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EMG-Based Essential Tremor Detection Using PSD Features With Recurrent Feedforward Back Propogation Neural Network

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ABSTRACT

Essential tremors (ET) are a slow progressive neurological disorder that reduces muscular movements and involuntary muscular contractions. The further complications of ET may lead to Parkinson's disease, and therefore, it is very crucial to identify at the early onset. This research study deals with the identification of the presence of ET from the EMG of the patient by using power spectral density (PSD) features. Several PSD estimation methods such as Welch, Yule Walker, covariance, modified covariance, Eigen vector based on Eigen value and MUSIC, and Thompson multitaper are employed and are then classified using a recurrent feedback Elman neural network (RFBEN). It is observed from the experimental results that the MUSIC method of estimating the PSD of the EMG along with RFBEN classifier yields a classification accuracy of 99.81%. It can be concluded that the proposed approach demonstrates the possibility of developing an automated computer-aided diagnostic tool for early detection of essential tremors.

KEYWORDS

Classifier, EMG, Essential Tremor, Parkinson's Disease, Power Spectral Density, Recurrent Neural Network

1. INTRODUCTION

Electromyography (EMG) is the quantification of the electrical activity of the muscles and this provides a measure of the muscular contraction. After a series of works conducted to discern and distinctly analyze Essential Tremors (ET), Louis ED (2001a) concluded that these are transferred to successive generations through autosomal dominant transmissions and is mutagenic .These tremors originate from the central nervous system and are more evidently observed by the involuntary contractions of muscles even during activity. Various other EMG tremors like, postural tremor of the outstretched arms, intentional tremor of the arms and rest tremor in the arms are also not very uncommon in ET (Louis ED, 2001b). Unlike resting tremors observed in Parkinson's disease, Essential tremor has a unique frequency range of 4-12 Hz and is observed predominantly when the affected muscle is under work (Busenbark et al., 1999;Louis et al., 2000;Ctrichley 1949). Physical and mental stress may further exacerbate the ET.

ET and the resting tremors of Parkinson's disease (PD) can be Interpreted based on the degenerated part of the brain. Essential tremors originate due to the degeneration of the cerebellum in the brain whereas resting tremors of PD originates due to the degeneration of the Hypothalamus. On extensive

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experimentation carried out across the globe it is concluded that patients affected with ET may gradually develop Parkinson's as the risk of Parkinsonism is greater with patients of ET. Resting tremors last longer than the ET, for up to 8-9 seconds and the ET are generally postural and action tremors and they originate bilaterally and the tremor duration is only 1-2 sec (Pahwa et al., 1993).

Despite the fact that, research conducted so far in various parts of the world had been able to successfully differentiate ET and Resting tremors of PD, the scope for intense research is still open. The various stages of ET namely, definite Essential tremor, Probable essential tremor and Possible ET with the progress of tremors from head and neck in the first stage to arms in the second and the third stage is the tremors present during action and rest or continuous tremors in the arms (Kollet et al., 1989) which later progresses to other parts of the body which are yet to be recognized quantitatively through computer aided procedure.

Several works on EMG based tremor detection have been reported in the literature (Lingmei et al., 2011;Arvind et al.,2010; O'Suilleabhain et al., 1998; Hossen et al., 2010). Lingmei et al.,(2011) have applied single value decomposition to extract intrinsic mode function feature to distinguish Parkinsonian tremor from ET . Arvind et al., (2010) investigated the effect of PSD feature estimation by Welch and Burg's method on resting tremor. O'Suilleabhain & Matsumoto (1998) have discussed the effect of time-frequency analysis on essential, psychogenic and Parkinsonian tremors . Robichaud et al., (2009) investigated the effect of EMG signal as a biomarker for detection of Parkinson detection . Hossen et al., (2010) have proposed wavelet based decomposition for discriminating Parkinson and essential tremors. Woods et al (2014) showed significant differences in postural tremors with different attention and distraction tasks. The effect of influence of noise on EMG based essential tremor was reported (Seki et al., 2011). A specific quantification study has been proposed by Matsumoto et al., 2017 for EMG based essential tremor. A support vector machine based PD and ET classification was reported Haji et al., 2016.

Attempts have been made to make use of accelerometer to study the tremors which are indicators of only bodily movements (Ghassemi et al., 2016;di Biase et al., 2017;Luft et al., 2019). There is a need to understand the behavior of physiological tremor recordings through EMG recordings which provides crucial indication for the clinical community to handle the patients. Further recognition of essential tremors from normal activities needs appropriate selection /extraction of features and pattern classifiers. This study makes an attempt to exploit the various variants of power spectral density to recognize the tremor patterns from the collected EMG recordings. The application of recurrent feedback Elman neural network model further ensures the capability of the automated pattern classifier to perform the binary classification problem in a more efficient way with less false alarm rate

