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Gait assessment in Parkinson's disease patients through a network of wearable accelerometers in unsupervised environments

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Abstract— **Parkinson's disease (PD) predominantly alters the motor performance of the affected individuals. In particular, the loss of dopaminergic neurons compromises the speed, the automaticity and fluidity of movements. As the disease evolves, PD patient's motion becomes slower and tremoric and the response to medication fluctuates along the day. In addition, the presence of involuntary movements deteriorates voluntary movement in advanced state of the disease. These changes in the motion can be detected by studying the variation of the signals recorded by accelerometers attached in the limbs and belt of the patients. The analysis of the most significant changes in these signals make possible to build an individualized motor profile of the disease, allowing doctors to personalize the medication intakes and consequently improving the response of the patient to the treatment. Several works have been done in a laboratory and supervised environments providing solid results; this work focused on the design of unsupervised method for the assessment of gait in PD patients. The development of a reliable quantitative tool for long-term monitoring of PD symptoms would allow the accurate detection of the clinical status during the different PD stages and the evaluation of motor complications. Besides, it would be very useful both for routine clinical care as well as for novel therapies testing.**

I. INTRODUCTION

Parkinson's disease is one of the most common neurodegenerative disorders. It occurs in about 1% of the population over the age of 60 and its prevalence increases with age. About 20% of people over the age of 80 have Parkinson's disease with associated gait disturbances. The major motor disturbances in PD are bradykinesia (i.e. slowed movement), hypokinesia (decreased amount of movements, especially automatic movements such as gesture and gait), resting tremor, rigidity and postural instability. They are largely a result of the loss of dopaminergic innervation of the basal ganglia. In addition to multiple other effects, the impaired basal ganglia function in PD leads to alterations in gait and balance. These motor changes in PD often restrict functional independence and are a major cause of morbidity and mortality among these patients [1-4]. The gait disturbances in PD may be divided into two types [5]: continuous and episodic [6, 7]. The episodic gait disturbances occur occasionally and intermittently and appear randomly. They include festination, start hesitation and freezing of gait [2, 8, 9]. The continuous changes refer to alterations in the walking pattern (temporal and spatial kinematic parameters). As the disease progresses, gait impairment and falls become increasingly frequent and severe and develop into one of the main concerns among PD patients and caregivers. Another gait feature in PD patients seems to be the inability to generate a consistent and steady gait rhythm, resulting in an increase in higher stride-to-stride variability [10]. The locomotor control system that regulates gait rhythm and timing is impaired in PD's patients. Increased of gait variability can be already detected even in the early stages of the disease when patients have not started taking anti-parkinsonian medications [10]. On the other hand, gait disorders are composed of elements, including freezing of gait, gait bradykinesia and postural instability. All of them result of the imbalance between midbrain structures, basal ganglia and cortical motor output. Due to such complexity, gait disorders reflect PD pathological mechanisms and are therefore a good target for quantitative estimation of the patient clinical status. It is important to develop portable devices to continuously monitor gait rhythm and other gait parameters for long periods of time (i.e. 16 hours) in order to achieve a quantitative estimation of motor fluctuations in daily activities and assess the effect of medication on different gait parameters. In the present work, some methodologies to evaluate quantitatively most relevant changes affected by PD are described.

II. DATASET

A. System for data collection

The wearable device used to record the accelerometer signals consists of a set of five tri-axial accelerometers used to record the accelerations of the movements at each patient limb and one accelerometer and gyroscope (on the belt) used to record body movement accelerations and angular rate. Sensors were placed in every limb and belt to allow the system to detect and quantify a wide range of symptoms related to Parkinson's disease patients i.e. tremor, bradykinesia, dyskinesias and freezing of gait. However, this

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work focuses on the continuous gait impairment assessment using the belt accelerometer. All sensors transmit data using Zigbee protocol to a Personal Computer (PC) that receives and stores all recorded signals. The sampling rate used was 62.5 Hz (16 milliseconds between each sample). The PC is equipped with an application for the detection of activities performed by the subject (sitting, hand movement and walking).

