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Gait feature extraction in Parkinson's disease using low-cost accelerometers

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***Abstract*— The clinical hallmarks of Parkinson's disease (PD) are movement poverty and slowness (i.e. bradykinesia), muscle rigidity, limb tremor or gait disturbances. Parkinson's gait includes slowness, shuffling, short steps, freezing of gait (FoG) and/or asymmetries in gait. There are currently no validated clinical instruments or device that allow a full characterization of gait disturbances in PD. As a step towards this goal, a four accelerometer-based system is proposed to increase the number of parameters that can be extracted to characterize parkinsonian gait disturbances such as FoG or gait asymmetries. After developing the hardware, an algorithm has been developed, that automatically epoched the signals on a stride-by-stride basis and quantified, among others, the gait velocity, the stride time, the stance and swing phases, the single and double support phases or the maximum acceleration at toe-off, as validated by visual inspection of video recordings during the task. The results obtained in a PD patient and a healthy volunteer are presented. The FoG detection will be improved using time-frequency analysis and the system is about to be validated with a state-of-the-art 3D movement analysis system.**

I. INTRODUCTION

Parkinson's disease (PD) is a chronic neurodegenerative disorder, clinically characterized by motor impairments [1] including limb tremor, decreased movement speed and amplitude, increased limb rigidity and gait disturbances. Common signs of Parkinson's gait include slowness, shuffling, short steps, and/or difficulty in initiating or stopping gait [2]. Patients may also have freezing of gait (FoG) and/or asymmetries in gait. In PD, the ability to regulate stride-to-stride fluctuations decreases and gait variability increases. These gait disturbances are a major source of disability and reduced quality of life in PD because they lead to limitations on mobility and autonomy and an increased risk of falls [3], [4]. Detecting subtle gait disturbances in PD remains challenging. The detection of motor asymmetry may be helpful for the increase of PD diagnosis accuracy [5]. Detecting FoG episodes, especially subtle ones, is a particular challenge, as freezing is a common cause of falls in PD [6]. To date there are no validated clinical instruments or device that allow a full characterization of gait disturbances in PD. The motor deficits are clinically evaluated using scales such as the Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [7]. However, the use of the MDS-UPDRS is limited because the scores given by MD are partly subjective. Indeed, the scores can vary across raters and for an individual rater at different times [8]. Objective quantitative measures can assist clinicians in evaluating mobility deficits. Several studies have focused on gait analyses in Parkinson's disease [4] as well as on healthy subjects [9] using various technologies such as visual marker-based systems [10], pressure sensors [11] or inertial sensors [9]. Visual marker-based systems such as the Codamotion [12] are often used as gold standards because of their three-dimensional gait analysis accuracy [13]. However, these systems are expensive and difficult to use in the daily clinical evaluation of PD patients [11]. Pressure sensors can be used to set up pressure-sensitive walkways to record gait variations [11]. However, these walkways are expensive and length-limited. Inertial sensors such as accelerometers are small, lightweight, well adapted for portable devices and can record components of the movements as accelerations or displacements [14]. Accelerometers have become a preferred choice for continuous, unobstrusive and reliable method in human movement quantification [15]. For example, using an accelerometer-based device placed on the lower back of first-degree relatives of PD patients, increased variability in gait has been observed in asymptomatic carriers of genetic mutation that predispose to PD [16]. In the present study, we propose an extension of this approach by using 4 accelerometers placed directly on the subjects' feet (heel and forefoot) to increase the number of parameters that can be extracted to characterize parkinsonian gait disturbances. This low-cost device allows, among others, the evaluation of gait asymmetries and FoG, unlike other widespread commercial systems [9], [17], while maintaining a functional gait. Section II describes the material, the method used to acquire the data and the features extracted. Section III presents the gait performances and the features extracted on a healthy volunteer and on a parkinsonian patient and discusses these results. Finally, section IV presents the conclusion and future work.

