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A Comprehensive Motor Symptom Monitoring and Management System: The Bradykinesia Case

J. Cancela, M. Pansera, M.T. Arredondo, J.J. Estrada, M. Pastorino, L. Pastor-Sanz, J.L. Villalar

Abstract— **The current work describes a methodology to automatically detect the severity of bradykinesia in motor disease patients using wireless, wearable accelerometers. This methodology was tested with cross validation through a sample of 20 Parkinson's disease patients. The assessment of methodology was carried out through some daily living activities which were detected using an activity recognition algorithm. The Unified Parkinson's Disease Rating Scale (UPDRS) severity classification of the algorithm coincides between 70 and 86% from that of a trained neurologist depending on the classifier used. These severities were calculated for 5 second segments of the signal with 50% of overlap. A bradykinesia profiler is also presented in this work. This profiler removes the overlap of the segments and calculates the confidence of the resulting events. It also calculates average severity, duration and symmetry values for those events. The profiler has been tested with a bogus dataset. Future work includes better training for the severity classifier with a larger sample and testing the profiler with real, long-term patient data in a projected pilot phase in three European hospitals.**

I. INTRODUCTION

Bradykinesia can be defined as the slowed ability to start and continue movements and the impaired ability to adjust the body's position. It can be a symptom of neurological disorders, particularly Parkinson's Disease (PD) and the family of diseases known as Parkinsonisms. These diseases affect the activity of control exerted by neuron structures in the brain generally referred to as the basal ganglia [1].

The current work is related to a hardware and software platform that assesses the severity of the bradykinesia symptom in motor disease patients and condenses the information in a way that is easily analyzable and useful to the physician. The work is embedded in PERFORM, a R&D project of the Information and Communication Technologies (ICT) work programme of the European Commission. The design and construction of all the components used or presented in this work (i.e. data acquisition, bradykinesia severity assessment and bradykinesia behavior profiling) have been carried out within the PERFORM project [2].

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J. Cancela, M. Pansera, M.T. Arredondo, J.J. Estrada, M. Pastorino, L. Pastor-Sanz, J.L. Villalar are with Life Supporting Technologies, Technical University of Madrid (UPM), Madrid 28040, Spain (phone: +34915495700; author e-mails: jcancela@lst.tfo.upm.es, mpansera@lst.tfo.upm.es, mta@lst.tfo.upm.es, jjestrada@lst.tfo.upm.es, mpastorino@lst.tfo.upm.es, lpastor@lst.tfo.upm.es, jlvillal@lst.tfo.upm.es).

This paper describes the methodology used to assess the severity of Bradykinesia, the results of the performance tests of such methodology, the algorithm used to produce bradykinesia profiles (also referred to as the bradykinesia model) and the way in which these profiles are being tested.

II. STUDY DESCRIPTION

A. Subjects and measurement setup

The performance of the previously described bradykinesia severity assessment method was evaluated through several design phases. During the first design phase, data were collected on test patients in a supervised environment, with the collaboration of clinic's medical staff.

This methodology was tested with patients from the University Clinic of Navarra (Spain) and the Ioannina University Hospital (Greece). Each subject performed a supervised protocol both in On and Off states [1]. During each measurement, patients were evaluated using the Unified Parkinson's Disease Rating Scale (UPDRS) [3].

Patients involved in this phase were required to be aged between 18 and 85 years old, to be suffering from Parkinson's disease, who were ambulatory patients, to be capable of complying with study requirements, to be receiving stable dopaminergic treatment and to be experiencing motor fluctuations. Dementia, Psychosis (simple visual hallucinations excluded) and significant systemic diseases (such as cancer, hepatic or kidney dysfunction) were the exclusion criteria applied when selecting the participants. The dataset used in this study includes trials with twenty Parkinsonian patients, ten in the Navarra and ten in Ioannina, resulting in twenty full cross validations used to train the algorithm and test the method (see TABLE I and TABLE II).