B. Inclusion and Exclusion Criteria

Patients fulfilling the following criteria were eligible for the study: diagnosed of Parkinson's disease, aged between 40-70 years old, ambulatory, capable of complying with study requirements, receiving stable dopaminergic treatment, experiencing motor fluctuations and being supported by a responsible caregiver who can cooperate with patient and doctor. The exclusion criteria for this study were suffering from dementia, hallucinations or any significant systemic disease.

C. Protocol for data collection

All patients were asked to move freely and perform their daily activities. The recording sessions were scheduled to get data from two situations, both ON state (times of the day with the symptoms minimized by the medications) and OFF state (times of the day with the complete presence of the symptoms severity) from the same subject. In each case Unified Parkinson's Disease Rating Scale (UPDRS) evaluation was performed by a clinician.

D. Patients data

TABLE I shows the number of walking events recorded with a specific symptom severity from the 10 patients involved in the pilot.

TABLE I
DATASET

UPDRS	0	1	2	3	4
	Number of walking events (ON/OFF)				
Gait	32/35	18/0	0/7	0/2	0/13
Bradykinesia	29/9	21/19	0/5	0/24	0/0
Rigidity Left Leg	19/12	31/18	0/7	0/7	0/13
Rigidity Right Leg	20/18	25/17	5/7	0/2	0/13
Rigidity Left Wrist	19/8	31/29	0/0	0/7	0/13
Rigidity Right Wrist	15/10	22/16	13/16	0/2	0/13

III. HYPOTHESIS

The observation of the signals recorded by the accelerometers in the belt of PD patients and the ones in a healthy subject is the first step before starting the mathematical approach of the problem. Fig. 1 and Fig. 2 show the acceleration in the belt sensor for each axis in a healthy subject and in a PD's patient. It is possible to verify that x-axis (the axis along the body) and z-axis (the perpendicular axis to the thorax) contain most of the information related with the walking movement. During forward movement and as consequence of each step the z-axis is suffering acceleration, although the result is the subject moving in constant velocity. Also as consequence of the forward movement, when the subject impulses himself, the x-axis suffers the acceleration in the sagittal plane. Both x-axis and z-axis show these accelerations periodic pattern related with the normal walking process, while the y-axis reflects the movements within the coronal plane. Acceleration in this plane appears when the subject turns, although there is also a periodic component due to the cadence during walking.

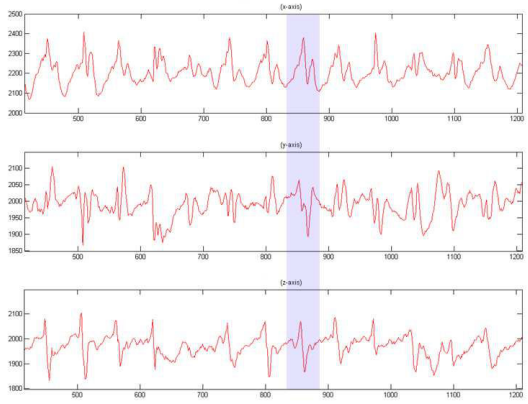

Fig. 1 Signals from the trunk sensor in a healthy subject. From top to bottom the figure shows the x-axis, y-axis and z-axis. The units of horizontal axis are samples and the vertical is directly the value provided by the accelerometers.

By contrast, motor signals from PD patients show an important distance with the aforementioned pattern. Essentially, the presence of bradykinesia and rigidity in PD patients lead to a complication in the walking process. Patients are unable to move correctly and that modifies the healthy walking pattern in a more complex and entropic signal. This approach constitutes an important tool for the detection of a PD walking pattern. Performing some methods of signal processing it is possible obtain a wide range of features which can be linked with a healthy pattern gait. In addition, the analysis of the movement pattern in healthy subjects helps to establish a comparison with the output of the PD's patient recording.

