the beginning of each stride annotated in the dataset and the ones calculated by the algorithm were calculated and is presented in the Table 1 (*mean error start stride*). The same was retrieved for the end of the stride, the average of the differences between the samples referring to the end of each stride annotated and the ones calculated by the algorithm is also presented in the Table 1 (*mean error end stride*). These average errors are very low and have the same modulus value for detecting the beginning and the end of each stride, which means that there is only a lag of about 1 sample leading to an equal stride time between the annotated values and the ones retrieved by the algorithm developed. These results show a great accuracy of the algorithm to identify gait events, more specifically FO, compared to other methods of gait events identification (Barth et al., 2015).

Table 2 presents the results of gait segmentation for the right and left foot of 97 subjects, inpatient geriatric patients, from the *Validation of Gait Parameters* dataset of the eGait database. Four patients were excluded from the dataset because there were inconsistencies in the data provided. The validation of the stride annotations was carried out in the same way as mentioned for the previous dataset. The table shows the total number of strides annotated by the dataset in the 10-meter path, the number of strides detected by the algorithm, and the average number of strides per subject during the acquisition period. To check the accuracy of the algorithm, the average period of the strides and the average error were also calculated, as presented in the previous table 1. The results for this dataset proved the accuracy of stride detection, since all strides have been correctly identified with a small average error leading to a stride period's mean difference of milliseconds . In the next section, the results of the temporal gait metrics and the stride length for this dataset will be evaluated.

3.2 Gait Parameters Results

This section presents the results for the gait metrics retrieved for the second dataset. The metrics calculated were stride length, stride time, stance time and swing time, as shown in the Table 3. The results were from 97 subjects of 101 patients of the dataset. The Table shows the average errors (*Mean error*), defined by the average of the differences between the metrics calculated by the developed system and the metrics provided in the annotated dataset, the absolute error (*Abs. Error*), which is the average of the absolute errors and the correlation that is defined by the Spearman correlation coefficient.

Compared to the study of (Rampp et al., 2015), which uses the same dataset to analyze the same parameters of the gait, it is possible to verify that the mean and absolute error of the stride time calculated in our study for the right foot are smaller (Mean error=0.002 ± 0.043, Abs.error=0.023 ± 0.044) than in the previous study (Mean error = 0.002 ± 0.068, Abs error = 0.029 ± 0.062) and for the left foot

Table 2: Results of Stride Segmentation of the eGait Dataset - *Validation of Gait Parameters*. *mean number of strides per patient*, *mean stride period* annotated in the dataset, *mean stride period calculated* by the algorithm, *mean error of the initial of each stride*, and *mean error of end of each stride* are given as mean ± standard deviation.

Foot	Annotated Nr. Strides	Detected Nr Strides	Mean Strides per Patient	Annotated Stride Period (samples)	Detected Stride Period (sec.)	Mean error Start Stride (sec.)	Mean error End Stride (Samples)
Left	663	663	6.84 ± 1.98	1.22 ± 0.19	1.22 ± 0.18	-0.09 ± 1.05	0.44 ± 1.81
Right	659	659	6.79 ± 1.96	1.23 ± 0.19	1.23 ± 0.18	-0.15 ± 1.07	0.25 ± 0.17

Table 3: Results of Gait Parameters of the eGait Dataset - *Validation of Gait Parameters*. Mean error and abs. error are given as mean ± standard deviation. Time in sec and length in cm.

Foot	Parameter	Mean (Inertial-Sensors)	Mean (GAITRite)	Mean Error	Abs. Error	Correlation	Total
Right	**Stride Time**	1.22 ± 0.18	1.22 ± 0.18	0.002 ± 0.043	0.023 ± 0.044	0.97	756 Strides
	Stance Time	0.78 ± 0.15	0.85 ± 0.15	-0.07 ± 0.05	0.07 ± 0.04	0.96	
	Swing Time	0.44 ± 0.08	0.37 ± 0.08	0.07 ± 0.04	0.07 ± 0.04	0,91	97 Subj.
	Stride Length	83.0± 23.7	83.0 ± 21.3	-0.90 ± 9.76	7.45 ± 6.03	0.90	
Left	**Stride Time**	1.23 ± 0.19	1.23 ± 0.19	0.003 ± 0.039	0.023 ± 0.045	0.98	759 Strides
	Stance Time	0.78 ± 0.15	0.84 ± 0.16	-0.07 ± 0.04	0.068 ± 0.039	0.96	
	Swing Time	0.45 ± 0.07	0.38 ± 0.07	-0.068 ± 0.03	0.068 ± 0.038	0.86	97 Subj.
	Stride Length	82.0 ± 25.4	83.0 ± 22.0	-0.98 ± 9.76	8.61 + 9.71	0.89	