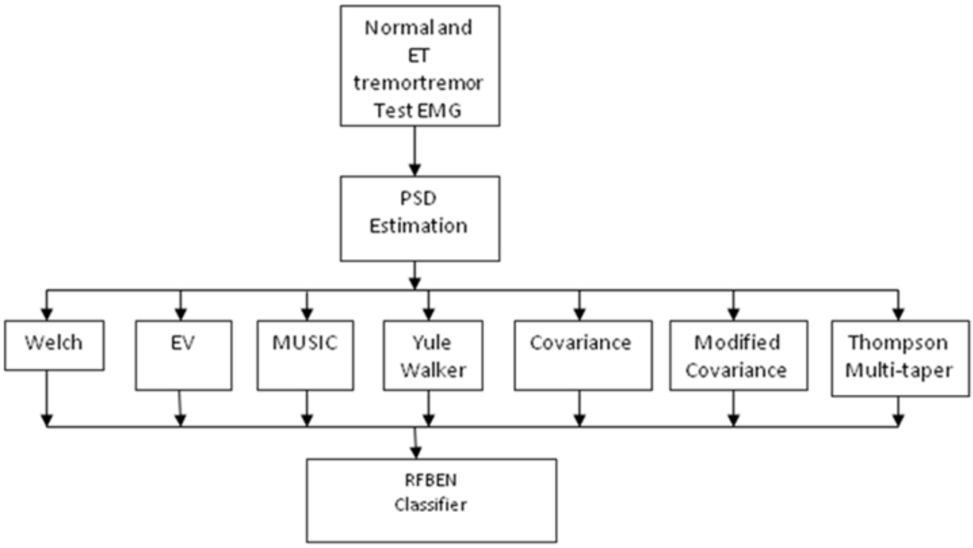
The estimation of the power spectral density of the signal gives a more feasible way to recognize tremor pattern and hence ensures accurate classification from that of normal muscular activity. The estimation of PSD of the signal gives the distribution of power (variance) over the given frequency range. Muscular conduction occurs at the frequency of 7-20Hz. However, those of the essential tremors are less than 5Hz in frequency. Hence in this proposed work, the power spectrum is estimated using various methodologies like Welch, Yule Walker, covariance (CV), modified covariance (MCV), Eigen vector based on Eigen value (EV) and MUSIC and Thompson Multitaper (TMT). The spectrum is analyzed and subjected to classification using a recurrent feedback Elman neural network (RFBEN). The experimental results are then compared to bring out a comprehensive model that will provide an optimum configuration and high classification accuracy. Figure 1 shows the proposed scheme.

2. MATERIALS AND METHODS

2.1 Data Description

The signals were obtained using Nihon Kohden MEB-2200 EMG system at a sampling frequency of 1KHz. The EMG recordings were procured from various subjects (under the age group of 40-50

Figure 1. Proposed PSD feature based ET detection



years) diagnosed as normal and patients with Essential tremor from the Neurology Department of Sri Ramachandra University, Chennai, India. Various conditions were observed and recorded for analysis such as rest, involuntary tremors, activated muscular contraction and normal muscle activity. All the signals obtained were ensured noise free and free from any electrical interference. Recording technique is normally belly tendon method (active electrode on belly of muscle and reference / inactive electrode on tendon (no muscle) (with small muscle in hand (palm and volar/ dorsum area, used bony prominence as reference and muscle bulk as active). Figure 2 shows the sample recordings.

3. FEATURE EXTRACTION

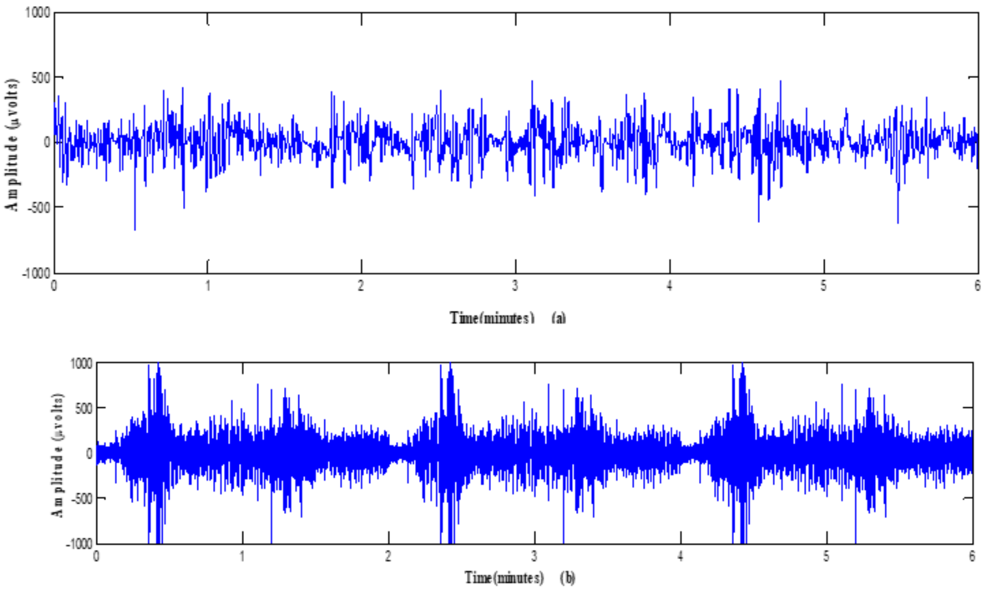
The PSD of the signals were estimated using the following methods to ascertain the best parameter that can be used for classification: Welch, Yule Walker, covariance, modified covariance, Eigen vector estimation methods and Thompson Multitaper are employed to estimate the PSD of the EMG signals. The estimation of PSD is carried out in the following way. The estimation of the autoregressive (AR) model is the base for the estimation of any PSD Spectrum. The AR components are estimated as:

$$X_t = c + \sum_{k=1}^{p} \phi_i X_{t-i} + e_t \tag{1}$$

Where $\phi_1,........\phi_p$ are the parameters of the model with c as its constant and e_t is the error component.

