

Quantification of Parkinson Tremor Intensity Based On EMG Signal Analysis Using Fast Orthogonal Search Algorithm

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Abstract: The tremor injury is one of the common symptoms of Parkinson's disease. The patients suffering from Parkinson's disease have difficulty in controlling their movements owing to tremor. The intensity of the disease can be determined through specifying the range of intensity values of involuntary tremor in Parkinson patients. The level of disease in patients is determined through an empirical range of 0-5. In the early stages of Parkinson, resting tremor can be very mild and intermittent. So, diagnosing the levels of disease is difficult but important since it has only medication therapy. The aim of this study is to quantify the intensity of tremor by the analysis of electromyogram signal. The solution proposed in this paper is to employ a polynomial function model to estimate the Unified Parkinson's Disease Rating Scale (UPDRS) value. The algorithm of Fast Orthogonal Search (FOS), which is based on identification of orthogonal basic functions, was utilized for model identification. In fact, some linear and nonlinear features extracted from wrist surface electromyogram signal were considered as the input of the model identified by FOS, and the model output was the UPDRS value. In this research, the proposed model was designed based on two different structures which have been called the single structure and parallel structure. The efficiency of designed models with different structures was evaluated. The evaluation results using K-fold cross validation approach showed that the proposed model with a parallel structure could determine the tremor severity of the Parkinson's disease with accuracy of 99.25% \pm 0.41, sensitivity of 97.17% \pm 1.9 and specificity of 99.72% \pm 0.18.

Keywords: Fast Orthogonal Search, Orthogonal Basic Functions, Parkinson, Tremor Intensity.

1 Introduction

PARKINSON'S disease (PD) is a degenerative disorder of the central nervous system which mainly affects the motor system. The motor symptoms of Parkinson's disease result from the death of dopamine-generating cells in the substantia nigra-a region of the midbrain [1]. The cause of this cellular death is less

known. Early symptoms of the Parkinson's disease are movement-related symptoms such as shaking (tremor), rigidity, slowness of movement (bradykinesia), and postural instability [2]. Parkinson's disease is more common in the people older than 50 years. The anti-Parkinsonian medications such as L-DOPA and dopamine agonists, are usually useful in the early stages of the diseases. Diet and some kinds of rehabilitation have been effective to some extent. Surgery and deep brain stimulation have been used to reduce motor symptoms as a last resort in severe cases where drugs fail to affect. In other words, determining the types and doses of medications and adopting the effective rehabilitative strategy depend on the severity level of the Parkinson's disease. Thus, it is essential to specify the exact level of severity of the disease in the patients. The severity of Parkinson's disease is determined according to tremor intensity [2]. Tremor or muscle

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shaking in Parkinson's disease occurs at rest position [2]. In practice, the level of disease is determined in a range of zero to five, called Unified Parkinson's Disease Rating Scale (UPDRS). The classification of patients in this range is based on neurologist advice. In the early stages of Parkinson's disease, resting tremor can be very mild and intermittent. The diagnosis of patients with low levels of the disease is erroneous. In other words, putting the patient in a correct division is problematic.

In some researches, measurement and analysis of the tremor signal using the kinematic data and electromyography has been studied [3,4]. The previous studies have shown that there is a significant relationship between the amplitude of estimated tremor and UPDRS in Parkinson's patients [5]. Also it has been proved that there is a high correlation between the features extracted from the EMG signal and UPDRS value. Such quantitative characteristics have been introduced as indices for tremor estimation and quantification [6-9]. In another study, a multiple linear regression model has been used to quantify tremor severity [10]. It has been shown that the logarithm of the peak in the power spectrum in the tremor is strongly correlated with averaged clinician scores [10]. In the most of the studied papers, no scaling was considered for quantification of Parkinson's disease (tremor intensity) and they have focused on specifying the quantities which are strongly correlated with the UPDRS index of patients [4-11]. In other cases, multiple linear regression models have been mentioned. While there is a highly nonlinear behavior relationship between the index of UPDRS and EMG signal characteristics.

