Assessment of Tremor Activity in the Parkinson's Disease Using a Set of Wearable Sensors

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***Abstract*—Tremor is the most common motor disorder of Parkinson's disease (PD) and consequently its detection plays a crucial role in the management and treatment of PD patients. The current diagnosis procedure is based on subject-dependent clinical assessment, which has a difficulty in capturing subtle tremor features. In this paper, an automated method for both resting and action/postural tremor assessment is proposed using a set of accelerometers mounted on different patient's body segments. The estimation of tremor type (resting/action postural) and severity is based on features extracted from the acquired signals and hidden Markov models. The method is evaluated using data collected from 23 subjects (18 PD patients and 5 control subjects). The obtained results verified that the proposed method successfully: 1) quantifies tremor severity with 87% accuracy, 2) discriminates resting from postural tremor, and 3) discriminates tremor from other Parkinsonian motor symptoms during daily activities.**

***Index Terms*—Hidden Markov models (HMMs), Levodopa-induced dyskinesia (LID), Parkinson's disease (PD), posture recognition, tremor.**

I. Introduction

Tremor is defined as a rapid back-and-forth movement of a body segment [1]. It is one of the most common movement disorders encountered in clinical practice and is a readily apparent motor phenomenon in most instances. Tremors are classified either based on behavioral (rest, postural, and kinetic tremor) or etiological factors (physiological, enhanced physiological, essential, dystonia) [2]. Parkinson's disease (PD) tremor is mainly present at rest and tends to disappear during posture or movement [3]. In the later stages of the disease, however, rest tremor may remain present, in some patients, during hand posture or movement [4]. Resting tremor is a common symptom of PD and occurs in a body segment while this body segment is maintained at rest. Resting tremor typically ranges from 3.5 to 7.5 Hz [5]. The presence and severity of resting tremor can change during the day, and as such, detection, assessment, and followup of the changes of these signs during daily activities are of great interest [5]. Postural tremor occurs in body segments during the maintenance of a posture, such as holding a cup. It is triggered by maintaining a position against gravity and often causes a significant disability. The frequency of postural tremor is usually from 4 to 12 Hz [1]–[3]. Resting and postural tremors are very hard to distinguish, examining only their frequency print and thus, their discrimination prerequisites, the recognition of body position. There are several works which use body fixed sensors (BFS), such as accelerometers, to recognize posture or specific activities [6]–[10]. Most of these methods use signal features to classify body's position. A similar approach is used here to classify resting and posture state. Clinical tremor assessment is mainly based on subject-dependent methods such as clinical scales (Unified PD Rating Scale (UPDRS) [5], [11], Schwab and England Activities of Daily Living Scale, Hoehn and Yahr scale, and Webster scale) and assessment of hand-writing or drawing of an Archimedes spiral [5]. Although administered under clinician observations, these scales lack validation against actual tremor amplitude and the coarse resolution of the ratings is insufficient for assessing minute changes in tremor severity. Moreover, the extent of interclinician and intersubject rating variability is unknown [5], [11]. Several research groups have proposed objective methods to detect and quantify tremor [1], [5], [11]–[28]. More specifically, detection and quantification of tremor has been achieved by computational methods such as time-domain analysis [12], spectral analysis [13], time-frequency analysis [14], and nonlinear analysis [13]. Recently, there has been a growing interest in applications of body-BFS [15]–[17] and in particular kinematic sensors for long-term monitoring of PD patients [1], [18]. Several researchers have used accelerometers [15], [16], [18], [19], [25]–[28], gyroscopes [17], [25], electromyography (EMG) [1], handwriting and drawing samples [13], [20], actigraphy [21], electromagnetic tracking [22], [23], and a laser system for transducing velocity [24] to objectively detect and assess tremor activity. However, the aforementioned methods present several limitations such as:

1) mainly focus on tremor detection and not on tremor severity assessment [1], [12], [14]–[17], [21]–[24];
2) use simulated data [13];
3) mainly present qualitative results [19], [21];

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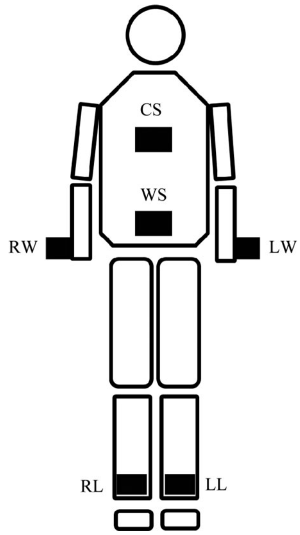

Fig. 1. Sensor placement on subjects body (RW: right wrist; LW: left wrist; WS: waist; and CS: chest).

4) since resting tremor is considered the typical parkinsonian symptom, most of these studies focus only on this tremor type, not differentiating between resting and action/posture tremor [1], [12], [15]–[17], [21], [24], [26];
5) have very narrow focus related to the PD motor symptoms, i.e., mainly focus on tremor detection and not in discrimination of tremor from other PD motor symptoms [1], [12], [14], [17], [21]–[24];
6) the employed data were collected from rather controlled environments and/or a limited number of conducted tasks is included [1], [12], [14]–[16], [23]–[25], [27].

Therefore, the application of those methods in real-life conditions might not be feasible.