TABLE I
PATIENTS SAMPLES IN OFF PHASE

	OFF				
UPDRS Score	0	1	2	3	4
Number of patients	3	8	5	8	2

TABLE II
PATIENTS SAMPLES IN ON PHASE

	ON				
UPDRS Score	0	1	2	3	4
Number of patients	10	19	1	0	0

In order to comply with ethical requirements, all procedures were carried out with the approval of the Clinic's and Hospital's Institutional Review Boards. Data were collected following a standard clinical protocol in which patients performed daily basic activities (i.e. walking, lying, sitting, drinking a glass of water, opening and closing a door) during two cycles of on-off oscillations in response to levodopa during the same day and under the supervision of a clinician. The reason is that Levodopa-based therapies are successful for some time, but most patients eventually develop motor complications including wearing-off, the abrupt loss of efficacy at the end of each dosing interval and dyskinesia [4].

B. *Sensors and material*

The data collection was performed with a network of wireless 3-axis accelerometers located on the limbs, trunk and belt of the patient. The accelerometers are easy to wear and can collect continuous data for up to an entire day. The devices used were ALA-6g (ANCO, Athens, Greece), Fig. 1. They work as acceleration sensor (node) in an IEEE 802.15.4 Star type beacon based wireless network.

Fig. 1. Accelerometer sensors used during the tests

III. ASSESSMENT METHODOLOGY

A. *Accelerometer signal analysis and classification*

Once the data have been stored in the base station, the processing begins. As described, the first intention is to determine the severity of bradykinesia. The steps to achieve this can be described as: 1) selecting the data that corresponds to activities of interest (e.g. walking and arm extension); 2) calculating the resultant vector from the data of each of the three axes; 3) filtering the resultant vector; 4) extracting features, and 5) classifying the features (Fig. 2). The calculation of the resultant vector was carried out using the standard Euclidean vector method. The filter used was a digital Band-Pass IIR Butterworth 4th order (1-3 Hz) filter to cut off continuous components [4].

The underlying idea is that the filtered signals contain only the low frequencies, useful to calculate the slowest movements of patients. As mentioned, filtered signals were analyzed after running an activity recognition algorithm designed to identify time frames when the patient was either walking or extending/flexing his arms [5]. Since bradykinesia is only evident when the patient moves, this step was crucial to avoid processing irrelevant information. The signal was then split in 5-second intervals, 50% overlap epochs, while the features used as input of the classification module were extracted from each of those epochs. Statistical features like Rms, entropy, Range of values and cross correlation have been already used to solve similar classification problems [4]. The features were used in 12 different combinations avoiding combinations that implied functional relations: rms (root mean square) + SampEn (sample entropy) + Range, rms + ApEn (approximate entropy) + Range, xcorr (cross-correlation) + SampEn + Range, xcorr + ApEn + range, rms + range, xcorr + range, rms + ApEn, rms + SampEn, xcorr + ApEn, xcorr + SampEn, range + ApEn and Range + SampEn. We excluded combination of rms + xcorr and ApEntropy + SampEn because of their functional relationships.

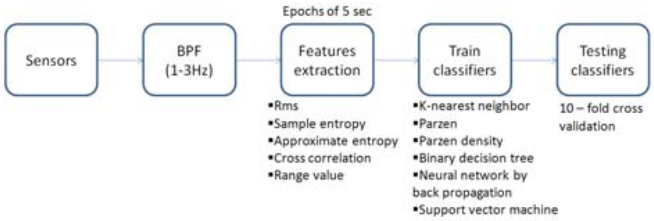

Fig. 2. Flow diagram used for the data processing

To classify the epochs, 6 classifiers were used: Knnc K-nearest neighbor classifier, ParzencParzen classifier, ParzendcParzen density based classifier, Treec Construct binary decision tree, Bpxnc Train neural network classifiers by Back-propagation and SVC support vector classifier. All the classification techniques used are characterized by high performances when using huge amount of data. However, as each classifier has different computational charge, all the techniques were tested to find the optimum solution in terms of accuracy and calculation time.

The implemented method gives, as output, the severity level of Bradykinesia symptom, according to the UDPRS, where 0 describes the absence of the symptom and 4 describes the highest possible value (Fig. 3 is a snapshot that serves as illustrating example of the classification results). This methodology has been translated to a C# library, and represents a part of the study of the symptoms of a PD patient.