The AR model computes the parameters of the signal first and then computes the spectral estimate from the extracted parameters. Since this method is easier to estimate the spectrum of the signal AR model has been widely adopted for signal processing and extraction applications (Lingmei et al., 2011;Arvind et al.,2010; O’Suilleabhain et al., 1998; Hossen et al., 2010; Pardey et al., 1996;Muthuswamy et al., 1998;Akin et al., 2000;Guler et al., 2001; Kiymik et al., 2004).

Figure 2. Sample recordings of EMG obtained from (a) normal/healthy subject (b) subject with ET



3.1 Welch Method

Welch method is an improved method of estimating the PSD (Welch, 1967). The given time series is divided into overlapping segments with a maximum overlap of 50%. This method divides the data into eight segments by default with a maximum of 50% overlap between them and uses a Hamming window; usually the windowing function affects the computation of the periodogram at the centre of the segment than at the edges, which results in a loss of information. To avoid this loss of information, overlapping of the segments is carried out. Discrete Fourier transform is applied to compute the periodogram of each segment. Then the estimated periodogram is time-averaged, in order to reduce the variances of individual power estimates. This result is called the Welch estimate (Welch, 1967)].

A given time $x_m(n)$ with m^{th} window zero padded frame is denoted by

$$x_m(n) = w(n)x(n + mR), n = 0,1.....M - 1; m = 0,1,......K - 1 \tag{2}$$

Where w(n) is the rectangular window containing M non-zeros samples. 'R' is defined as window hopsize,'K' denoted the number of available frames. The PSD based on Welch method is given by

$$P_{Welch}(f) = \frac{1}{K}\sum_{m=0}^{K-1} Px_m, M^{(w_k)} \tag{3}$$

where

is the periodogram of the m^{th} block.

3.2 Yule –Walker Method

The Yule-Walker Method also called the autocorrelation method, employs an autoregressive (AR) model to the windowed given time series and it also minimizes the forward prediction error in the least squares logic (Marple,1987). This strategy leads to the Yule-Walker equations, which are solved by Levinson-Durbin recursion. The outputs of the Yule-Walker blocks are always nonsingular. The PSD based on Yule-Walker is given by

$$P_{Yule}(f) = \frac{1}{a^H \left|e(f)\right|^2} \tag{4}$$

Where ‘a’ is the vector of all-pole filter coefficients.

3.3 Covariance and Modified Covariance Method

The covariance method (CV) computes the PSD of a signal by fitting an AR linear prediction filter model to the signal which minimizes the forward prediction (Kay,1988). The spectral estimate is the squared magnitude of the frequency response of this AR model. On the other hand, the modified covariance simultaneously minimizes the forward and backward errors. The PSD of Covariance method is given by

$$P_{CV}(f) = \frac{e}{\left|1 + \sum_{k=1}^{p} a_k e^{-jwk}\right|^2} \tag{5}$$

The modified covariance method (MCV) estimates the AR components in the same method as the covariance method; however the speed of calculation and the computational complexity is reduced as reported(Kay,1988). The output vector, contains the normalized estimate of the AR system parameters, A(z), in descending powers of z. The PSD of the signal is given by

$$\frac{\theta}{\left|A(\theta^{j\omega})\right|} = \frac{\theta}{\left|1 + \Sigma_{k-1}^{p} a(k)\theta^{-j\omega k}\right|^2} \tag{6}$$

3.4 EIGEN VECTOR BASED ON MUSIC METHOD

The multiple signal classification (MUSIC) is a model-based spectral estimation method that yields excellent resolution of the frequencies than FFT-based methods (Marple,Schmidt et al., 1986). Compared to other classical methods, this works on subspace decomposition method and ensuring high resolution. This method first estimates the correlation matrix R_p of the input time bound signal and obtains the eigenvectors $V_1, V_2, ..., V_p$ and Eigen values $\lambda_1, \lambda_2, ..., \lambda_p$. The Eigen vectors $V_1, V_2, ..., V_M$ with large Eigen values form the signal subspace. The remaining eigenvectors $V_{M+1}, V_{M+2}, ..., V_p$ form the noise subspace. The signal subspace also can be represented by group vectors of complex sinusoids $e(f_1), e(f_2), ..., e(f_M)$. The vector of a complex sinusoid is defined as follows:

$$e(f_i) = \left[1, e^{2\pi fi} e, \ldots, e^{2\pi fiM}\right] \tag{7}$$

If a time series contains a frequency component at f_i, the vector $e(f_i)$ is uncorrelated with V_{M+1}, V_{M+2}, ..., V_p. Accordingly, the following equation generates a peak value at f_i:

$$P_{MUSIC}(f) = \frac{1}{\sum_{k=M+1}^{P} \left| e^T(fi) v_k \right|^2} * \frac{1}{\Delta f} \tag{8}$$