The aim of this study is to provide a mechanism to determine tremor intensity based on analysis of electromyogram signal automatically, with high accuracy, and no need for the physician presence.

2 Methods and Materials

2.1 Proposed Strategy for Quantification

According to this strategy, the determination of the tremor intensity was fulfilled by a modeling technique. The main idea presented in this study is to apply a model based on orthogonal basic functions. The Fast Orthogonal Search is a time-domain method for identifying of nonlinear systems [12]. The basic purpose of this method is to minimize the mean square of the estimation error by selecting the best orthogonal basis functions [13]. The block diagram of the proposed quantification method has been shown in Fig. 1. The first stage is to record electromyogram signal and the next stage is the feature extraction. In the proposed strategy, some linear and nonlinear extracted features are entered into the model, which is identified using FOS algorithm, and the model output determines the severity of tremor by assigning a number between 0-5.

Finally, the model output was compared to the desired output to specify the accuracy of the proposed quantification method. The desired model output which is each patient's UPDRS value was determined accurately by the corresponding neurologist.

In fact, the purpose is to use the proposed model instead of a classifier which can distinguish the different levels of the tremor intensity. In general, the proposed model describes the relationship between tremor intensity and extracted features from EMG signals. The proposed model was designed based on two different structures which have been called the single structure and parallel structure.

2.1.1 Single Structure Model

In this structure, a single model was identified in order to determine all levels of tremor severity. In this situation, the extracted features from electromyogram signals were entered into the model, and the model output should estimate and classify them into six different levels (0-5). In fact, a single model should be trained in order to differentiate all six levels of tremor. Fig. 2 shows a block diagram of a single structure model.

2.1.2 Parallel Structure Model

In this structure, six models identified by FOS were used in parallel forms. In this manner, a specific FOS-based model was assigned for each level of tremor. In other words, each model was identified by the feature vectors extracted from the patient's recorded EMG signals. For an example, model 1 was recognized and formed upon specifications and feature vectors of signals related to level one. Block diagram of a parallel structure is shown in Fig. 3. In this structure, each model has been assigned to estimate a specific intensity level. Therefore, six models were envisioned for estimation of six tremor intensity levels. The same feature vector was the input of six models. In the parallel structure, the possible outputs of the models were 1 or -1. Each model whose output is 1 determines the level of tremor. It means that the number of that model (0,1,...) is considered as the estimated level of tremor.

2.2 Data Collection

The first step in quantifying the tremor intensity was recording electromyogram signal according to a specific protocol. The number of twelve patients with PD (4 females, 8 males) participated voluntarily in this study. This study was approved by the Human Ethics committees of Islamic Azad University of Mashhad. Those PD patients who suffering from other diseases which might interfere with motor functions were excluded from the study. They were examined and

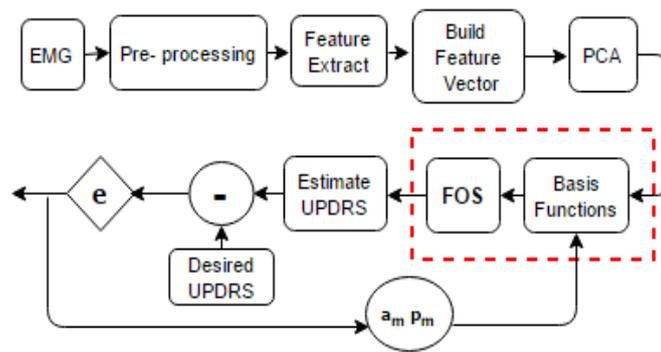


Fig. 1 The block diagram of the proposed tremor intensity quantification method.

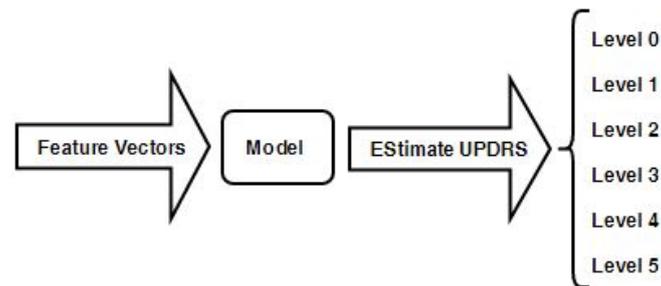


Fig. 2 Block diagram of the model based on single structure.