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II. MATERIAL AND METHODS

The system is composed of four tri-axis accelerometers (Fig. 1) recording accelerations up to $\pm$ 10 g (1 g = 9,81 m/s^2). Accelerometers have been calibrated using a minimization function based on the norm and direction of the gravity field [18]. Accelerometers were placed on the dorsal

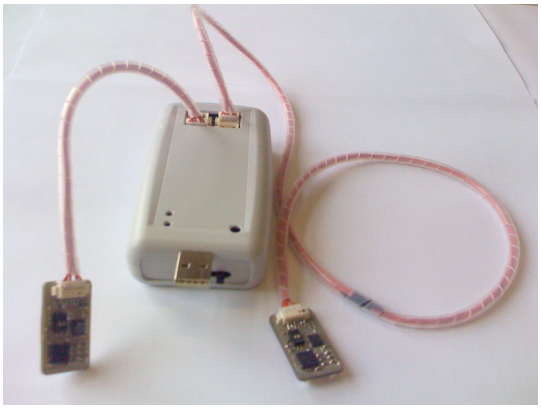

Fig. 1. The accelerometer-based device can count up to 4 sensors recording accelerations up to $\pm$ 10 g at the sampling frequency of 100 Hz.

part of the distal end of the first metatarsian, just before the metatarsophalangian joint with the hallux (hallux sensor) and above the lateral malleolus (heel sensor) of each foot. Data were recorded at the sampling frequency of 100 Hz. The z-axis of the accelerometer is vertically perpendicular to the associated limb, the x-axis is parallel and the y-axis is horizontally perpendicular. Parkinsonian patients and healthy volunteers were recruited at the Cyclotron Research Center and at the University Hospital Center, Department of Neurology, in Liege. They provided written informed consent. This research protocol has been approved by the local ethical committee. Subjects were asked to walk 20 meters in a straight hallway, at their preferred, self-selected usual speed. Subjects walked with their usual shoewear. Performances were recorded by camera to allow evaluation by movement disorder specialists. All data have been processed with Matlab 7.6.0 (MathWorks, Natick, MA, USA).

First, a period of steady state walking is selected by removing the acceleration and deceleration phases. The first processing step is to epoch the recorded data to isolate each stride from the heel sensors. For each foot, a new stride is defined when the heel hits the ground (heel strike), which results in a high amplitude and high frequency peak in the heel sensor x-axis signal. A step is defined between two successive heel strikes of both right and left feet. These peaks have been identified using the high-pass filtered version of this signal. The high-pass filter is a 4^{th} order Butterworth filter with a cut-off frequency of 10 Hz. Within each stride, several events are then detected from the hallux sensors: the time when the toes hit the ground (toe strike), the time when they leave the ground (toe-off) and the time for maximum toe-off acceleration (Fig. 2).

According to these events, features can be extracted. The *gait velocity* is first computed as the time needed to walk the 20 meters. The *step time* is the mean time interval of two successive heel strikes between both right and left feet. The *step frequency* is also a feature of interest. The *stride time* is the mean time interval between two successive heel strikes of each foot. The strides are defined for the right foot and the left foot. The stride-based features are thus computed once for each foot. The *stride length* is the mean length of the stride for each foot. It is computed from the stride time and the gait velocity. The *stride frequency* is also computed. The *stance phase*, i.e. the mean percentage of the stride time when the foot is on the ground, is defined between the heel strike and the toe-off events (Fig. 2). The *swing phase*, i.e. the mean percentage of the stride time when the foot is off the ground, is defined between the toe-off and the next heel strike event. The *single support phase*, i.e., for the right foot, the mean percentage of the right stride time when the left foot is off the ground, is defined between the left toe-off and the next left heel strike event. The *double support phase*, i.e., for the right foot, the mean percentage of the right stride time when both feet are on the ground, is defined between the right heel strike and the next left toe-off event. FoG is clinically defined as an episodic inability to generate effective stepping [6]. The *FoG* episodes are detected according to the difference between each individual double support time and the mean double support time. The mean time of the freezing episodes is depicted in the *FoG time* feature. For the stride-based features, the strides with long episodes of FoG are removed to avoid biased features. The mean *maximum acceleration at heel strike* depicts the strength of the heel contact on the ground and is extracted from the norm of the heel sensor signals. The mean *maximum acceleration at toe-off* depicts the strength of the swing phase initiation and is extracted from the norm of the hallux sensor signals. The *variability* of each feature is determined by calculating the coefficient of variation : 100 $\times$ standard deviation/mean. The *regularity* and *symmetry* features are based on the unbiased autocorrelation function A [19]. For *regularity*, the autocorrelation coefficients A_m are the sum