3.5 Eigen Vector Using Eigen Value (EV) Method

Eigen vector method computes the Eigen values EV, noise subspace frequency estimator. Initially, an autocorrelation matrix of order P is calculated from the given time series (Marple,Schmidt et al., 1986). The resultant of the first stage is a matrix, which is then separated into vector subspaces, into a signal subspace and a noise subspace using a singular value decomposition method to obtain the Eigen values and vectors. The PSD estimation is based on the Eigen values using a weighted version MUSIC algorithm derived from Schmizt's Eigen space analysis. Pev(f) is given by

$$P_{eV}(f) = \frac{1}{\sum_{k=p+1}^{N} \left| v_k{}^H e(f) \right|^2 / \lambda_k} \tag{9}$$

Where
'N' is the dimension of the Eigen vector
Vk is the K^{th} Eigen vector of correlation matrix of given time series.
The inner product V_k^H e(f) refers to the Fourier transform operation
λ_k is the smallest Eigen Value

3.6 Thomson Multi Taper

Thomson Multi Taper(TMT) method was devised by Thomson to estimate the power spectrum S_X of a stationary ergodic finite-variance random process X, given a finite contiguous realization of X as data. The method to estimate the PSD is as follows:

Consider the output from the EMG machine, i.e the signal, which is one dimensional to be the input row matrix X(t). It represents simultaneous measurement of electrical activity of those p channels. Let the sampling interval between observations be Δt, so that the Nyquist frequency is $f_N = 1 / (2\Delta t)$. The TMT estimator utilizes several different data tapers of Slepian seqeunce which are orthogonal to each other (Cox 1996; Thomson,1982;Slepian,1978;Wiezorek &Simons,2007)

Consider 'K' Slepian sequence, the DFT of the 'K' Eigen vector components is defined as

$$y_k(f) = \sum_{t-0}^{N-1} x(t) v_k(t) e^{-2\Pi ift} \tag{10}$$

Where
x(t) is the time series to be analyzed
N is the number of data points in the time series
t is the time variable (t = 0,1,….N-1)
f is the frequency variable
λ_k is the Eigen value of Sleepian sequence

'K' is the number of tapers/Sleepian sequence

To determine the PSD by TMT, frequency dependent weight $d_k(f)$ need to be calculated as shown in (11)

$$d_k(f) = \frac{\sqrt{\lambda_k}}{\lambda_k s(f) + (1 - \lambda_k)\sigma^2} \tag{11}$$

Where σ^2 is the variance of the time series.

The PSD of MTM is then given by (12)

$$P_{TMT}(f) = \frac{\sum_{k=0}^{K-1} d_k^{\,2} \left| y_k(f) \right|^2}{\sum_{k=01}^{K-1} d_k^{\,2}} \tag{12}$$

In conventional nonparametric spectral analysis techniques, to reduce variance, we break up the data into overlapping segments (as in Welch's overlapped segment method), estimate the cross-spectrum or power spectrum for each segment and then average over the segments. Such methods have severe bias problems for short data. In the multitaper method, for reducing variance we average over different tapers using the full data. Since the data length is not shortened, the bias is smaller(Hossen et al., 2010).

4. RECURRENT NEURAL NETWORK CLASSIFIER

In this proposed study, recurrent feed forward backpropogation neural network (RFBNN) model is used. This model as proposed by Elman comprises of three layers, namely, input layer, hidden layer and a output layer along with a special context units which serves as a memory for storing network information(Elman,1990). These units as attached to the hidden layer establish a positive feedback and make the network recurrent. Such procedure in association with the backpropogation learning rule helps in ensuring the minimization of mean square error (MSE). Many authors have used this network for pattern classification problem due to its favorable characteristics, such as self learning, adaptability and parallelism (Pravin kumar et al., 2010;Marra & Morabitto 2005; Ubeyili 2008). Figure 3 shows the typical architecture used for the proposed study(Marra & Morabitto 2005).

The performance of the proposed RFBNN is evaluated in terms of three parameters as defined:

$$\text{Sensitivity} = \frac{\text{Total number of normal patterns correctly detected}}{\text{Total number of applied EMG patterns}} \tag{13}$$

$$\text{Specificity} = \frac{\text{Total number of Essential tremor patterns correctly detected}}{\text{Total number of applied EMG patterns}} \tag{14}$$