In this study, a methodology for resting/action-posture tremor severity assessment in PD is presented. The methodology is based on the analysis of signals obtained from accelerometers attached to specific body segments. The sensors are placed at six different positions of the subjects body: right and left wrists (RW and LW), right and left legs (RL and LL), waist (WS), and chest (CS); the sensor placement on the subjects is shown in Fig. 1. In order to assess the tremor severity, several features are extracted from the recorded signals, related to time- and frequency-domain characteristics. The aim of this paper is to monitor patients in daily activities and robustly detect tremor in ubiquitous environment. Thus, it is crucial to be able to correctly discriminate common PD motor disabilities since misclassification of a different PD symptom (such as Levodopa-induced dyskinesia, LID) as tremor would lead to a false patient's assessment. To this end, features indicative of LF movements are also extracted, allowing the differentiation of tremor from other PD symptoms. Using a feature selection method, a subset of features is selected and incorporated into a hidden Markov model (HMM) for tremor severity recognition. For the discrimination of tremor type (resting/postural), spatial features were extracted based on the gravity force applied on each accelerometer axis and the angles between different body segments. Again, a subset of features is selected using a feature selection method, and these features are fed into a second HMM for body action/posture recognition. The information from the two HMMs is merged, resulting into a thorough tremor assessment addressing both its severity and type. In order to overcome the aforementioned limitations (differentiating between resting and action/posture tremor, narrow focus related to the PD motor symptoms), the proposed method is evaluated using 18 PD patients [10 PD with tremor and 8 with other motor symptoms such as bradykinesia, LID, Freezing of gate (FoG)] and 5 healthy control subjects. In the following section, the basic steps of the methodology are described. The dataset is described in Section III. The results of the method are presented in Section IV and are discussed in Section V. The conclusions of our work are given in Section VI.

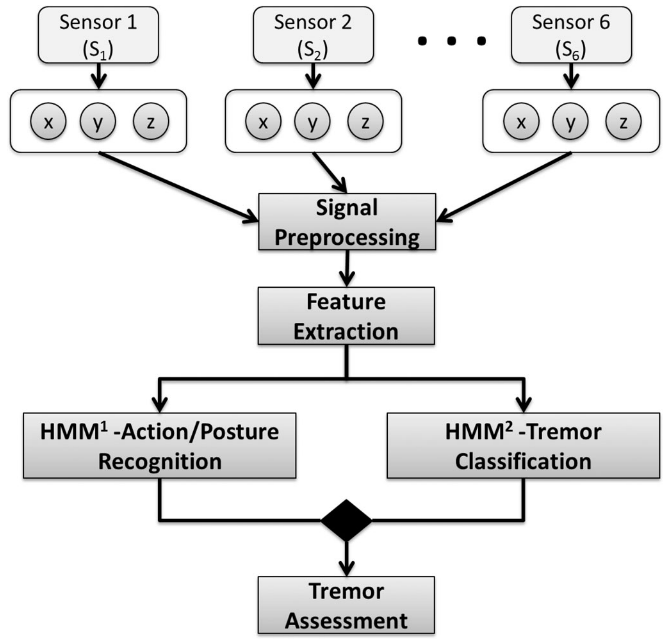

Fig. 2. Flowchart of the proposed method for tremor assessment.

II. Methodology

The proposed methodology consists of the following steps.

1) Signal preprocessing.
2) Feature extraction.
3) Body action/posture and tremor severity recognition.
4) Tremor assessment.

A flowchart of the methodology is presented in Fig. 2 and each step is described in detail in the following sections. In action/posture-HMM (HMM^1), five basic body action/postures are recognized:

1) rest in bed (*R-1*);
2) rest in chair (*R-2*);
3) standing up (*R-3*);
4) standing up with hands extended (*P*);
5) standing up with hands moving (*A*).

Postures 1–4 are illustrated in Fig. 3(a)–(d), respectively. The tremor-HMM recognizes four tremor severities (severity 0: *S-0;* severity 1: *S-1*; severity 2: *S-2*; and severity 3: *S-3*).

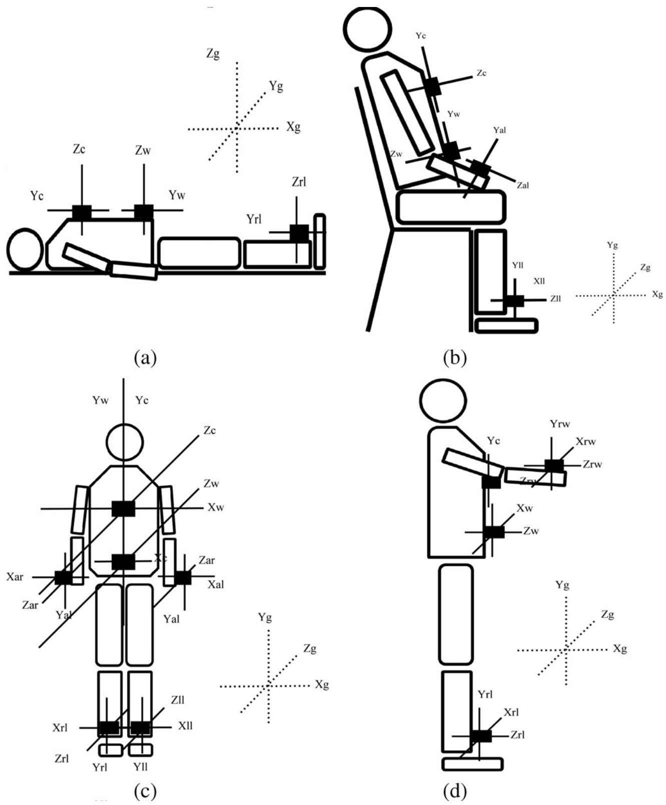

Fig. 3. Body postures recognized: (a) lying on bed, (b) sitting on chair, (c) standing up with hand in rest, and (d) standing with extended arms.