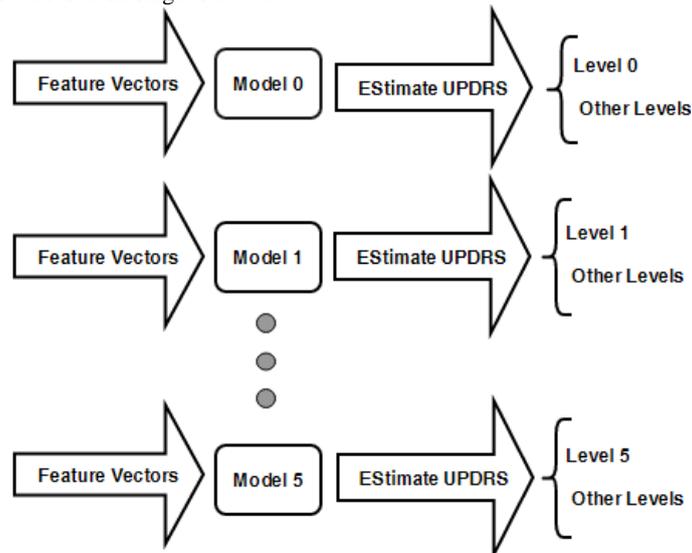


Fig. 3 Block diagram of the model based on parallel structure.

confirmed by a neurologist and the disease intensity was determined precisely between 0-5. The evaluation of PD symptoms was done according to standardized rating scales such as the UPDRS. Patient's information is shown in table 1. It should be noted that due to some clinical limitations, no PD patients with the UPDRS of four was visited during the research.

The protocol of recording was devised according to SENIAM protocol and a neurologist's opinion. Electromyogram signal was recorded from two muscular groups of hand. The position of the muscles is shown in Figure 4. The channel A is related to position of Extensor Carpi Radialis Brevis (ECRB) Muscle, and channel B is related to position of Flexor Carpi Ulnaris

(FCU) Muscle. Point C is related to position of wrist Carpals Bone. This area was electrically inactive. For this reason it was chosen as reference point of recording. Two electrodes were placed on both (ECRB and FCU) muscular groups. The right position of the corresponding muscles was located by isometric contraction of wrist under supervision of a neurologist. Before connecting the electrodes, the related position was cleaned with alcohol in order to reduce skin-electrode impedance. The corresponding area of skin should be clean and free of grease and hair. To record signals, elliptical electrodes of Ag/AgCl with diameter of 10 mm (Skintight mark) were used with conductive gel. The electrodes were placed along the muscular

Table 1 Patient's information.

PD patient	Gender	Age [ys]	PD duration [ys]	UPDRS
1	M	61	3	5
2	M	68	8	0
3	M	56	1	5
4	M	60	2	1
5	F	67	1	0
6	M	74	2	1
7	F	61	10	2
8	F	61	10	2
9	M	75	4	1
10	F	65	10	2
11	M	80	3	3
12	M	62	3	1