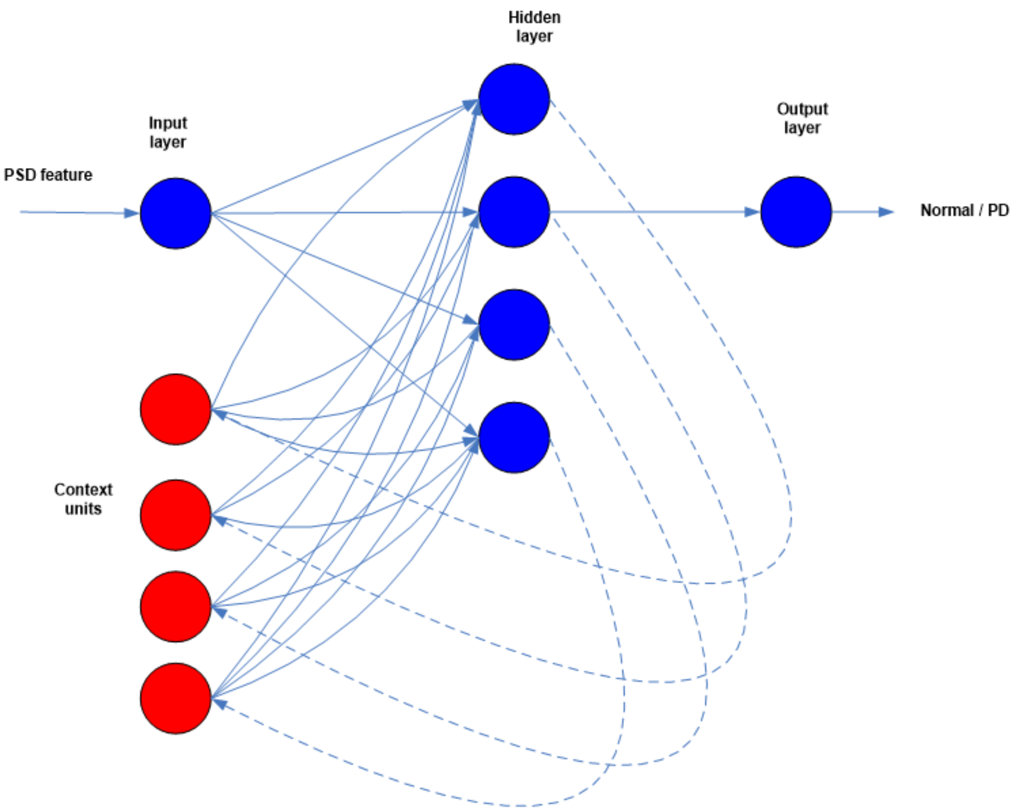
$$\text{Classification accuracy} = \frac{\text{Total number of normal patterns correctly detected} + \text{Total number of ET patterns correctly detected}}{\text{Total number of applied EMG patterns}} \tag{15}$$

5. PERFORMANCE EVALUATION

The PSD estimated based on the different methods for ET signals are shown in Figure 4.

It is evident from Figure4 that the PSD of the Essential tremor signals are very high in magnitude. The PSD values obtained using different methods for normal and ET signals are then applied to RFBNN classifier. The RBFNN network is configured optimally in order to achieve high classification

Figure 3. Eecurrent feedback Elman neural network (RFBEN) Architecture



accuracy. A total of 1800 EMG patterns (for normal and ET respectively) were considered, 1000 patterns were used for training and 800 for testing. Two learning algorithms were applied, namely, gradient descent with least momentum (GDX) and resilient propagation (RP). Table 1 shows the optimal configuration results using GDX learning algorithm. It was observed during the simulation that the GDX learning procedure showed better CA than the RP.

It can be observed from Table 1 that the Eigen vector based methods showed good convergence with minimal MSE values compared to other PSD methods. In order to classify the unseen patterns, a threshold point is fixed in such a manner that any binary value lies between 0 to less than 0.4, will be referred as normal and anything above 0.7 to 1 is considered as essential tremor activity. All the threshold points were fixed based on trial and error method to obtain the best CA values. Table 2 shows the results obtained using the testing patterns. The CPU processing time that includes both the training and the testing sessions is also given.