Tremor assessment is produced combining the outcomes of action/posture-HMM (HMM^1) and tremor-HMM (HMM^2).

A. Signal Preprocessing

The accelerometer signals consist of two main components: 1) the acceleration due to gravity force and 2) the acceleration due to body movements. The component corresponding to body movements can also be divided into the LF components, which usually correspond to intentional movements or in the case of PD patients involuntary movements due to other PD motor symptoms, and HF components, which mainly correspond to tremor activity. A low-pass finite-impulse-response (FIR) filter with cutoff frequency 3 Hz is used to extract the signal, which contains the gravity force components and the LF body movement component (s^L) . In addition, a band-pass FIR filter with frequencies from 3 to 12 Hz is used to extract the signal (s^H) corresponding to tremor-induced movements. This procedure is applied to each channel of the recordings.

B. Feature Extraction

Two feature sets are extracted from the filtered signals. The first one is used for body action/posture recognition and the second for tremor detection and quantification (see Table I). Feature extraction is based on a moving window technique using a 3 s duration window and 1.5 s overlapping.

TABLE I
FEATURES EXTRACTED FOR TREMOR ACTION/POSTURE RECOGNITION

Tremor Recognition		Action/Posture Recognition	
Feature	Code name	Feature	Code name
Dominant Freq.,	T1	LW∠X,Y,Z	P1,P7,P13
Energy on Dom. Freq.	T2	RW∠X,Y,Z	P2,P8,P14
High Freq. energy	T3	CH∠X,Y,Z	P3,P9,P15
Low Freq. energy	T4	WH∠X,Y,Z	P4,P10,P16
Spectrum Entropy	T5	LL∠X,Y,Z	P5,P11,P17
Mechanical energy	T6	RL∠X,Y,Z	P6,P12,P18
O.b.s.e.	T7	WH∠LL	P19
T3/(T3+T4)	T8	WH∠ RL	P20
T1*T2	T9	CH∠ LL	P21
		CH ∠RL	P22
		WH∠ LW	P23
		WH ∠RW	P24
		CH∠ LW	P25
		CH ∠RW	P26
		RL ∠RW	P27
		LL∠ LW	P28
		WH∠ CH	P29
		LF Energy LW	P30
		LF Energy RW	P31
		LF Energy LL	P32
		LF Energy RL	P33
		LF Energy CH	P34
		LF Energy WH	P35

O.b.s.e.: Other body segment energy.
∠ is the angle calculated between two sensors or a sensor and the *X*, *Y*, and *Z* axes.

1) Features Extracted for Action/Posture Recognition:

Two sets of features are extracted from the LF signal (s^L) of each sensor.

1) The angle between two sensors i and j, denoted as $\theta_{i,j}$, as well as the angle of a sensor i with X, Y, and Z reference axes denoted as $\theta_{i,X}$, $\theta_{i,Y}$ and $\theta_{i,Z}$, respectively, are given as follows:

$$\theta_{i,j} = a\cos\frac{G_i^T G_j}{\|G_i\|\|G_j\|} \tag{1}$$

$$\theta_{i,X} = a\cos\frac{G_i^T X}{\|G_i\|}, X = [1,0,0] \tag{2}$$

$$\theta_{i,Y} = a\cos\frac{G_i^T Y}{\|G_i\|}, Y = [0,1,0] \tag{3}$$

$$\theta_{i,Z} = a\cos\frac{G_i^T Z}{\|G_i\|}, Z = [0,0,1] \tag{4}$$

where G_i is the vector with the mean accelerations for all axes ($X, Y,$ and Z) of sensor i, defined as $G = \{G_x, G_y, G_z\}$ and calculated by:

$$G_r = \frac{1}{|W|}\sum_{i\in W} s_r^L(i), \qquad r = \{X,Y,Z\} \tag{5}$$

where $s_r^L(i)$ is the ith sample in the window W of the LF signal corresponding to the r axis of the sensor.

2) *LF energy:* The average acceleration energy of the three axes of the low-frequency signal of each sensor is calculated as follows:

$$E_L = \sum_{i\in W}\left((s_x^L)_i^2 + (s_y^L)_i^2 + (s_z^L)_i^2\right). \tag{6}$$

