An Automated Method for Levodopa-Induced Dyskinesia Detection and Severity Classification

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Abstract— **In this paper we propose an automated method for Levodopa-induced dyskinesia (LID) detection and classification of its severity. The method is based on the analysis of the signals recorded from accelerometers which are placed on certain positions on the patient's body. The signals are analyzed using a moving window and several features are extracted. Based on these features a decision tree is used to detect if LID symptoms occur and classify them related to their severity. The method has been evaluated using a group of patients and the obtained results indicate high classification ability (95% classification accuracy). Furthermore, extensive evaluation has been done in order to determine the optimal positioning of the sensors and the selection of the classification algorithm.**

Keywords— **Levodopa-induced dyskinesia detection, Levodopa-induced dyskinesia severity classification, automated diagnosis.**

I. INTRODUCTION

Levodopa-induced dyskinesia (LID) is a disabling and distressing complication of chronic levodopa therapy in patients who suffered from Parkinson's disease [1]. LID is more commonly known as a jerky, dance-like movement of the arms and/or head. These movements (called as choreic or dystonic) range from 1-5 Hz [1,2]. LID symptoms can be rated in various ways by their topography (affected body regions), by their duration or consistency of effect, by the disability they impart, by the extent of enhanced severity from activation due to volitional movement and by the severity [2]. The presence and severity of LID can change during the day and as such, detection, assessment and following the changes of these signs during daily activities are of great interest. In addition, the effective characterization and quantification of LID not only improves our understanding of its pathophysiological mechanisms, but also helps diagnosis and the evaluation of treatment.

Current assessment of LID mainly relies on clinical methods [2,3]. Unfortunately, clinical methods lack objectivity and they are not feasible for long-term assessment by the experts [2,4]. To overcome the limitations of subjective assessment of LID and to gain insight into their pathophysi-ology several computer-based methods are developed using quantitative instrumental techniques such as: movement sensors (accelerometers and gyroscopes) [2-6], electromyography (surface) [2,7], force gauges (which are instruments used to measure the force during a push or pull tests) [2,8], position transducers (force transducer that measured arm movements) [2,8] and Doppler ultrasound systems [2,8,9]. Methods which are based on accelerometer signal analysis, greatly differ in the body segments, from which movements are measured, and the number of accelerometers per segment. A major challenge for a method that automatically assesses LID is to be able to distinguish dyskinesias from voluntary movements. Most of the studies tried to detect LID focused on the frequency domain of the signals from the movement sensors, while time-domain features have also been used. Severity of LID has been determined using linear discriminate analysis and artificial neural networks (ANNs). An important drawback of the aforementioned studies is the small number and the short-time of tasks involved as well the fact that they have been performed in laboratory settings. Keijsers et al. [6] monitored patients while performing a large variety of daily life activities in a natural environment for a long period of time. Hoff et al. [10] use a continuous ambulatory multi-channel accelerometry (CAMCA) to identify accelerometer characteristics of LID.

In this study we propose a method for LID detection and classification of its severity. Six accelerometers are placed on the patient's body and the recorded signals are analyzed in order to extract several features. The analysis is performed using moving windows. All features extracted from a specific window of the signal for all signals (from different sensors) form a feature vector that is used to detect if LID symptoms which are present on this window and determine their severity. The classification technique that is employed is a decision tree. Several experimental settings related to the number of sensors used have been evaluated and the results are presented. In addition, based on the best experimental settings determined from the above analysis, other classifications techniques are also tested and the obtained results are presented.

II. MATTERIALS AND METHODS

A. Experimental Setup

In this study three patients, two males (aged 65 and 75 years) and one female (aged 60 years) were enrolled. They suffered from LID and showed a severity of LID varying between no dyskinesia to moderate (rating between 0 and 3 on the Unified Parkinson's Disease Rating Scales (UPDRS) [11]. The experiments were approved by the Medical Ethical Committee of the Hospital of the University of Ioannina in Greece.