Figure 4(a). *Welch method*

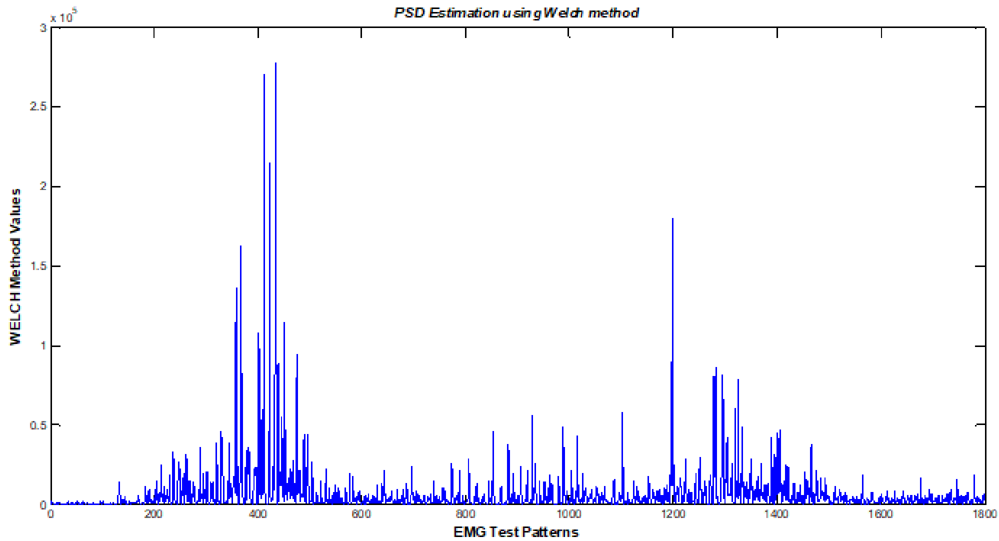


Figure 4(b). Yule-Walker method

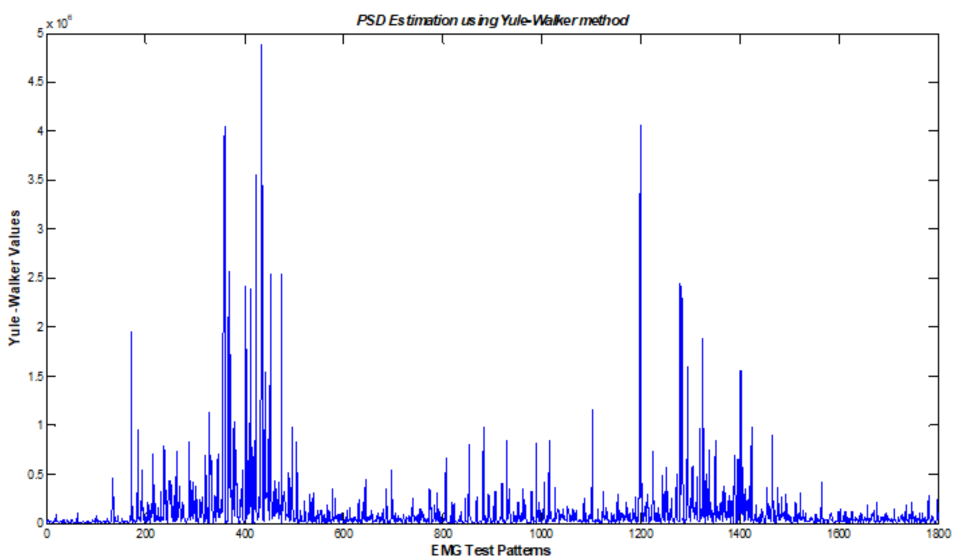


Figure 4(c). *MCV method*

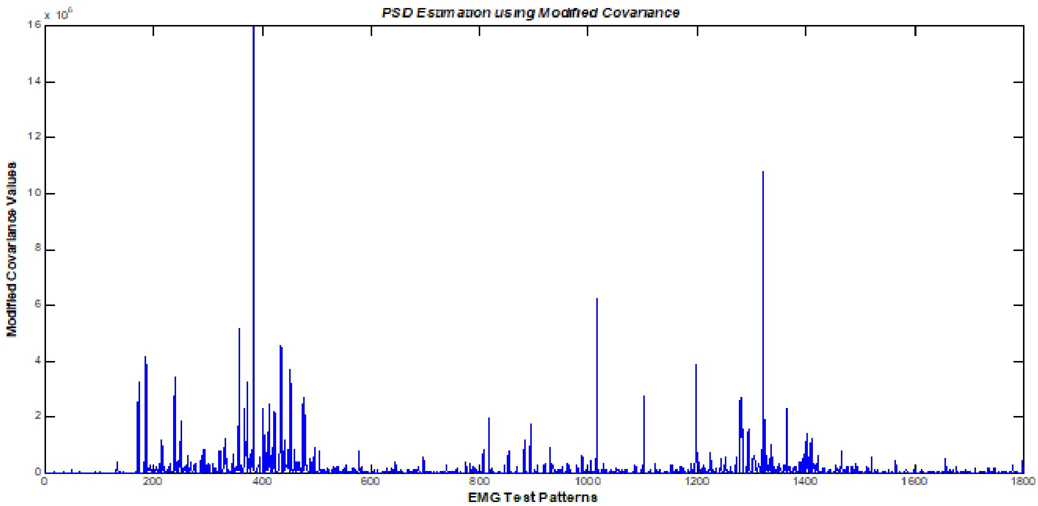


Figure 4 (d). *EV method*

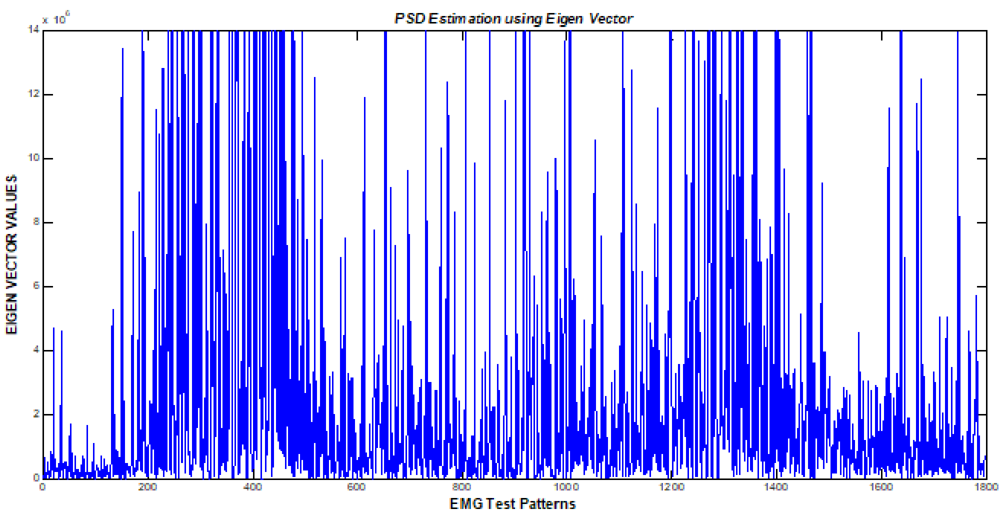


Figure 4 (e). *MUSIC method*

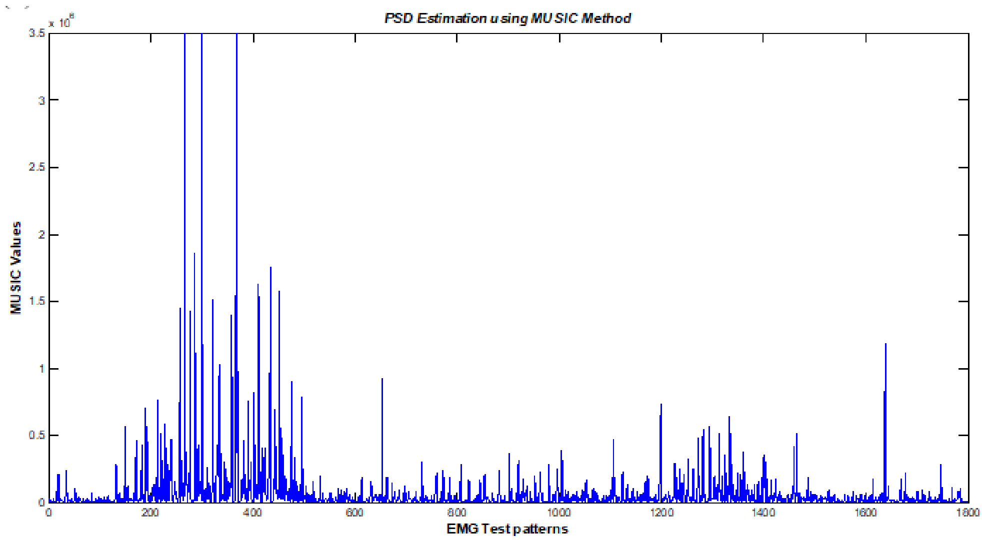