2) Features Extracted for Tremor Severity Classification: For tremor severity classification, two sets of features are extracted. In contrast to the action/posture recognition, where features are a combination of different sensor readings, the features extracted for tremor severity classification are extracted from each sensor separately since tremor can affect one or more body parts at the same time. The first set of features are used for the classification of tremor severity. Some of those features are presented in previous studies in the literature [15]–[17]. The second set is a set of features introduced in order to discriminate tremor from other motor symptoms. The features used for tremor severity classification are extracted mainly from the power spectrum of the signal corresponding to tremor-induced movements (s^H) of each sensor, where f is the frequency. The power spectrum is calculated using the fast Fourier transform. Initially, the dominant frequency f_D and the amplitude of the dominant frequency A_{f_D} are calculated as follows:

$$f_D = \arg\max P(f) \tag{7}$$

$$A_{f_D} = \max P(f). \tag{8}$$

Then, a feature analogous to the mechanical energy of the motion is calculated, the energy for a harmonic motion: $E_h = \frac{1}{2} m\omega^2 A^2$, where A is the amplitude of the motion and ω the frequency. For the accelerometer signals, we calculate the dominant frequency Ω from 4 to 12 Hz and the energy of the dominant frequency E_Ω, which is proportional to A^2. The feature extracted, analogous to E_h, is the product $(1/2)E_\Omega \cdot \Omega$. In the case of an harmonic motion, consisting of a sum of sinusoids, the energy is given as: $E'_h = (1/2)m\sum_i \omega_i^2 A_i^2$. The feature corresponding to the aforementioned energy, extracted also from the power spectrum of the signal is

$$\hat{E}'_h = \frac{1}{2} \sum_{f\in[4-12Hz]} fP(f). \tag{9}$$

In order to discriminate tremor, we selected a number of features that could differentiate a specific frequency motion (such as tremor), from more stochastic motions related to daily activities and other motor symptoms (i.e., LID). The initially set of examined features include:

1) Spectrum entropy. In the cases of a harmonic motion, a high energy concentration in specific frequency bands is expected. The spectrum entropy H is calculated from the spectrum $P(f)$:

$$H = -\sum_f p(f)\log p(f) \tag{10}$$

where $p(f) = \frac{P(f)}{\sum_f P(f)}$.

2) *LF and HF energy:* The average acceleration energy of the three axes of the LF signal of each sensor, as given in (6), and HF signal of each sensor, is calculated as follows:

$$E_H = \sum_{i\in W} \left((s_x^H)_i^2 + (s_y^H)_i^2 + (s_z^H)_i^2\right). \tag{11}$$

3) *Ratio of high to total energy:* During subjects actions, such as walking and hand movements, there is energy in both the LF and HF bands of the signal, while during tremor, there is energy mainly in the HF bands. The ratio of high to total energy is calculated as follows:

$$R = \frac{E_H}{E_H + E_L + \epsilon} \tag{12}$$

where ϵ is a small positive constant in order to avoid division by zero. This ratio is expected to be high during tremor and rather low during other activities.

4) *Other body segment energy:* In order to discriminate segments of body movement, such as walking, LID, and bradykinesia motor symptoms, we employ the average LF energy of other body segments (legs, waist, and chest) of the subject.

C. Body Action/Posture and Tremor Severity Classification

Tremor presents time dependency; thus, a dynamic model such as HMM is suitable for exploiting tremors behavior. The states that are included in an HMM are not directly visible, while the output of the model, which depends on the included states, is visible. The parameters of an HMM model are as follows.

1) Prior probability of the states $P^0(S_i)$, where S_i is the ith state.
2) State transition matrix $P(S_i^{t+1}|S_j^t)$, given the probability that we are in state S_j at time t, to transit to state S_i at time $t+1$. The state transition matrix is considered constant and independent of t .
3) The parameters of output distribution for each state. The output distribution is considered as a multivariate Gaussian distribution for each state $P(x|S_i) \propto N(x;\mu_i,\Sigma_i)$, where μ_i is the mean of observation under the i state and Σ_i the covariance [29].

The training process of HMM with L states $\mathbf{S} = \{S_1, S_2, \ldots, S_L\}$ and M gaussian observations involves the identification of the prior probability of the states $P^0(S_i)$, the state transition matrix $P(S_i^{t+1}|S_j^t)$, and the Gaussian parameters of the features for each state $\{\{\mu_1,\Sigma_1\},\{\mu_2,\Sigma_2\},\ldots,\{\mu_1,\Sigma_1\}\}\}$. In the case of diagonal covariance matrices, the resulting HMM model can be considered as a time-dependent extension of the Naive Bayes classifier. We first introduce the function $\Delta_s(i)$, which is defined as follows:

$$\Delta_s(i) = \begin{cases} 1, & \text{if sample } i \text{ belongs to the } s \text{ state} \\ 0, & \text{otherwise.} \end{cases} \tag{13}$$

In our experiment, we consider a uniform prior distribution on the states. For the rest parameters, the *maximum likelihood* parameters of the HMM are given by:

$$P(S_i^{t+1}|S_j^t) = \frac{(1/N-1)\sum_{k=1}^{N-1}\Delta_i(k)\Delta_j(k+1)}{\frac{1}{N}\sum_{k=1}^{N}\Delta_j(k)} \tag{14}$$

$$\mu_i = \frac{1}{N}\sum_{k=1}^{N}\Delta_i(k)\mathbf{x_k} \tag{15}$$

$$\Sigma_i = D\left[\frac{\sum_{k=1}^{N}\Delta_i(k)(\mathbf{x_k}-\mu_i)(\mathbf{x_k}-\mu_i)^T}{\sum_{k=1}^{N}\Delta_i(k)\mathbf{x_k}}\right] \tag{16}$$

where $D[\bullet]$ is an operator, which preserves the diagonal elements of a matrix and sets the off-diagonal elements equal to zero.