Following a standard procedure, used also in clinical trials with medication which accepted in the literature, patients should have received the last dose of their medications 12 hrs before testing time, which is usually around 8 pm of the night before. Twelve hours after the last dose of medication the patient is expected to be in the "off" state. Recording started with the patient always being in the "off" state and lying on his bed. The protocol consists of three major tasks:

- lying on bed (5 min),
- rising from the bed and sitting on a chair located just by bed (5 min),
- standing up from the chair and performing a series of activities (for totally of approximately 8 min): walking for a distance of 5 m, opening a door, closing the door, opening the door step out of the room, walking in the corridor for a straight distance of 10 m, returning in the room, making a stop, drinking a few sips from a glass of water, returning to the chair.

Then, the patient takes his first dose of medication for that day and when he turns "on" (verified on site by an expert neurologist), another cycle of recording with the above prespecified tasks follows. If the patient had LID (while in the "on" state) then the recording is selected for this study. UPDRS obtained immediately before the patient started performing the predefined tasks. The final annotation related to the LID severity based on UPDRS is made based on video recordings obtained during the protocol procedure from the patient.

B. Experimental Setup

The movements and postures are measured using accelerometers and a portable data recorder. Six sets of three orthogonal accelerometers (ANCO Devices [12]) are used. These are placed at six different positions of the body: right and left wrist (LW and RW), right and left leg (LL and RL), chest (CH) and waist (WS). Each accelerometer records

three signals, one for each axis (x,y and z axis). The above sensor's placement on the patient's body is illustrated in Fig. 1. All sensors transmit data using Bluetooth to a portable PC equipped with data acquisition hardware and software to collect and store the signals. The sensors' size is no bigger than a matchbox. Sensors on the arms and legs are attached on specially designed elastic bands which allow fixation to any wrist or ankle size. Sampling rate is set to 62.5 Hz.
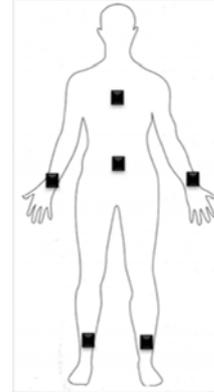

Fig. 1 Schematic overview of the position of accelerometers on the patient's body.

C. Signal Analysis

The recorded signals are used for feature extraction. A moving window with 2 seconds duration and 1.75 seconds antepossition is used over a single lead and, for each window the mean value of the signal is calculated:

$$m_i(j) = \frac{1}{2fs+1} \sum_{n=w(j)-fs}^{w(j)+fs} x_i(n), \qquad (1)$$

where $m_i(j)$ is the mean value of the jth window of the ith signal, fs is the sampling frequency, $w(j)$ is the time position of the jth window and $x_i(n)$ is the nth sample of the ith signal. The above procedure is applied to each recorded signal. Then, very slow movements are modeled:

$$y_i(j) = \frac{1}{2fs+1} \sum_{n=j-fs}^{j+fs} x_i(n), \qquad (2)$$

and subsequently subtracted from the recorded signals:

$$x_i' = x_i - y_i. \qquad (3)$$

A moving window with 2 seconds duration and 1.75 seconds anteposition is used over a single lead and for each window the standard deviation of the signal is calculated:

$$s_i(j) = \sqrt{\frac{1}{2fs+1} \sum_{n=w(j)-fs}^{w(j)+fs} (x_i'(n) - \vec{x_i'})^2}, \qquad (4)$$

where $s_i(j)$ is the standard deviation of the jth window of the ith signal and $\vec{x_i'}$ is the corresponding mean value.

D. LID Assessment

For each window a feature vector is created. This vector consists of the two features (m_i, s_i) for each signal. Thus, the dimension of the feature vector is $2 * 3N$, where N is the number positions on the patient's body (for each position three signals are recorded). This feature vector is used for LID assessment using a decision tree. Decision trees are a widely used classification technique. They represent the acquired knowledge in the form of a tree. The tree can be easily transformed to a set of rules with mutually exclusive and exhaustive rules.

The construction of the decision tree is implemented using the C4.5 inductive algorithm [13]. This algorithm constructs a decision tree from the training data. Each internal node of the tree corresponds to a principal component, while each outgoing branch corresponds to a possible range of that component. The leaf nodes represent the class to be assigned to a sample. The C4.5 algorithm applies to a set of data and generates a decision-tree, which minimizes the expected value of the number of tests for the classification of the data.