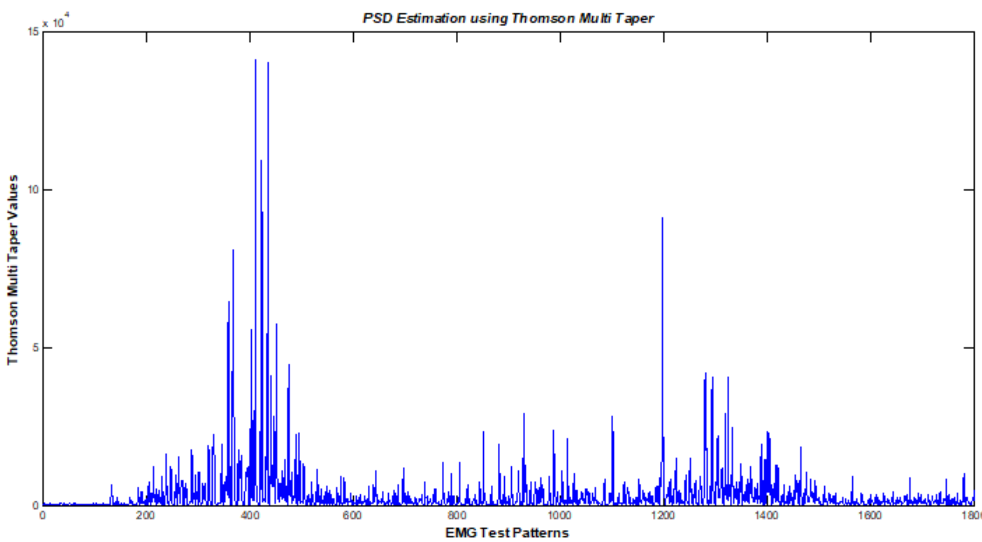


Figure 4 (f). *TMT method*



It can be observed from Table 2 that only three PSD methods, modified co variance, Eigen value and MUSIC detects the ET effectively. The maximum CA is obtained using MUSIC features with the RBFNN classifier with a minimal CPU processing time.Figure5 shows the RBFNN classifier output using MUSIC features.

