On Assessing Motor Disorders in Parkinson's Disease

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Abstract. In this paper we propose an automated method for assessing motor symptoms in Parkinson's disease. Levodopa-induced dyskinesia (LID) and Freezing of Gait (FoG) are detected based on the analysis of signals recorded from wearable devices, i.e. accelerometers and gyroscopes, which are placed on certain positions on the patient's body. The signals are initially pre-processed and then analyzed, using a moving window, in order to extract features from them. These features are used for LID and FoG assessment. Two classification techniques are employed, decision trees and random forests. The method has been evaluated using a group of patients and the obtained results indicate high classification ability, being 96.11% classification accuracy for FoG detection and 92.59% for LID severity assessment.

Keywords: Parkinson's disease motor symptoms assessment, Levodopa-induced dyskinesia, Freezing of Gait, accelerometer, gyroscope.

1 Introduction

Parkinson's disease (PD) is a disorder that affects nerve cells in a part of the brain that controls muscle movement. Symptoms of PD may include resting tremor, bradykinesia, rigidity, forward stopped posture, postural instability and freezing of gait (FoG) [1]. Levodopa is highly effective in reducing the symptoms of the disease and remains the standard drug for patients suffering from PD [2]. However, long-term levodopa treatment is often complicated by significantly disabling fluctuations and dyskinesias, referred as levodopa-induced dyskinesias (LIDs).

FoG is a paroxysmal phenomenon commonly seen as an advanced symptom in PD. The FoG events are transient, generally lasting for a few seconds, tending to increase in frequency as the disease progresses [3]. The management of FoG is difficult and often ineffective [4]. Clinical assessment of FoG is largely based on subjective patient reports, such as the Unified Parkinson's Disease Rating Scale (UPDRS). Only a few computerized methods, for the detection of the FoG symptoms, have been presented in the literature. These can be grouped into two basic categories: a) those which are based on the analysis of electromyography signals, and b) those which are based on motion signal analysis [3, 4].

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LID is a disabling and distressing complication of chronic levodopa therapy in patients who suffered from PD [2]. LID symptoms can be rated in various ways by their topography (affected body regions) and their duration or consistency [2]. Thus, their detection and assessment during daily activities is of great interest. Current LID assessment mainly relies on clinical methods [2, 5] which lack of objectivity and they are not feasible for long-term assessment. To overcome these limitations several computer-based methods are developed using quantitative instrumental techniques such as: accelerometers and gyroscopes [5, 6], electromyography (surface) [7], force gauges [7], position transducers [8] and Doppler ultrasound systems [5, 7]. An important drawback of the aforementioned studies is that they employ a small number of motor tasks that have been performed in laboratory settings.

In this study we propose a three-stage methodology for the automated detection of FoG events and LID severity assessment using signals received from accelerometers/gyroscopes placed on different positions of the patient's body. In the first stage the pre-processing of the signals is performed, while a feature vector is extracted (for each second of the recorded signals) in the second stage. In the third stage this feature vector is used for FoG and LID assessment using Decision Tree (DT) and Random Forests (RF) algorithms.

2 Materials and Methods

In this study 16 subjects are enrolled with 24 recordings, 5 healthy subjects and 11 PD patients presenting all types of PD motor disabilities such as tremor, dyskinesia, FoG and LID (Table 1). The movements and postures are automatically measured using accelerometers/gyroscopes and a portable data recorder. Six sets of three orthogonal accelerometers are used, which are placed at: right and left wrist (RW, LW), right and left leg (RL, LL), chest (CH) and waist (WS). Additionally, two gyroscopes are used, that are placed in the chest and waist. All sensors transmit data using ZigBee protocol to a portable PC equipped with data acquisition hardware and software to collect and store the signals. Sampling rate is set to 62.5 Hz.