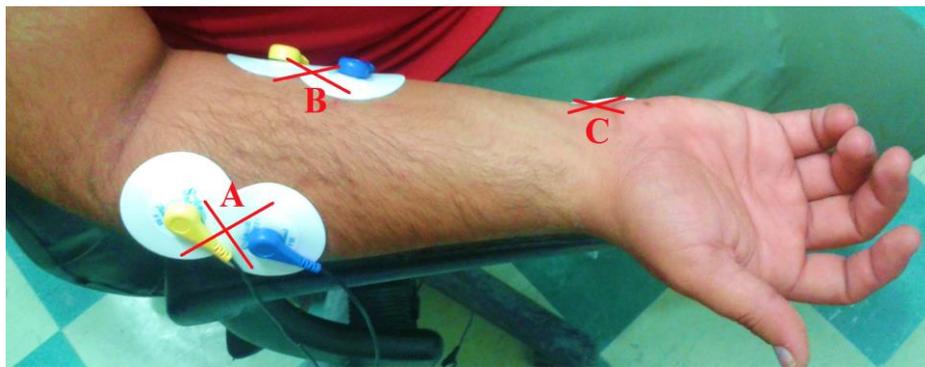


Fig. 4 Location of electrodes on wrist extensor and flexor muscles

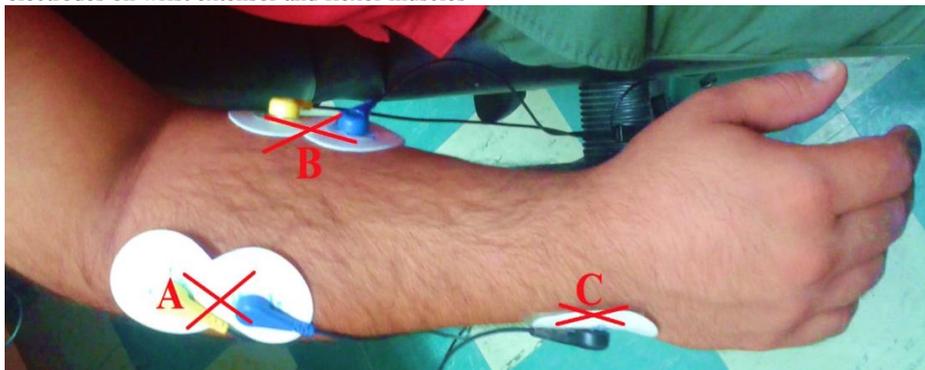


Fig. 5 Placement of EMG recording electrodes for simultaneous recording from ECRB and FCU muscles at rest position.

fibers. Once the patients were ready, the recording of signal began.

To record the signals, a portable recording device called FlexComp (Thought Technology Ltd., T7555M, with 10 channels) was used. The sampling rate and recording time was set on 2048 HZ and 60 seconds, respectively. Before data recording, the process of test operation was explained in detail to subjects in order to be able to do their job properly. The patients were asked to sit on a chair and put their hands with tremor on the armrest, because resting tremor in PD patients appears at resting position. Each subject was tested in three sessions. After each session, the subjects were allowed to rest for a minute. At the same time, electromyogram signal was recorded simultaneously from wrist extensor and flexor muscles (Fig. 5). In this manner, each recording process was repeated three times for each

patient. Since the number of patients was 12, 36 recording trial were carried out. Besides, the 4-second time window was used for data segmentation. Thereby, the number of used data hits 1141. The length of time window (4 second) was chosen by try an error to achieve the best accuracy.

In order to prepare the signals, the raw data was preprocessed. Firstly, a band-pass filter with a cut frequency from 10-500 HZ was used. Secondly, data were normalized and then the signals were divided into 4-second windows.

2.3 Feature Extraction

Six different types of variables (i.e., features) were applied in order to analyze EMG signal. All features were calculated for each 4-s window of signal. The linear features used in this study were:

1. Root mean square variable (RMS)
2. Standard deviation variable (SD)
3. Mean variable (M)
4. Kurtosis (K)

And the nonlinear features used in this study were:

1. Crossing rate variable (CR)
2. Recurrence rate variable (%REC)

The features were extracted because there was a significant relationship between tremor intensity and them [6-8]. In other words, the UPDRS values which were determined clinically by a neurologist, were correlated with these features [6-8]. Also, they were introduced as characteristics with potentiality for assessing and quantifying the intensity of tremor in PD [6-8].

• **Root Mean Square Variable (RMS)**

One of the most common features in the field of time is RMS which may be used for analyzing surface EMG signals, particularly in isometric contractions [14]. This feature can be obtained from the following equation

$$RMS = \sqrt{\frac{1}{N} \sum_{i=1}^N X_i^2} \quad (1)$$

where X_i is the i^{th} sample of a signal and N is the number of samples in each time window.