III. RESULTS

Based on the signal analysis described above a classification dataset was formed. The number of instances related to the patients and the LID severity are shown in Table 1.

Table 1 The Dataset used in this Study.

LID severity	Patient			Total instances per LID severity
	1	2	3	
0	4109	0	1359	5468
1	2264	446	3780	6490
2	0	2482	1857	4339
3	0	4748	47	4795
			Total	21092

Several different experimental settings have been used, related to the combination of signals which are used for LID assessment. For each one of them, results are obtained in terms of sensitivity, specificity and classification accuracy. The 10-fold stratified cross validation is used in all cases. The various combinations of signals used in each experimental setting and the obtained classification accuracy are presented in Table 2.

Additionally, for the final two experimental settings i.e. the hands, legs and chest sensors (setting 22 in Table 2) and hands, legs and waist sensors (setting 23 in Table 2),

Table 2 Classification Accuracy (%) of the Experimental Settings

Experimental setting	Positions	Classification Accuracy (%)
1	LW	82.4
2	RW	80.6
3	LL	85.4
4	RL	85.4
5	CH	83.3
6	WS	88.9
7	LW, CH	87
8	LW, WS	89.7
9	RW, CH	87
10	RW, WS	89.1
11	LL, CH	89.3
12	LL, WS	89.4
13	RL, CH	88.8
14	RL, WS	89.4
15	LW, RW	85
16	LL, RL	89.4
17	LW, LL	89.1
18	RW, RL	87.1
19	LW, LL, WS	89.3
20	RW, RL, WS	90
21	LW, RW, LL, RL	90.2
22	LW, RW, LL, RL, CH	92
23	LW, RW, LL, RL, WS	90.4

other classifiers are evaluated. This include Naive Bayes Classifier (NBC), k- Nearest Neighbour (k-NN), Fuzzy Lattice Reasoning (FLR [14]), Decision Trees (C4.5) and Random Forests (RF [15]). The results in terms of classification accuracy (%) are presented in Table 3.

Table 3 Classification Accuracy (%) for the 21 and 22 Experimental Settings (Table 2).

Classifier	Experimental setting	
	LW, RW, LL, RL, CH (21)	LW, RW, LL, RL, WS (22)
NBC	73.06	73.75
k-NN	92	90.41
FLR	71.84	72.51
C4.5	92	90.4
RF	92.4	90.8

IV. Discussion

A method for the automated LID detection and classification of its severity based on the analysis of signals obtained by accelerometers placed on the patient's body is presented. The method has been evaluated using recordings from three patients that presented LID severities 0 to 3 at the UPDRS. The features extracted from the signals carry sufficient information for the LID severity detection and classification since they are the local mean value, which is related to very slow dystonic movements, and local standard deviation, which depicts the faster jerky, dance-like movement of the limps and/or head. LID effects may be present in a single part of the patient's body (i.e. only one hand) or to several (i.e. both hands and head). Also, the effects may be present in the limps (hands/legs) or affect the whole body (waist/chest). Thus, the feature vector included accelerometer signals from several positions of the patient's body. The obtained results indicate that the proposed method is highly efficient for automated LID severity detection and classification.

The results presented in Table 2 indicate that experimental settings that include signals from almost all positions of the patient's body present the best results. However, this conclusion was anticipated since (as mentioned earlier) LID effects may be present to a single or to several parts of the patient's body. This also confirms that in our dataset the presence of LID effects to the patient's body is time varying i.e. the same patient may presents LID effects in different parts of his body for different time intervals. Thus, a method that is based on a selection that includes signals from several position of the patient's body (such as experimental settings 22 and 23) is expected to present the best results (compared to selections that include a limited number of recorded signals).

In this study, the classification technique that is selected is a decision tree based on the C4.5 algorithm. The results presented in Table 3 indicate that a selection of a more advanced technique, such as random forests, does not improve significantly the obtained results.

Acknowledgment

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