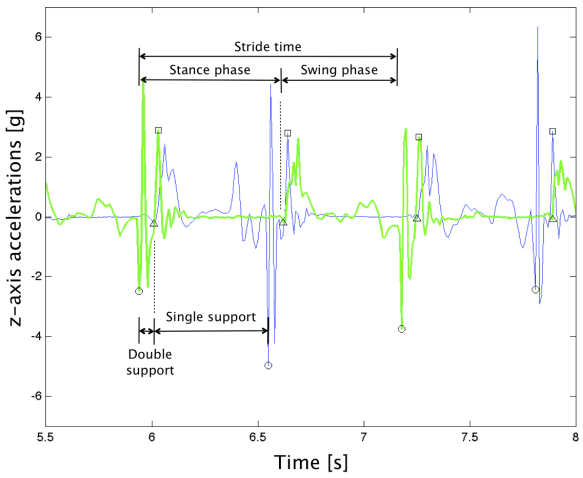

Fig. 2. z-axis signals of the hallux sensor of right and left feet of a healthy volunteer. In thin line, the left sensor and in thick line, the right sensor. The circles are represented when the heel hits the ground (detected on the heel sensors). The squares are represented when the toes hit the ground (*toe strike*) and the triangles when they leave the ground (*toe-off*).

of the products of one foot hallux sensor norm signal n_i ($i = 1, 2, ..., N$) multiplied by the time-lagged replication of the signal (n_{i+m}), where m is the lag parameter (1).

$$A_m = \frac{1}{N - |m|} \sum_{i=1}^{N-|m|} n_i \, n_{i+m} \quad (1)$$

The autocorrelation function is then normalized to obtain 1.0 at zero lag. The first dominant period in the signal A represents a phase shift of one stride. The signal amplitude is then an expression of the regularity of the acceleration norm between two neighboring strides. For the *symmetry*, the autocorrelation coefficients A_m are the sum of the products of the right foot hallux sensor norm signal multiplied by the time-lagged left one. The signal amplitude of the first dominant period reflects the symmetry of the acceleration norm between right and left strides.

III. RESULTS AND DISCUSSION

The first processing step was to epoch the recorded data in order to isolate each stride. Then, within each stride, the toe strike, toe-off and maximum acceleration at toe-off were detected to extract the features. This epoching algorithm requires one parameter - expressing the position of the stride peak detection windows - to be tuned for PD patients.

According to the video analysis, the healthy volunteer had a normal gait, without asymmetry or FoG. This observation is confirmed by the feature profile, as presented in Table I. No episodes of FoG are detected, the features values are similar for both right and left feet except for the maximum accelerations at heel strike and toe-off, that are larger for the left side. The stride times and thus the stride lengths are identical, expressing a balanced gait. The parkinsonian patient showed an asymmetric FoG, on the right side. The patient used a compensatory mechanism since its gait automaticity was deficient. The patient overstepped the right movements to help initiate the gait. The left side movements were only performed in order to maintain balance. The feature profile leads to the same conclusions (Table I). The gait is very slow and the FoG is only present on the right side, as presented in Fig. 3. As the patient presents long episodes of FoG, brief episodes are not accounted in the FoG feature. These long episodes have been removed for the stride-based features. The double support ratio is higher (11 %) for the right swing phase initiation, reflecting difficulties to take off the right foot of the ground. On the contrary, the double support ratio for the left swing phase initiation is similar to those of the healthy volunteer, showing no freezing on the left side. The stride times and lengths are similar for both sides, reflecting the ability of the patient to maintain a balanced gait. The stance/swing phase ratios reflect the asymmetry of the gait. The larger right swing phase ratio reflects the overstepped right movements. The small left swing phase ratio reflects the fact that the left movements are only performed to maintain balance. The maximum acceleration at heel strike is larger on the right side. On the contrary, the swing phase initiation accelerations are similar for both feet. The maximum acceleration at heel strike may be dependent of the subject's weight and type of shoes. This feature should thus be interpreted cautiously. The stride regularity is quite small for both side. The very low value of the symmetry feature further emphasizes the fact that the gait is asymmetric. Except for accelerations, the