• **Standard Deviation Variable (SD)**

Standard deviation is one of the dispersion indices showing on average how far the data are away from average values. If a standard deviation of set of data is close to 0, it indicates that the data are close to the mean and have a small variation, while a higher standard deviation indicates that there is a higher variation of data. The standard deviation is given by

$$S.D. = \sqrt{\frac{\sum (X_i - \bar{X}_i)^2}{N}} \quad (2)$$

where X_i is the i^{th} sample of a signal, \bar{X}_i is mean of signal, and N is the number of samples in each time window.

• **Mean Variable (M)**

It can be stated that the mean can show the place of data distribution. So we have

$$\bar{X} = \frac{\sum_{i=1}^N X_i}{N} \quad (3)$$

where X_i is the i^{th} sample of a signal and N is the number of samples in each time window.

• **Kurtosis (K)**

The kurtosis variable is the fourth central moment of a time series which can be expressed in this way:

$$k = \frac{E \left\{ (X_i - \mu)^4 \right\}}{\sigma^4} \quad (4)$$

where X_i is the i^{th} sample of a signal and μ is the mean of the sample values and σ is the standard deviation. In fact, kurtosis shows the amount of variation around the mean point. The reason for calculating kurtosis variable of EMG signal was to assess the sharpness of the EMG sample distribution. Since the PD-like EMG signals are typically spikier than those of healthy people [6,15].

• **Crossing Rate Variable (CR)**

The CR variable was calculated for the EMG time series from the expansion of crossing rates. Firstly, the CR expansion was formed by calculating the CRs at given threshold levels as described in [15]. Secondly, the width of the expansion was defined at the level of 50 crossings/s and the height was defined as the maximum value of crossing rates at all threshold levels. Finally, the CR variable was calculated as the width/height of the expansion [6].

• **Recurrence Rate Variable (%REC)**

The recurrence rate measures the percentage of recurring structures in a time series. The variable was introduced to analyze the physiological systems by Webber and Zbilut in 1994 [16]. The calculation of the recurrence rate is based on the system reconstruction in the phase space. We calculated the recurrence rate of EMG as described for EMG time series in [17,18].

2.4 Model Implementation

After feature extraction, feature vectors z were formed by using concatenated and normalized (with zero mean and unit standard deviation) EMG variables.

$$Z = [RMS_1 \ RMS_2, \ M_1 \ M_2, \ SD_1 \ SD_2, \ K_1 \ K_2, \ CR_1 \ CR_2, \ REC_1 \ REC_2] \quad (5)$$

where the subscripts 1 and 2 denote the extracted features from EMG signals relating to two different muscles.

The dimensionality of the feature vectors was reduced by using the principal component analysis (PCA). In this approach, the feature vector z for each subject is decomposed into orthogonal basis vectors $\varphi_1, \dots, \varphi_k$. That is, each feature vector is modeled as a weighted sum of these basis vectors. For the j^{th} subject, the weighed sum will be as the following:

$$z_j = \varphi_1 \theta_j (1) + \varphi_2 \theta_j (2) + \dots + \varphi_k \theta_j (k) + v_j \quad (6)$$

where the scalar weights $\theta_j(1), \dots, \theta_j(k)$ are called the principal components and v_j is the model error. The basis vectors and the principal components are obtained for a group of feature vectors using the eigenvalue decomposition method as described in [19]. Utilizing the PCA, not only results in dimensional reduction but also results in obtaining the uncorrelated features (principal components).

In the next step, FOS algorithm was applied for the identification of the nonlinear models. FOS is a time-domain method for rapid identification of nonlinear system [20,21].

The FOS estimate takes the form of a summation of M linear or nonlinear functions $p_m(n)$ with coefficients a_m

$$y(n) = \sum_{m=1}^M a_m p_m(n) + e(n) \tag{7}$$

where $y(n)$ is the measured output, $e(n)$ is the estimation error and $\sum_{m=1}^M a_m p_m(n)$ is the estimated output.