Table 1. Number of recordings and motor disabilities for PD patients

Patient Number	Number of recordings	Tremor	Bradykinesia	FOG	LID
1	4	√	√	√	
2	1			√	
3	1				
4	3	√	√	√	√
5	2				
6	2				√
7	2			√	√
8	1		√	√	
9	1				√
10	1				√
11	1				√

2.1 Methodology

In the first stage of the methodology, pre-processing of the signals is applied. The missing values, presented since there is loss of data in case of disconnection of a wireless sensor from the base station, are reconstructed using linear interpolation. Then, a finite impulse response (FIR) high-pass filter is used in order to remove the low frequency components of the raw signal.

The processed signals are used for feature extraction. A moving window with 2 second duration and 1 second overlapping is used and, for each window, the mean entropy is calculated as:

$$e_i(j) = \sum_{n=w(j)-fs}^{w(j)+fs} (p(x_i(n)) logp(x_i(n)), \quad (1)$$

where $e_i(j)$ is the entropy of the j-th window for the i-th signal, fs is the sampling frequency, $w(j)$ is the time position of the j-th window, $x_i(n)$ is the n-th sample of the i-th signal and $p(x_i(n))$ is the probability of $x_i(n)$ (calculated using the histogram of x_i). Since eight sensors are used and each sensor records three signals, one for each axis (x,y and z axis), a total of 24 signals are collected and thus the feature vector characterizing each window contains 24 features (entropy for each axis for each sensor). However, several different experimental settings have been used, related to the selection of sensors which are employed. For each one of them, the number of features in the feature vector may vary based on the number of used sensors.

The feature vector is used for the assessment of each window of the signal related to FoG and LID. For this purpose, two classification techniques have been tested, decision trees (DT) and random forests (RF) [9]. A DT represents the acquired knowledge in the form of a tree. In order to construct the decision tree we use the C4.5 inductive algorithm [10]. This algorithm has the advantage of solving the overfitting problem by employing a post pruning technique which is based on the pessimistic error rate (sub-tree replacement). RF is a classifier consisting of a collection of tree-structured classifiers. Each classifier votes for one of the classes and an instance being classified is labeled with the winning class. For the construction of each tree of the forest a new subset of samples is selected from the dataset (bootstrap sample). The tree is built to the maximum size without pruning. In our study the RF consists of 10 trees.

3 Results and Discussion

Several different experimental settings (sensors selection) have been evaluated with two classification techniques (DT and RF) for FoG detection and LID severity assessment. For each one of the experimental settings, results are obtained in terms of classification accuracy, while the 10-fold stratified cross validation technique is used in all cases. The various combinations of signals used in each experimental setting and the obtained classification accuracy for DT and RF techniques, for both FoG detection and LID assessment are presented in Table 2.

Table 2. Experimental settings and classification accuracy results (%) using DT and RF classification techniques, for FoG detection and LID severity assessment

Sensors	Number of features	FoG Detection		LID assessment	
		DT	RF	DT	RF
LW,RW	6	-	-	89.01%	91.46%
LL,RL	6	93.74%	93.90%	89.99%	90.07%
CH	6	92.68%	93.11%	89.82%	90.81%
WS	6	93.13%	94.00%	90.29%	91.21%
LW,RW,LL,RL	12	94.83%	95.89%	90.54%	91.19%
CH,LW,RW,LL,RL	18	94.45%	96.05%	92.33%	92.81%
WS,LW,RW,LL,RL	18	94.57%	96.07%	92.23%	92.33%
CH,WS,LW,RW,LL,RL	24	95.08%	96.11%	92.58%	92.59%

The proposed methodology aims to automatically detect FoG events and LID assessment severity in patients with PD using features extracted from accelerometer and gyroscope sensors. The obtained results indicate high efficiency in distinguishing FoG and LID from other PD symptoms and in LID severity classification. Also, the methodology is able to deal with FoG detection and LID asessment under real-life conditions, since it has been developed using a dataset that reflects real-life conditions, since it includes all kinds of symptoms that a PD patient may suffer from and a variety of voluntary movements.

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