After training the HMM using a training dataset, the most probable state for a new sequence of observation is given by the forward–backward algorithm [30], [31]. Two HMMs were used, one for action/posture and one for tremor severity classification. The action/posture-HMM (HMM^1) has five states: *R-1*, *R-2*, *R-3*, *P* [stand with extended arm(s)], and *A* (arm(s) movement). The first three states of posture-HMM (*R-1*, *R-2,* and *R-3*) correspond to resting positions, are therefore, after estimating each state probability, the three states are merged into one (resting *R*). The same applies to the final two stages (*A* and *P*) that correspond to arm(s) posture positions and activities, which are merged into one (action/posture: AP)

$$p(R) = p(R-1) + p(R-2) + p(R-3) \tag{17}$$

$$p(AP) = p(P) + p(A). \tag{18}$$

The second HMM (tremor severity HMM—HMM^2) has also five states corresponding to the four tremor severities: *S-0*, *S-1*, *S-2*, *S-3*, plus the *other* state, related to segments with intentional body movements (normal) or involuntary motor symptoms (LID). This is an artificial class used to construct a more robust classifier. Both *S-0* and *other* states correspond to non-tremor; however, they present significant differences in the feature distribution and thus treating those states as a unique one might cause confusion for the classifier. Thus, they are initially considered as different states and once the probability of each class is estimated, the results of the two states are merged.

The final tremor assessment consists of 8 states, i.e., the combinations of the four (4) tremor severities (*S-0* and *other*, *S-1*, *S-2*, *S-3*) and the two (2) tremor types (R, P). The probability of the combined state is given as:

$$\begin{aligned} &P(\text{action/posture} = i \text{ and severity} = j) \\ &\quad = P_{HMM^1}(\text{action/posture} = i) \\ &\qquad \times P_{HMM^2}(\text{severity} = j). \end{aligned} \tag{19}$$

The aforementioned holds since we can consider body action/posture and tremor mutually independent.

III. Dataset

The proposed methodology is based on a set of sensors [32], each one consisting of three orthogonal accelerometers. The sensor placement on subject's body is depicted in Fig. 1. The sensors size is $49 \times 35 \times 10$ mm^3. The sensors on the arms and legs are attached on specially designed elastic bands, which allow fixation to any wrist or ankle size. The sensors in the chest/waist are attached to a specifically designed t-shirt. Each sensor's accelerometer records a signal corresponding to a specific axis (*x*, *y,* and *z*). Thus, each sensor records 3 signals (one for each axis) and the recording includes in total 18 channels. All sensors transmit wirelessly data using the ZigBee protocol to a portable PC, with sampling rate 62.5 Hz. Synchronization of the signals transmitted from the sensors is performed from the transition protocol. Transmition range is 20 m. Twenty three subjects are enrolled in this study and they are divided into three groups.

1) Group I: 10 PD patients with tremor symptom (resting and/or action-postural).
2) Group II: 8 PD patients not presenting tremor symptom, but other PD symptoms (LID, bradykinesia, and FoG).
3) Group III: 5 healthy individuals served as control subjects.

Groups I and II are patients of the neurology clinic of the University Hospital of Ioannina, diagnosed with idiopathic PD; the medical ethical committee of the hospital approved this study. PD patients with tremor symptom (group I) are aged 56–72 years old, 63.9 ± 6.2 years, having 2–17 years since diagnosis, 2–14 years of Levodopa intake, and 1–4 Hoehn and Yahr stage. They present tremor with various severities, ranging from 0 (no tremor) to 3 (moderate tremor), according to the UPDRS scale [33]. In Fig. 4, the total number of recorded minutes for each tremor severity is shown. The patients of the second group (group II) suffered from several PD motor symptoms (LID, bradykinesia, and FoG) and they did not present the tremor symptom. They are aged 57–71 years old, 64.9 ± 5 years, having 9–35 years since diagnosis, 8–34 years of Levodopa intake, and 1–4 Hoehn and Yahr stage. The healthy subjects (group III) did not have any neurological disease or medical condition associated with tremor and they are used as control group.

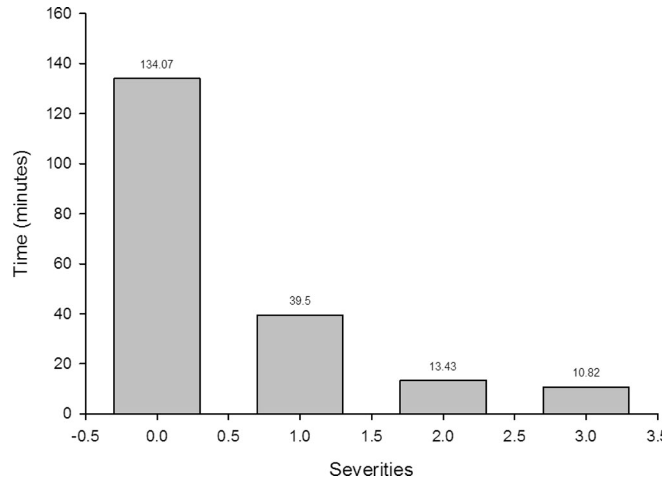

Fig. 4. Total number of minutes for each tremor severity in the dataset, according to experts' annotation.