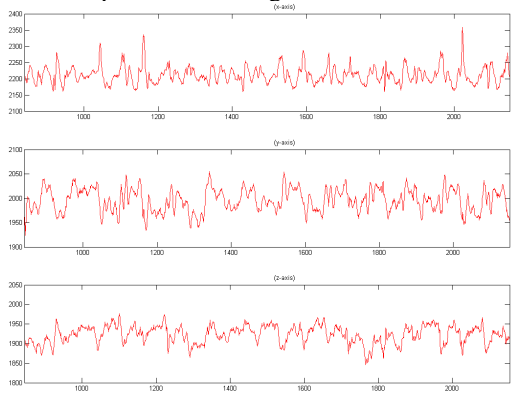

Fig. 2 Signals from the trunk 3-axis accelerometer in a Parkinson's disease patient. From top to bottom the figure shows the x-axis, y-axis and z-axis. The units of horizontal axis are samples and the vertical is directly the value provided by the accelerometers.

The intuitive conclusions that have been extracted previewing the signal can be easily confirmed performing a

spectrum analysis. Taking the whole signal of a healthy subject and transforming it in the frequency space a signal with a significant peak around 1.5Hz - 2Hz is obtained, where more than the 90% of the signal power is accumulated. This peak represents the step frequency. Performing the same proceeding in the PD signal a different pattern is obtained. The power spectrum is wider in this case and the power in the main peak has moved to different frequency bands, generating new peaks with a significant power. This degradation of the signal is useful to measure the subject abnormal gait. Besides this also implies that the capacity of the system for the extraction of features of the gait, such as: step frequency or speed will be strongly affected by the poor quality of signal and in some cases the values obtained from this kind of signal could be far away from reality.

IV. Methodology

After the overview of the accelerometers signals from the belt of the healthy subject, the PD patient and the qualitative approximation, some measures related with the magnitudes previously described have been defined. In previous works [11], these features were used to compare PD patients and healthy subject. In the present work, these measures have been compared from the same patient in OFF state and ON state. Identifying which of them characterized both states more accurately in an unsupervised environment. Next paragraphs explain each measure and the procedure carried out to implement them.

A. Step Frequency

The reduction of the step frequency, number of steps in time, and the shortening of stride length are a common symptom of PD gait alteration. Therefore studying variations in these features along the day will help to detect an abnormality of the motion. To measure the step frequency algorithms based on the autocorrelation have been implemented. Autocorrelation is the cross-correlation of a signal with itself. Informally, it represents the similarity between observations as a function of the time separation between them. It is a mathematical tool for finding repeating patterns, such as the presence of a periodic signal which has been buried under noise, or identifying the missing fundamental frequency in a signal implied by its harmonic frequencies. The algorithm calculates the main frequency of the signal coming from the sensor attached on the belt. The assessment of the main frequency of gait is performed calculating the main frequency of "unbiased" auto-correlation function of the z axis [11, 12]. In order to validate this algorithm, some of the patients were asked to perform a simple protocol in the hospital. During the protocol the patients were wearing the sensors and they were video recorded walking in the corridor for a straight distance of 10 m. The output of the algorithm was compared with the visual examination of the step frequency over 147 periods of walking activity (larger than 5 seconds) both in ON and OFF state. The average error in the step frequency characterization was 1.88 %.

B. Stride length and speed

The algorithm used to measure the stride length during walking is based on the "double pendulous" model [11-14]. The algorithm measures the distance between two "toe off" using the signal coming from the belt accelerometer and the length of the subject's leg. The average speed is computed multiplying step frequency and step length.

C. Entropy

In a signal processing environment, the entropy is the measure of the uncertainty or unpredictability associated to a specific variable, or in other words, it is a measure of the disorder. In the previous discussion it was concluded that signals coming from healthy patients seem to be more organized than the ones coming from PD patients. Former works [11, 12] have shown how to use the technique "Sample Entropy" to calculate the variability and complexity of gait in PD disease. Sample entropy quantifies the regularity of a time series. It reflects the conditional probability that two series of "m" consecutive data points which are similar to each other will remain similar when one more consecutive point is included [15]. It is considered that two data series are similar if the value of a specific measure of distance is less than a parameter "r". In the present work the "m" and "r" values chosen were: m = 2 and r = 0.1 according to our previous test [11, 12].