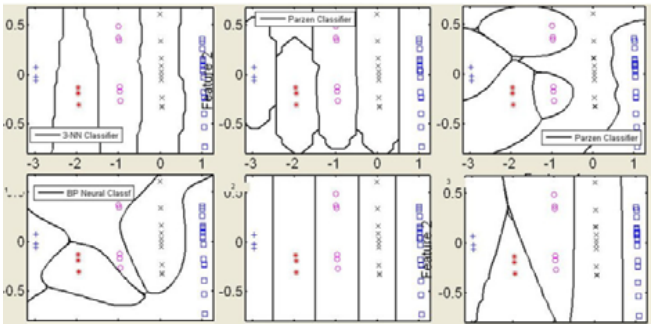

Fig. 3. Example of output to the classification of SampEn + RMS features according to different classifiers. Each symbol is related to one of the classes identified by the classifier. Every classifier uses its own technique to split the space and to classify providing different accuracies.

The software developed selects the best possible combination of sensors and statistical features, as shown in TABLE III. It allows relating the output provided by the accelerometers to the UPDRS values –used by clinicians to follow the progression of the disease– without the use of the standardized clinical tests. The C# library in mention also allows physicians to insert UPDRS values manually as new input to re-train the classifiers.

TABLE III
RESULTS OF THE BRADYKINESIA CLASSIFIER TEST

Sensors combination	Features	Classificator	Classification accuracy
	Walking		
4 + 1 trunk	rms+range	SVN	70.83%
4 + 1 belt	rms+range	SVN	75%
2 sensors arms	rms+range	SVN	70.83%
2 sensors legs	rms+range	SVN	70.83%
1 trunk	rms+range	SVN	70.83%
1 belt	rms+range	SVN	70.83%
	Hand Movements		
1 sensor	rms+range	SVN	86.48%

B. *Evaluation and profile generation*

Up to this point the model has achieved the assessment of the bradykinesia every 5 seconds (with a 50% overlapping) or, in other words, it has been sampled a signal of the severity of the symptom. In this step the goal is take this signal, study it and provide useful information for the clinical diagnosis automatically.

As a first step in the profile generation, the model removes noise from the symptom severity signal outputted by the classifier and fuses the epochs to generate events. After merging epochs into events, the model studies the statistics of each symptom signal and evaluates the bradykinesia symptom with respect to the On and Off status assessment, an assessment that is not covered in this work. This second part of the module studies all these events in order to find out useful information for the clinician, such as the average event duration, the average event severity and the asymmetry of the symptom.

TABLE IV
DATASET USED FOR THE BRADYKINESIA MODEL TEST

Section number	Type	DT Start	DT End	# of epochs
1	NO_DATA	00:00	10:00	null
2	DATA	10:00:00	10:21:13	2
3	DATA	10:21:13	10:21:18	5
4	DATA	10:21:18	10:21:23	1
5	DATA	10:21:23	11:03:29	2
6	DATA	11:03:29	13:08:34	4
7	NO_DATA	13:08:34	24:00	null

In order to test the event creation module, a set of bogus data were used to feed the algorithm and analyze the output it produces (TABLE IV). As intended, the bogus dataset has severity peaks (i.e. noise) that the module actually removes. The criterion followed to distinguish a peak from a short event is given by the clinician recommendations. For the case of bradykinesia, the clinically significant time length is seconds. That means sections in the signal of less than 15 seconds will be tagged as noise. Furthermore, the algorithm returns a list of the events detected, providing start and end times, severity and confidence.

Once the information from the repository is retrieved, the bradykinesia model determines the periods of the day where there are data to be processed. Consequently an algorithm scans all the epochs of the day and determines where there are epochs to be analyzed. Such algorithm classifies all the day in structures called “sections”, each section has a start time, an end time and a field that points out whether it is a section with data or without data. TABLE V shows the output for the bogus data used in the test.

TABLE V
OUTPUT OF SECTION DETECTION FOR THE TEST DATASET

Section number	Type	DT Start	DT End	Epochs id
1	NO_DATA	00:00	10:00	null
2	DATA	10:00	13:08:34	[0…4000]
3	NO_DATA	12:00	18:00	null

Before starting with the event creation, the data retrieved from the repository should be preprocessed. The reason for this preprocessing is to undo the overlapping of the epochs. A unique time-UPDRS value relation should be determined before the process continues. The overlapping scheme is shown in Fig. 4 when the percentage of overlapping differs from 50%, so as the algorithm will work with time slots of two different lengths.