All subjects follow a specific recording protocol, which includes the following activities:

1) sitting on a chair with the hands resting in their lap;
2) lying on the bed;
3) holding the upper limbs outstretched with the hands in supination, parallel to the floor;
4) walking in the hospital corridor (approximately 10 m) freely, without any help;
5) picking up and holding an object;
6) finger to nose (movements of one upper limb with the hand first resting on the thigh and then touching the nose with the index);

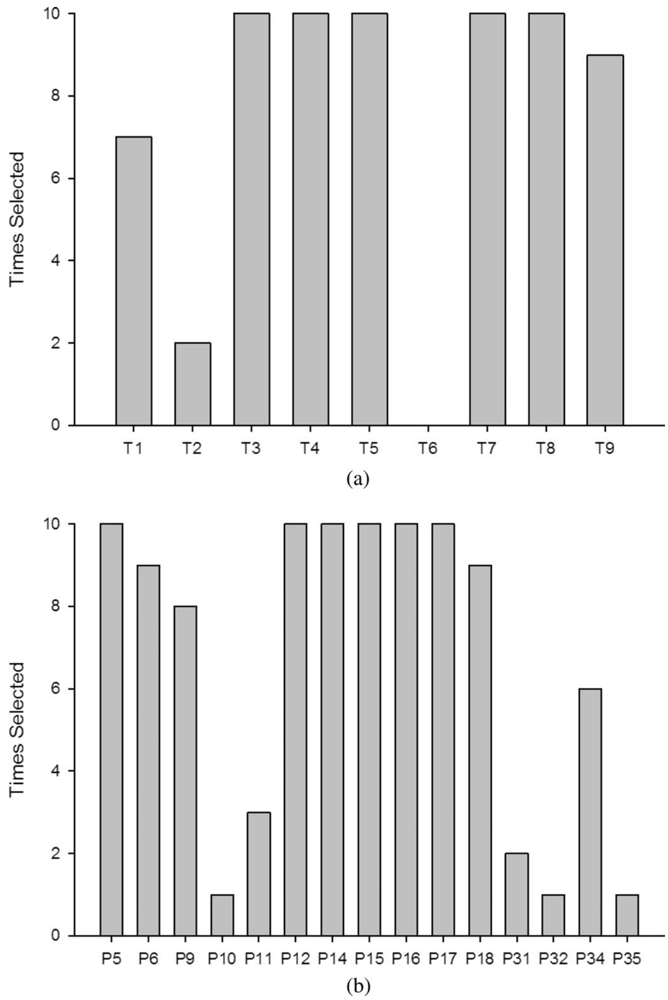

Fig. 5. Number of each feature was selected using the 10-fold cross validation *Wrapper* method for: (a) action/posture and (b) tremor severity classification.

TABLE II
CORRELATION (CORRELATION COEFFICIENT ABSOLUTE VALUE) BETWEEN (T1–T9) FEATURES (DEFINED IN TABLE I)

	T2	T3	T4	T5	T6	T7	T8	T9	S.
T1	0.29	0.23	0.24	0.33	0.13	0.18	0.29	0.20	0.21
T2		0.98	0.35	0.50	0.85	0.17	0.70	0.98	0.53
T3			0 34	0.48	0.87	0.15	0.72	0.99	0.54
T4				0.04	0.21	0.62	0.36	0.39	0.55
T5					0.32	0.01	0.57	0.45	0.26
T6						0.06	0.44	0.87	0.34
T7							0.20	0.18	0.51
T8								0.72	0.63
T9									0.56

S.: severity.

7) finger to finger (touching the examiner's finger, which is moved and stopped in different locations in space);
8) standing up with the hands resting.

The order and duration of each one of the activities is not strict; several subjects changed the order of activities or repeated some of them, whereas in several cases, they prolonged or shortened the predefined duration of the activity. In addition, the subjects are instructed to freely make voluntary movements or talk. Consequently, several activities such as putting on sleepers before walking, relocating objects, avoiding obstacles, etc., are present in the recordings. In the case of the patients' groups, UPDRS scores were obtained just before the patient started performing the predefined tasks. Two experts separately annotated each recording related to tremor epochs and severity via inspection of the video recordings obtained during the data collection procedure. In cases of disagreement, the final annotation is reached after consensus.

TABLE III
CONFUSION MATRIX OF ACTION/POSTURE RECOGNITION HMM WITH LEAVE ONE PATIENT OUT

	Classified as						
Class	*R-1*	*R-2*	*R-3*	*P*	*A*	Sens.	Spec.
R-1	15346 (0.95)	332 (0.02)	0 (0.00)	104 (0.01)	384 (0.02)	0.95	0.98
R-2	394 (0.02)	13626 (0.63)	0 (0.00)	3914 (0.18)	3588 (0.17)	0.64	0.69
R-3	0 (0.00)	38 (0.02)	1460 (0.78)	8 (0.00)	362 (0.19)	0.78	1
P	0 (0.00)	264 (0.14)	0 (0.00)	1544 (0.79)	136 (0.07)	0.79	0.79
A	0 (0.00)	372 (0.10)	0 (0.00)	66 (0.02)	3110 (0.88)	0.88	0.66
Acc			**0.81**				

Acc: accuracy; Sens: sensitivity; Spec: specificity.