TABLE I
GAIT FEATURES VALUES

	Healthy			**Parkinson**		
	gait	right	left	gait	right	left
Gait vel. (m/s)	0.985	-	-	0.232	-	-
Step time (s)	0.616	-	-	1.035	-	-
variability (%)	*2.389*	-	-	*93.80*	-	-
Step freq. (Hz)	1.624	-	-	1.234	-	-
FoG (-)	-	0	0	-	2	0
FoG time (s)	-	0	0	-	4.775	0
Stride time (s)	-	1.233	1.233	-	1.718	1.697
variability (%)	-	*1.734*	*2.136*	-	*11.13*	*13.08*
Stride freq. (Hz)	-	0.812	0.812	-	0.589	0.598
Stride length (m)	-	1.214	1.214	-	0.399	0.394
Stance phase (%)	-	55.44	55.57	-	51.42	66.59
variability (%)	-	*1.804*	*1.470*	-	*8.935*	*6.377*
Swing phase (%)	-	44.56	44.42	-	48.58	33.41
variability (%)	-	*2.245*	*1.840*	-	*9.457*	*12.71*
Single supp. (%)	-	44.29	44.56	-	34.19	49.24
variability (%)	-	*2.371*	*2.552*	-	*13.85*	*9.465*
Double supp. (%)	-	5.305	5.804	-	6.068	11.15
variability (%)	-	*15.84*	*16.31*	-	*44.01*	*26.91*
A. heel strike (g)	-	3.100	5.175	-	3.210	1.937
variability (%)	-	*10.69*	*26.79*	-	*24.75*	*19.96*
A. toe-off (g)	-	4.153	5.328	-	2.634	2.632
variability (%)	-	*20.72*	*15.82*	-	*18.18*	*18.16*
Regularity (-)	-	0.618	0.589	-	0.140	0.205
Symmetry (-)	0.858	-	-	0.058	-	-

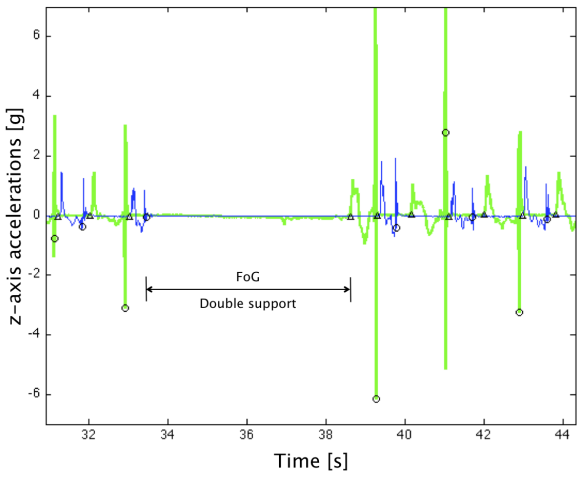

Fig. 3. z-axis signals of the hallux sensor of right and left feet of the parkinsonian patient. In thin line, the left sensor and in thick line, the right sensor. The circles are represented when the heel hits the ground (detected on the heel sensors) and the triangles when the toes leave the ground (*toe-off*). The double support time allows the detection of FoG events as both feet are on the ground during FoG. In this figure, the freezing is present on the right swing phase initiation.

feature variabilities are larger for the parkinsonian patient.

Preliminary analysis performed on a larger number of individuals showed that parkinsonian patients have various feature profiles depending on their disabilities. Patients without asymmetry and FoG showed notwithstanding an increased variability for several features.

IV. CONCLUSIONS AND FUTURE WORKS

One of the major disabilities in Parkinson's disease are gait disorders, characterized by a slow and shuffling gait, and that can include FoG or gait asymmetries. The daily used clinical scales are not well adapted for a full characterization of these disabilities, on the contrary of technologies such as visual marker-based systems, pressure sensors or inertial sensors. Only the latter answers the need for a usable tool in the daily clinical practice, that maintains a functional gait. The new accelerometer-based device proposed in this paper meets those requirements and may allow a deeper quantification of gait asymmetries and FoG than other commercial systems [9], as presented for one healthy volunteer and one parkinsonian patient. The quantification of gait asymmetry is a matter of interest since it may be helpful for the increase of PD diagnosis accuracy [5]. Detecting subtle episodes of FoG could help in improving care of patients by adapting treatment strategies in order to reduce the risk of falls. Moreover, the stride epoching and the feature extraction method allow the computation of features variability that could be usefull in the detection of presymptomatic motor changes, e.g. among PD relatives who have an increased risk of developing PD [16].

A larger set of subjects is about to be formed to validate the system and the extracted features with a state-of-the-art 3D movement analysis system. Subjects' gait will be simultaneously recorded using the Locometrix system [17], the new accelerometer-based device and the Codamotion system [12], used as ground truth.

The set of extracted features will be expanded. Indeed, the toe strike event detection has still to be improved for certain parkinsonian patients. This detection can be difficult, especially for patients who "drag their feet". Using the heel strike and the toe strike events, a feature quantifying the foot reception phase can be computed. Moreover, one of the advantages of this new system is the FoG quantification. However, even if the double support ratio may be a good indicator of the difficulties to take off the feet of the ground, which defines FoG, FoG detection can be improved. Time-frequency analysis will be performed, as it is an appropriate approach [6] to detect brief and subtle episodes of FoG.

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