Additionally, $p_m(n)$ and a_m are the basis functions and their corresponding coefficients, respectively. The FOS method seeks to find basis functions in a manner that leads to reduction of the mean-square error (MSE) value which is defined as follows

$$e^2(n) = \overline{[y(n) - \hat{y}(n)]^2} \tag{8}$$

where $y(n)$ is the measured output, $e(n)$ is the estimation error and $\hat{y}(n)$ is the estimated output.

In the current application, the basis functions $p_m(n)$ are composed of the available input variables, such as the EMG signals. In this research, the polynomial functions were considered as the basis functions. Naturally, the feature vectors were the input variables of the basis functions. To obtain a_m through conventional methods, complicated and time-consuming calculations are required. In [20], some orthogonal functions called $q_m(n)$, which were the orthogonalized form of $p_m(n)$, were used and the corresponding coefficient of g_m can be obtained by using these functions. Therefore, we have:

$$y(n) = \sum_{m=1}^M g_m q_m(n) + e(n) \tag{9}$$

In which, g_m is the coefficients of the orthogonal basis functions $q_m(n)$, which are orthogonal over the model input data [12].

$$\overline{q_i(n)q_j(n)} = 0 \quad , \quad i, j \in [1M] \quad , \quad i \neq j \tag{10}$$

where $j < m$. Each computed orthogonal function is “parallel” to previous orthogonal functions. The orthogonal functions $q_m(n)$ can be obtained by Eq. (11).

$$\begin{aligned} q_1(n) &= p_1(n) = 1 \\ q_2(n) &= p_2(n) - \alpha_{21}q_1(n) \\ &\vdots \\ q_m(n) &= p_m(n) - \sum_{r=1}^{m-1} \alpha_{mr}q_r(n) \end{aligned} \tag{11}$$

where coefficient α_{mr} is the projection of q_r onto p_m , that is calculated as

$$\alpha_{mr} = \frac{\overline{q_r(n)p_m(n)}}{\overline{q_r^2(n)}} \quad , \quad m = 2, \dots, M \quad ; \quad r = 1, \dots, m-1 \tag{12}$$

Now the coefficient g_m that minimizes the MSE can be obtained as follows [12]

$$g_m = \frac{\overline{y(n)q_m(n)}}{\overline{q_m^2(n)}} \quad , \quad m = 1, \dots, M \tag{13}$$

According to [12,20], for obtaining a_m , only the coefficients α_{mr} and g_m should be known. Moreover, there was a recursive solution for obtaining α_{mr} and g_m . Therefore, through multiplying q_m by the two sides of Eq. (6), the numerator and dominator of α_{mr} were obtained, respectively. Also, through multiplying y by the two sides of Eq. (6), the numerator and dominator of g_m were obtained as well.

After formation of orthogonal functions, FOS algorithm looks through all the orthogonal functions to choose the best functions among the candidate basis functions which cause the maximum reduction of MSE [13]. To choose the best basis function, the MSE reduction must be calculated according to the following relationship [13].

$$\overline{e_{M+1}^2} = \frac{\overline{y(n)q_{M+1}(n)}}{\overline{q_{M+1}^2(n)}} \tag{14}$$

If estimation error is high, one orthogonal basis functions is added and the search algorithm is repeated again. The added term (basis function) reduce the MES [21,22]. The process continues until the additional basis function does not reduce MES more.

3 Result

Initially, the 60 percent of data were assigned to data training set and the 40 percent of data were assigned to data test set. They were selected randomly. As it was previously explained, the proposed model was designed based on two different structures called single structure model and parallel structure model. The achieved results will be discussed in the next subsections.