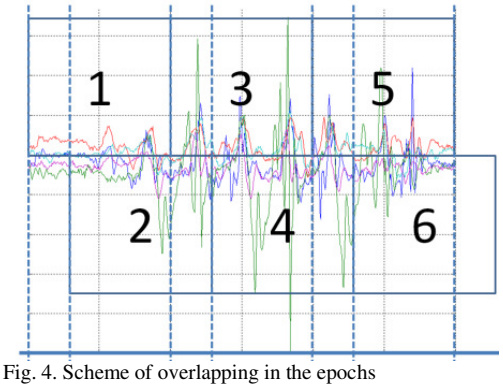

Fig. 4. Scheme of overlapping in the epochs

For each of these slots now there are two UPDRS values and two confidences, so there is a need to merge both values in one value of UPDRS and confidence.

$$P_i = \frac{\sum_{I=1}^{n} w_i x_i}{\sum_{i=1}^{n} w_i} \qquad (1)$$

Hence, given a certain timeslot, the information from two epochs can be merged using a weighted sum; the new value will take the information from the UPDRS and confidence values, according to the expression (1).

Then, it is searched the UPDRS value closest to the output, which is assigned to the current timeslot. Therefore this method uses the confidence of each value as the weight the value itself has in the output. Subsequently, a confidence value is assigned to that UPDRS value depending on the distance between the weighted sum result and the actual value assigned to the slot., e.g. if we have 1.65 as output of the weighted sum and the assigned value was 2 (the closest one), therefore the distance between our output and the final value is 0.35 which leads us to a confidence in result of 70% (the maximum distance is 0.5).

After undoing the overlapping, the event creation process is started. Up to this point each time slot has been analyzing individually and a UPDRS and a confidence values have been assigned depending on the values in the given time slot. The next step is to study the signal from a widened view. That involves that, given an epoch, their neighbors are studied to decide if the value assigned has sense in its environment. The aim of this step is to remove noise from the signal. The clinicians provided crucial clues on the bradykinesia symptom behavior and how much the symptom could change in an epoch length time (in about three seconds). In this case there are five seconds long epochs and an overlapping of 50%; hence time slots are of 2.5 seconds. Concluding that bradykinesia should not change from one time slot to the next, it could be also used the information of the neighbors to confirm that the value is correct and to fix some errors generated by the classifiers. Again the technique used is the weighted sum: the value of a given epoch will take into account the value of the following and previous epochs.

Next, in the event detection step, the main purpose is to identify contiguous epochs with the same value and with a clinically significant time length (that is 15 seconds for the case of bradykinesia according to the clinicians involved in the tests).

TABLE VI
LIST OF EVENTS AUTOMATICALLY GENERATED BY THE MODEL

Event #	Sev.	DT Start	DT End	Epoch id	Conf.
1	1	10:00	10:13:18	0-1010	99.12%
2	T	10:13:24	10:13:32	1011-1017	
3	4	10:13:32	13:08:34	1017-4000	100%

TABLE VI shows the list of events that comes out from the model following the described process using the above dataset. It can be seen that it removes all the peaks in the signal which are shorter than 15 seconds, conveniently detecting all the relevant events which are present in the signal.

Finally, after generating the events, the last step in the profiling process is the calculation of clinically relevant statistics for the physicians.

Up to now, the algorithm has been working with epochs which store a UPDRS consistent assessment. Nevertheless, the evaluation of the system is related to five seconds of the signal and, at this point, the aim of the model is to provide an estimation of the symptom for the whole day, relating the value to the On and Off status and for each body position separately (legs, arms, chest and belt).

Furthermore, the bradykinesia model will provide another parameter widely used in the assessment of the bradykinesia such as the asymmetry, that means the difference of the UPDRS value between the right and left side of the body and the top and bottom limbs.

IV. DISCUSSION

To the best of our knowledge, there are no other reports of quantifying bradykinesia severity without requiring standard motor tests. The novel method presented above, using unconstructed, daily life activities, may be causing the symptom severity accuracies within the range of 70%-86%. Future work in this part includes the collection of a larger data sample and the implementation of a meta-analysis to improve accuracy.

As for the bradykinesia profiling component of the system, the structure of the method so far is meaningful in that it allows physicians to monitor and detect changes in the symptomatic behavior as quickly as the changes appear. A remotely installed system, at the patient's home, with such capabilities could eventually redefine the paradigm of taking care of motor neurodegenerative disease patients, providing far more and richer information to be used by doctors at the time of making decisions or designing treatments.

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