besides being higher (Mean error=0.003 ± 0.039, Abs.error=0.002 ± 0.045), the values are very similar. The correlation coefficient of the stride time metric is higher in this study, 0.97, since the correlation achieved in the previous study was 0.95. With this information it is possible to verify that the segmentation algorithm developed in our study is quite accurate.

However, for the remaining metrics, stance time, swing time and stride length, the results are not so comparable. The average errors obtained in the study of (Rampp et al., 2015) were -0.008 ± 0.045, 0.009 ± 0.069, -0.26 ± 8.37, for the respective metrics. The average errors calculated by the developed algorithm, for the time metrics, are higher, with an order of one decimal place of difference. The reason for the values being so different is related to the approach used to calculate the IC and FO events. There are differences in the literature in the method used to identify the events at the beginning and at the end of the gait. According to (Ferrari et al., 2016), the IC and FO events are considered the negative peaks of angular velocity in the medio-lateral axis, whereas according to the study of (Rampp et al., 2015), the FO events are considered to be the instants when the gyroscope signal in to the same axis crosses the zero.

The stride length presents a mean error of less than 1 cm, both for the right foot and for the left foot, which is a very small error considering the use of this system for rehabilitation purposes. However, the average and absolute errors are much higher than the one calculated in the study of (Rampp et al., 2015) (Mean error = -0.26 ± 8.37, Abs error = 6.26 ± 5.56). The authors calculated the drift of the gyroscope that is contained in the linear acceleration, withdrew its contribution, and after that the integration for the speed was accomplished. In this study, the only way of correcting the inertial errors was applying the ZUPT method, which corrects the linear velocity during the stride considering that in the moments of stance the velocity must be zero. This method only corrects the drift of the result of the integration of acceleration and does not correct the error associated with the gyroscope. However, in addition to the fact that this correction does not exist, the results do not differ significantly from the annotated values.

4 CONCLUSIONS

This study describes a foot-mounted IMU system for the calculation of gait parameters applied to different datasets of healthy people, geriatric patients and patients with PD, in order to integrate it into a real-time acquisition system and application of biofeedback. This system was divided into different steps: the identification of gait cycles and their events, the estimation of the path of the foot, which includes the estimation of the orientation of the foot, the application of methods to correct the error derived from the double integration of acceleration such as ZUPT, and finally the estimation of the different gait metrics.

There are different walking segmentation methods (Haji Ghassemi et al., 2018) more robust methods like msDTW, eDTW, sDTW and hHMM and more conventional methods like peak detection algorithms. A recent study of (Barth et al., 2015) showed that the peak detection algorithm used has, in the best of scenarios, around 84% accuracy and 90% F-Score, for geriatric patients and that when using the msDTW method the accuracy is between 88% and 90% and the F-measure is between 96% and 98%. Thus, the algorithm developed in the study, in addition to being based on conventional peak detection methods, can be compared to robust methods at the level of precision, given the results obtained in the identification of all strides for the datasets used. This method, also presents an ideal configuration for a possible integration in a real-time system, which is a prospective breakthrough in this work.

It was presented a complete algorithm that allows gait metrics to be calculated using data from inertial sensors in patients with motor difficulties, geriatric patients. This system presents adequate results to make the specific gait evaluation for the right and left foot. Although this system present less accurate results than the analogue study (Barth et al., 2015), is considered adequate for the scope of gait physiotherapy. In the future, we intend to calculate other gait metrics such as double support period, stride width, swing width and gait speed, which allow a more detailed analysis for people with Parkinson's, and also integrate it in a real-time system that allows feedback to patient whenever the algorithm evaluates a risky gait pattern, based on spatial parameters.

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