3.1 Quantification Using the Single Structure Model

For the sake of inevitable modeling error, the designed

single structure model may not generate an integer number as a feature vector to be the model input. Therefore, in this study a thresholding technique was used. According to the applied thresholding technique, the obtained model output was analyzed. If the obtained value was from a tremor intensity levels minus 0.4 to the tremor intensity level plus 0.4, that specific tremor intensity value would be considered as the model output. Since the tremor intensity level is an integer number ranging from 0 to 5, the output of the model using thresholding technique ranges from 0 to 5. The 0.4, as an extreme determining the decision range, was selected through try and error to reach the most plausible estimates. Figure 6 shows the estimated UPDRS valued by the single structure model before using the thresholding technique along with the actual UPDRS values. Since each recorded data was divided to some 4-second time windows, some 4-second time windows were selected randomly for the test. The estimated tremor level using each 4-second time window and actual tremor level corresponding to that time window are shown in Fig. 6.

The performance of the designed model was evaluated using K-fold approach ($k=5$). Accuracy, specificity and sensitivity, as the statistical measures, were calculated for any level of tremor, which are given in Table 2. Using this structure, accuracy of the total model was obtained $73.16\% \pm 0.32$.

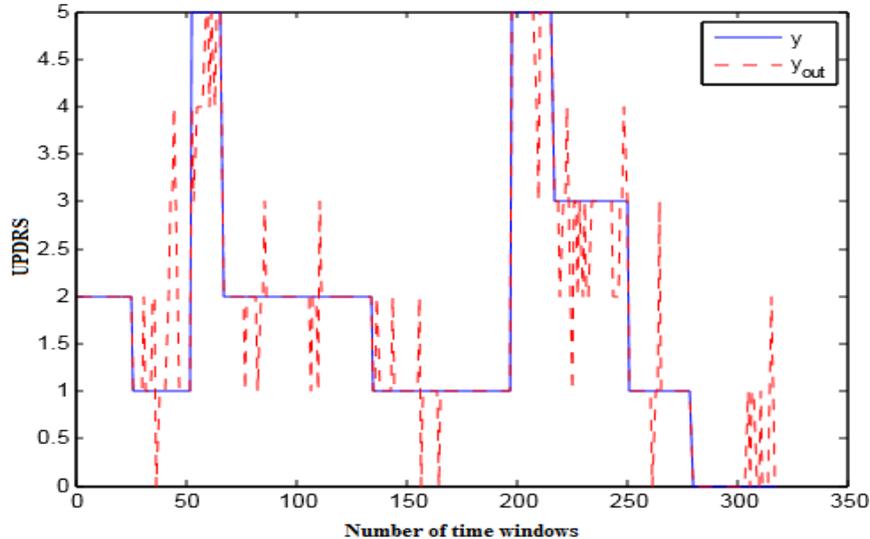


Fig. 6 The estimated UPDRS values using single structure model before utilizing the thresholding technique (solid line) and actual UPDRS values (dash line).

Table 2 Evaluation of the designed single structure model using K-fold approach.

Level of Tremor	Accuracy	Specificity	Sensitivity
0	91.40 % \pm 0.51	95.99 % \pm 0.51	71.61 % \pm 1.7
1	85.07 % \pm 0.77	91.35 % \pm 0.41	76.30 % \pm 1.5
2	83.18 % \pm 0.78	81.85 % \pm 1.87	85.99 % \pm 0.74
3	90.91 % \pm 0.52	95.49 % \pm 0.32	56.47 % \pm 1.3
5	92.31 % \pm 0.23	98.44 % \pm 0.71	49.30 % \pm 2.8

3.2 Quantification Using the Parallel Structure Model

As it was mentioned previously, in the parallel structure model, a specific model was designed and assigned for estimation of each specific level of tremor intensity. Fig. 7 shows the estimated UPDRS valued by the parallel structure model along with the actual UPDRS values. No thresholding techniques have been utilized. Clearly, the model was able to estimate UPDRS values with a high precision. Eventually, the results of parallel structure were evaluated using K-fold ($k=5$) approach. Accuracy, specificity and sensitivity were calculated for each model (Table 3). Obviously, using the parallel structure model the accuracy and specificity have been increased. The sensitivity also, has been improved considerably. Using this structure, accuracy of the total model was obtained $99.25\% \pm 0.41$.