6. DISCUSSION

Based on the simulation results, the following observations can be made for the recognition of essential tremors:

Table 1. Optimal Configuration of RFBNN

Feature	No. of hidden neurons	Activation Function		No. of Iterations	MSE
		Hidden layer	Output layer		
Welch	90	Tan sigmoid	Log sigmoid	68	0.0089
Yule-Walker	90	Tan sigmoid	Log sigmoid	112	0.0091
CV	60	Tan sigmoid	Log sigmoid	72	0.006
MCV	60	Tan sigmoid	Log sigmoid	81	0.0078
EV	60	Tan sigmoid	Log sigmoid	42	0.0042
MUSIC	20	Tan sigmoid	Log sigmoid	60	0.0031
TMT	60	Tan sigmoid	Log sigmoid	110	0.009

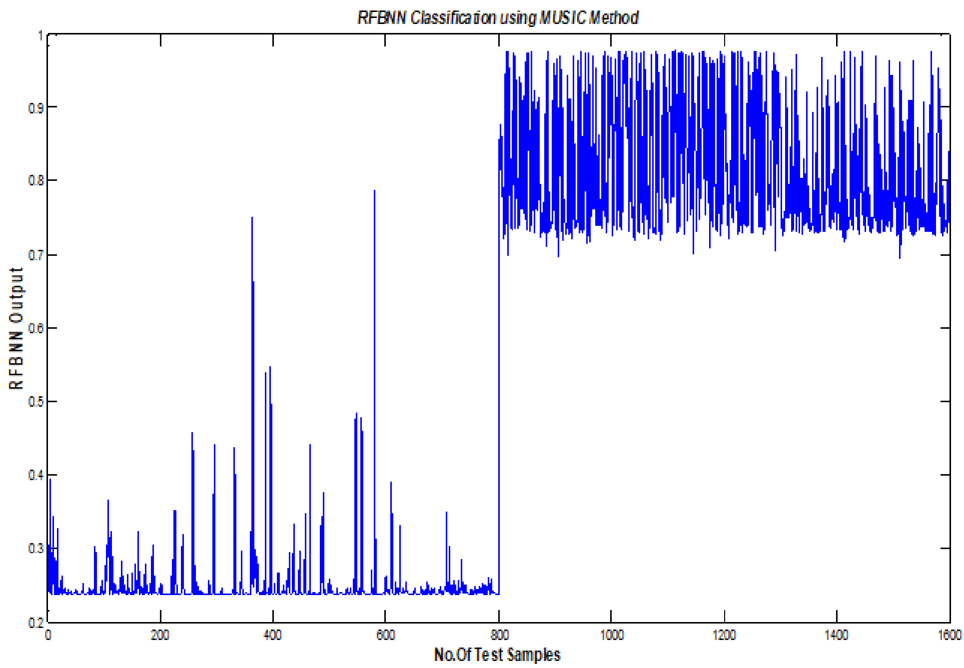
Table 2. Classification results using various PSD estimation methods

Feature	Sensitivity	Specificity	CA (%)	CPU time (min:sec)
Welch	767/800	721/800	93	11.2
Yule-Walker	742/800	691/800	89.5	12.0
CV	768/800	781/800	96.8	7.5
MCV	774/800	790/800	97.7	6.3
EV	789/800	794/800	98.9	4.2
MUSIC	797/800	800/800	99.81	2.8
TMT	785/800	781/800	97.87	10.5

1. In the proposed study, parametric methods are introduced as feature extraction method. Unlike non-parametric approach, this approach provides more accurate spectral estimates for short segments of EMG patterns. The leakage effect of windowing is minimized and thus provides greater frequency resolution. The selection of the AR model order is a critical factor in spectral estimation. For the EMG time series, prediction order ‘p’ was taken as 10 for all the PSD methods. This is due to the fact that for lower prediction order of 2, 4, CA falls below 80%.
2. It can be observed from Tables 1 and 2 that the Eigen vector based methods, such as Eigen value and MUSIC are found to be superior in terms of classification accuracy than other PSD based methods. These methods are based on Eigen decomposition of the correlation matrix of given EMG time series along with noise. The main advantage of these methods is that they produce frequency spectrum of high resolution at lower SNR.
3. Although reports have shown various schemes involved in detection of Parkinson Tremors, essential tremors, the scope for new techniques emerges due to the need for efficient detection for real-time operation. The selection of feature extraction methods plays an important role in designing efficient clinical decision support systems and in the proposed study, a classification accuracy of 99.81% shows the potential possibility of introducing such procedure for real-time operation. Since standard dataset were not available for ET, exact comparison cannot be performed with the existing techniques.

It can be inferred from the experimental study that the optimal configuration of the RBFNN confirms the efficiency of the classifier. The number of hidden neurons, number of epochs attained for convergence

Figure 5. Classification plot using MUSIC method



and MSE varies for each PSD methods and the best PSD method was chosen based on the maximum CA with minimal CPU time. From Tables 1 and 2, one can infer that the MUSIC method with RBFNN yields the best result.

7. CONCLUDING REMARKS

This paper presented an attempt to develop computer aided automated detection of essential tremor (ET) from the acquired EMG signals. Power spectral density (PSD) feature was used to discriminate normal from ET in association with a recurrent feed forward back propagation neural network (RBFNN) classifier. The PSD was estimated using several parametric methods, such as, Welch, Yule Walker, covariance, modified covariance, Eigen vector based on Eigen value (EV) and MUSIC and Thompson Multitaper. The performance of the classifier was evaluated with specificity, sensitivity and classification accuracy. It has been found from the experimental results that the PSD obtained using MUSIC with RBFNN classifier yields a classification accuracy of 99.81% with a CPU processing time of 2.8 minutes. The proposed scheme needs to be validated for a larger database to check its suitability to introduce in the clinical routine.

CONFLICT OF INTEREST STATEMENT

None declared.

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