TABLE IV
ORIGINAL AND AVERAGE NORMALIZED (AVERAGE PER PATIENT STANDARD DEVIATIONS LARGER THAN >0.05 ARE ALSO PROVIDED) CONFUSION MATRIX OF THE HMM TREMOR CLASSIFICATION WITH LEAVE ONE PATIENT OUT

	Classified as					
Class	*S-0*	*S-1*	*S-2*	*S-3*	Sens.	Spec.
S-0	33362 (0.89)	3046 (0.10)	224 (0.01)	23 (0.00)	0.91	0.94
S-1	72 (0.03)	1988 (0.84)	229 (0.13)	0 (0.02)	0.87	0.82
S-2	14 (0.03)	72 (0.18/0.11)	464 (0.71/0.11)	126 (0.09)	0.69	0.79
S-3	5 (0.00)	4 (0.00)	43 (0.14)	539 (0.86)	0.91	0.83
Acc		**0.87**				

Specificity, sensitivity per class, as well as total accuracy are also provided.
Acc: accuracy; Sens: sensitivity; Spec: specificity.

IV. RESULTS

In the following paragraphs, the results of the proposed methodology are presented. First, from the initial set of features extracted, applying a feature selection method, a subset providing the highest accuracy is extracted. Then, using the selected features, the two HMMs (HMM^1 for action/posture recognition and HMM^2 for tremor severity classification) are evaluated separately. Finally, the results of the combined HMMs, providing the overall tremor assessment, are presented.

A. Feature Selection

For feature selection, a method that takes into account the classifier (*Wrapper* method [34]) is selected, which makes use of the *best-first* search algorithm [35]. The basic criterion used in the specific feature selection algorithm is the increase of classification accuracy. For a more robust feature evaluation, the 10-fold stratified cross-validation procedure is employed.

TABLE V
NORMALIZED CONFUSION MATRIX OF THE TREMOR ASSESSMENT

	Classified as									
Class	$R-S-0$	$R-S-1$	$R-S-2$	$R-S-3$	$P-S-0$	$P-S-1$	$P-S-2$	$P-S-3$	Sens.	Spec.
$R-S-0$	0.94	0.05	0.00	0.00	0.01	0.00	0.00	0.00	0.94	0.97
$R-S-1$	0.03	0.9	0.07	0.00	0.00	0.00	0.00	0.00	0.90	0.52
$R-S-2$	0.00	0.16	0.71	0.11	0.00	0.00	0.02	0.00	0.71	0.81
$R-S-3$	0.00	0.01	0.10	0.85	0.01	0.00	0.00	0.03	0.85	0.88
$P-S-0$	0.00	0.00	0.00	0.00	0.82	0.18	0.00	0.00	0.82	0.81
$P-S-1$	0.00	0.63	0.00	0.00	0.03	0.32	0.02	0.00	0.32	0.55
$P-S-2$	0.00	0.00	0.00	0.00	0.14	0.07	0.67	0.12	0.67	0.70
$P-S-3$	0.00	0.00	0.00	0.00	0.00	0.00	0.24	0.76	0.76	0.83
Acc.	**0.74**									

Acc: accuracy; Sens: sensitivity; spec: specificity.

Wrapper is performed using the Naive Bayes classifier, which can be considered as a single time-step HMM with Gaussian observations. In order to remove possible bias in feature selection, we applied the aforementioned procedure on a balanced dataset (equally sampled classed). This dataset was obtained after resampling original dataset (from all three subject groups). In Fig. 5(a), we present the outcome of the *Wrapper* method in terms of the action/posture recognition features. Features, which are selected more than five times (out of 10) by the method, are incorporated in the action/posture HMM. In Table II, the correlation between the extracted features and the correlation of the features with the class are presented. The correlations between features and severities presented in Table II are indicative of the features selected by the Wrapper feature selection method, which are presented in Fig. 5(b). The least selected features are the dominant frequency (T2) and the mechanic energy (T6); these two features are not included in the tremor-HMM.

B. Action/Posture Recognition

For action/posture classification, the leave-one-patient-out cross-validation technique was employed. In Table III, we present the results of action/posture classification, including the normalized confusion matrix, sensitivity and specificity per class, as well as the overall accuracy. *R-1* class (rest in bed) is very accurately detected, while *R-2* class (rest in chair) has lower accuracy, mainly due to misclassifications of this position with *P* class (extended arms) and *A* class (arm movement). This is expected since in *R-2* state (rest in chair), subjects were free to move their hands.

C. Tremor Severity Classification

For tremor severity classification, the leave-one-patient-out cross-validation technique was employed. Table IV presents the results of the tremor severity classification HMM model, including the confusion matrix, sensitivity, and specificity per class, as well as the overall accuracy; *other* and *S-0* classes are merged. Furthermore, for each patient, we calculated a separate normalized confusion matrix, and the average and standard deviation of all individual confusion matrices is presented also in Table IV in brackets. With gray are marked the misclassifications in neighbor severities.

TABLE VI
OUTPUT OF THE HMM FOR TREMOR CLASSIFICATION FOR THE SECOND GROUP (GROUP II) IF PATIENTS WITH NO TREMOR SYMPTOM

	Classified as			
Symptom	*S-0* & Other	*S-1*	*S-2*	*S-3*
Normal	24793	1460	0	0
LID	2652	10	0	0
Bradykinesia	186	26	0	0
FoG	3727	39	0	0
Specificity	–	0.95	1	1

D. Overall Tremor Assessment

The results for tremor assessment are presented in Table V. The results are obtained using the leave-one-patient-out cross-validation technique and correspond to the overall method's ability to correctly discriminate resting from postural tremor as well as to recognize tremor's severity. Results are presented for resting (*R*) and action/posture (*AP*) while *other* and *S-0* classes are merged. In addition, we evaluated the methodology's ability to discriminate tremor from other symptoms (LID, bradykinesia, and FoG). This was performed using the second group (group II) of patients, which includes all other common motor PD symptoms but not tremor, and the results are presented in Table VI. In Table VI, the specificity of tremor recognition is given with respect to normal, LID, bradykinesia, and FoG. The proposed method presents high specificity for tremor with *S-1*(95%) and discriminates perfectly tremor with *S-2* and *S-3* from other activities (100%).