4 Conclusion

Quantification of the severity of the resting tremor in the patients suffering from PD has direct clinical implications on diagnostic and therapeutic management of PD. In early stages of PD, the resting tremor may be very mild and intermittent which makes clinical

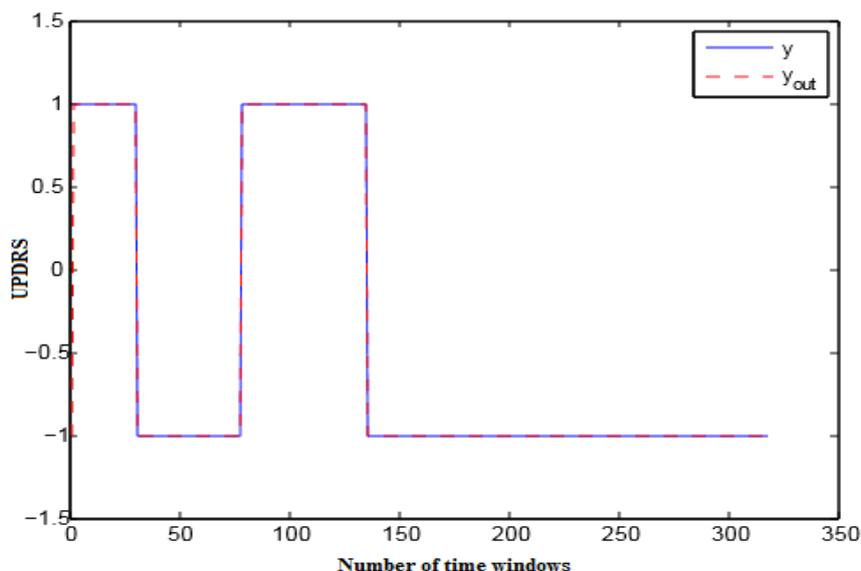


Fig. 7 The estimated UPDRS (solid line) using parallel structure model and actual UPDRS (dash line).

Table 3 Evaluation of the parallel structure model using K-fold approach.

Model number	Accuracy	Specificity	Sensitivity
Model 0	99.15 %	95.52 %	99.79 %
Model 1	98.61 %	96.70 %	99.68 %
Model 2	99.73 %	99.22 %	99.93 %
Model 3	99.32 %	94.61 %	99.79 %
Model 4	99.46 %	99.71 %	99.43 %
Mean \pm SD	99.25 % \pm 0.41	97.17 % \pm 1.9	99.72 % \pm 0.18

diagnosis difficult. Having a system that can record reliably the EMG signals and quantify the levels of resting tremor in PD may contribute to the early diagnosis of the disorder. In this study, we introduced a model for quantifying the severity of the tremor in Parkinson's disease. The extracted features from the surface electromyogram signals of the wrist muscles were the input of designed model. Two different structures for modeling including single structure and parallel structure were proposed. And FOS algorithm was utilized for model identification. Adopting the single structure model may result in occurrence of interference in learning. Because the model had to be adapted in such a way that had been able to differentiate any of 5 tremor levels while each tremor level characterizes its own dynamic specifications. The achieved results proved this conjecture, because the carried out evaluations elucidated that using the model with parallel structure led to significantly more accurate estimation. In addition, the accuracy of parallel structure is very high and remarkable (99.25 % \pm 0.41) in comparison with clinical methods in which the level of diagnosis is about 50%. This results from this reality that the clinical diagnosis is merely based on the evidences and neurologist's personal experiences [23]. In general, results of this pilot study show that the proposed model with parallel structure identified by using the FOS algorithm, is capable of providing

reasonably accurate estimation of the tremor intensity level in PD subjects.

It is worth noting that owing to some clinical restrictions, the number of patients was low. Therefore, we increased the number of recorded signals. In other words, we increased the number of EMG recording trials for data enrichment. Nevertheless, these primary results can be promising because at least it proves the potential of the proposed model for automatic quantification of tremor intensity.

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