V. Results and Discussion

During the experiment step frequency, stride length, entropy and arm swing were calculated from the 642 walking events coming from 10 PD patients. For each patient the features extracted from the recordings in OFF and ON state were confronted. Fig. 3 shows the average difference (in percentage) between the states (within the same patient) of all the patients and for all the features.

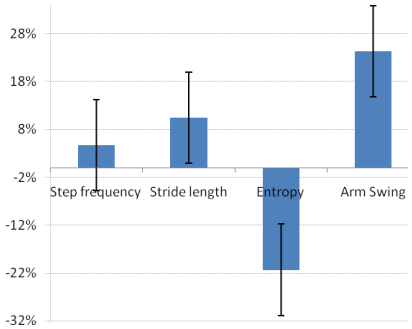

Fig. 3 Results of the tests. Average variability in percentage between the features in the change from OFF state to ON state.

Step frequency, stride length, entropy and arm swing present a significant variation between the OFF and ON in all the patients. Nevertheless, arm swing and entropy show a significant better performance. The measure of the entropy as proposed in previous works [11, 12] also shows an important change for the different status of the same patient. The entropy variation (lower values in the ON phase) reflects the predictability of the signals coming from the ON phase in

contrast with ones from the OFF phase. Finally, step frequency and stride length show higher values in the ON phase as it was expected. Additionally, parallel experiments indicated that it is not possible to create a generalization for all the patients. There is not a direct correlation between variation in the magnitudes and variation in the UPDRS, i.e. a specific variation between ON and OFF does not necessarily imply a direct variation of UPDRS. That means the system needs to be calibrated for each patient, indicating how are the specific parameters during the OFF and ON states of the patient. Finally Fig. 4 shows an example of output events for a specific patient. The first part of the figure (11:30:00 – 11:31:20) shows the events generated during the ON state. The right side (13:50:00 – 13:51:48) is the OFF state. In both states the arm swing and entropy were evaluated while the subject was walking. The averages of the three values where calculated for ON and OFF and are plotted with wider and darker lines. The three features followed the expected evolution in the change from ON to OFF i.e. decreased of the arm swing and increase of the entropy.

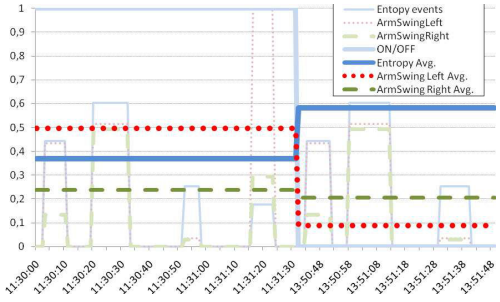

Fig. 4 Normalized outputs from arm swing and entropy events in ON state and OFF state.

VI. Conclusion

Apparently using only one accelerometer in the belt does not provide accurate and exact output; since the "double pendulous" model reflect, an indirect measure quite user dependent. The algorithm should be personalized with a constant depending on every subject in order to provide an accurate output. Moreover, the model uses the leg length as input parameter measured with shoes; this value will change according to the kind of shoe that the patient is wearing. Nevertheless, all these inaccuracies are relevant when looking for an exact value of velocity and stride length, but we are more interested in studying the same day variation of the patient. These systems can provide us with a detailed and accurate status of the impairment. Every patient walks following a different pattern, two patients can walk with different step frequency not because of the disease itself but because they are different. Besides, even the same subject walk differently depending on the situations. Working in unsupervised environments, parameters related with the walking analysis are not very representative and the use of alternative measures like entropy or the measure of the arm swing are a better choice. These features fluctuate according to the status of the patient during the day. Therefore, it is possible to develop a continuous monitoring system able to identify the different phases of the disease within the day. This system could easily alert the professionals when the patient faces an OFF phase indicating that a reschedule in the medication intake is needed. It is also important have in mind that dyskinetic movements will alter the entropy patterns.

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