V. DISCUSSION

In this paper, we propose a method for the assessment of tremor activity in PD. The method is based on the analysis of the signals recorded from accelerometers, which are placed on certain positions of the subjects' body. The obtained signals are analysed and several features are extracted. Based on these features, HMMs are implemented to detect if tremor symptoms are present and classify them according to their type (resting/postural) and severity. The advantage of the HMM lies in the incorporation of the time-dependent nature of the symptom, which increases the classification accuracy. The method has been evaluated using recordings from 23 subjects including patients that presented tremor of different severities, PD patients presenting other motor symptoms, as well as healthy individuals.

TABLE VII
RESULTS OF TREMOR RECOGNITION METHODS PRESENTED IN THE LITERATURE AND COMPARISON WITH OUR METHOD

Author (s)	Dataset Materials	Validation metrics	Results
Van Someren *et al.* [21]	8 PD patients & 10 controls	False positive error rate	4%
Hoff *et al.* [19]	7 PD patients/59 PD patients 43 controls	Sensitivity & Specificity Tremor-clinical score correlation	82% & 93%/ Spearman's rank correlation 0.66–0.77
Salarian *et al.* [17]	10 PD patients & 10 controls	Sensitivity & Specificity	99.5% & 94.2%
Patel *et al.* [16]	12 PD patients	Estimation error	2.5%
Zwartjes *et al.* [25]	6 PD patients &7 controls	Accuracy	84.5% & 94.1% Resting Tremor during Sitting &Standing (arm) 79.1% & 90.1% Resting Tremor during Sitting & Standing (thigh) 78.7% & 81.7% Kinetic Tremor during Sitting & Standing (arm)
This work	10 PD patients & 8 PD patients (no tremor) & 5 controls	Accuracy Sensitivity & Specificity	0.87 0.97 & 0.95 (*S-0*) 0.92 & 0.87 (*S-1*) 0.86 & 0.77 (*S-2*) 0.77 & 0.95 (*S-3*)

The obtained results indicate that the proposed method is highly efficient for tremor assessment.

Some of the features described in Section II-B may contain overlapping information or carry low information related to tremor-induced movements. In order to provide a robust classifier and avoid overfitting, a feature selection technique was necessary. In Table II, is it observed that the dominant frequency energy (T2) is rather correlated with the energy of the signal, which is expected in harmonic signals, such as those induced by tremor. Both features are also correlated with the estimation of mechanical energy of the motion as well as the LF energy. This is also the reason why energy on dominant frequency (T2) is excluded from the final feature set. Also, all HF-energy-related features have significant correlation with tremor severity. The features selected for action/posture recognition are mainly features corresponding to the characteristics angles of the body segment during each posture.

The tremor classification results indicate that most of the misclassifications occur to neighbored classes (see Table IV). In discrimination of *S-1* and *S-2* is also noticed the larger standard deviation of the per patient normalized confusion matrices. However, discriminating adjacent tremor severities is considered a difficult task even by experts [2], [11]. In our dataset, almost all annotation disagreements between the two experts are differences of one severity level, while experts' disagreements occurred almost in the 10% of the total instances. If misclassifications by just one severity level were ignored, the overall error rate would be less than 1%. The proposed method presents high accuracy in tremor severity classification (see Table V). In patients with other motor symptoms, the method presents very good specificity since it does not confuse tremor with other forms of dyskinesias such as LID and bradykinesia (see Table VI). Thus, this method could be the basis for reliable daily and long-term monitoring of PD patient's tremor activity.

A thorough assessment of tremor symptom could have direct clinical implications for the diagnosis and therapeutic management of PD. In early stages of PD, the tremor may be very mild and intermittently present, making diagnosis difficult if one relies on the short office visit. Having a method that can detect reliably the existence of the typical Parkinsonian tremor may help the early diagnosis of the disorder. In addition, such a method can also be helpful in the assessment in the evolution of the disease.

A comparison between our method and the results reported by other studies is difficult. The reason behind this is that these studies consider different number of subjects and make use of nonstandard and different databases, some of them not available publicly. Although a direct comparison is not feasible, in Table VII, we present a comparison of methods reported in the literature. Interestingly, from the results column of this Table VII, a clinician can easily understand the superiority of our method in tremor recognition, compared with the existing literature methods The majority of classification methods are simply detecting tremor and do not discriminate between tremor severities in different types of tremor.

VI. CONCLUSION

In this paper, an automated method for tremor assessment was presented. The method is based on features extracted from accelerometers mounted in different body segments, which are used as observations in two running parallel HMM models. The first one is used to quantify tremor severity and the second one to recognize body posture and action. Combining the output of the two models, a complete assessment of tremor activity is produced. The method was evaluated in 23 subjects and the results indicated high accuracy in tremor quantification as well as high specificity in tremor detection against other motor symptoms such as bradykinesia and LID. The proposed methodology is a step closer to the goal of a robust system, suitable for daily long-term monitoring of PD patients with tremor symptom, which can further assist in PD management and treatment.

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