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Discrimination of Parkinsonian Tremor From Essential Tremor by Voting Between Different EMG Signal Processing Techniques

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Abstract: Parkinson's disease (PD) and essential tremor (ET) are the two most common disorders that cause involuntary muscle shaking movements, or what is called "tremor". PD is a neurodegenerative disease caused by the loss of dopamine receptors which control and adjust the movement of the body. On the other hand, ET is a neurological movement disorder which also causes tremors and shaking, but it is not related to dopamine receptor loss; it is simply a tremor. The differential diagnosis between these two disorders is sometimes difficult to make clinically because of the similarities of their symptoms; additionally, the available tests are complex and expensive. Thus, the objective of this paper is to discriminate between these two disorders with simpler, cheaper and easier ways by using electromyography (EMG) signal processing techniques. EMG and accelerometer records of 39 patients with PD and 41 with ET were acquired from the Hospital of Kiel University in Germany and divided into a trial group and a test group. Three main techniques were applied: the wavelet-based soft-decision technique, statistical signal characterization (SSC) of the spectrum of the signal, and SSC of the amplitude variation of the Hilbert transform. The first technique resulted in a discrimination efficiency of 80% on the trial set and 85% on the test set. The second technique resulted in an efficiency of 90% on the trial set and 82.5% on the test set. The third technique resulted in an 87.5% efficiency on the trial set and 65.5% efficiency on the test set. Lastly, a final vote was done to finalize the discrimination using these three techniques, and as a result of the vote, accuracies of 92.5%, 85.0% and 88.75% were obtained on the trial data, test data and total data, respectively.

Keywords: Wavelet-decomposition, Statistical signal characterization, Hilbert transform, Parkinson tremor, Essential tremor, Discrimination efficiency.

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التمييز بين ارتعاش مرض الباركنسون والارتعاش الاضطرابي باستخدام التصويت بين عدة طرق مختلفة لمعالجة إشارة مخطط العضلات

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الملخص: من أكثر الإضطرابات العصبية شهرة: مرض الباركنسون والارتعاش الاضطرابي، وكلا المرضين يسببان الاهتزاز و الحركات اللاإرادية للعضلات. الباركنسون هو مرض عصبي يكون بسبب نقص أو فقدان ما يسمى بمستقبلات: "الدوبامين". الذي يعمل كمراسل بين المخ و العضلات لتنظيم حركة الجسم وفي حالة الباركنسون يتم فقدان السيطرة على حركة الجسم. أما الارتعاش الاضطرابي فهو عبارة عن اضطراب أكثر منه مرضاً، فهو يسبب الارتعاش ولكن ليس له علاقة نهائياً بالدوبامين، فهو على قول الأطباء: "إنه ببساطة ارتعاش فقط". في كثير من الأحيان يختلط التشخيص بين المرضين على الطبيب خاصة أن الطبيب يعتمد بشكل كبير على الأعراض الناتجة والتي هي جداً متشابهة بين هذين المرضين. هذا بالإضافة إلى أن وسائل الفحص المستخدمة في هذا الوقت معقدة ومكلفة فاللجوء إلى طرق أسهل وأرخص أمر مرغوب. ولهذا فإن هذه الدراسة تطمح إلى تطبيق طرق سهلة، رخيصة لتزيد من كفاءة التشخيص. هذه الدراسة تعتمد على استخدام معالجة الإشارات العضلية من الجسم، حيث جمعت بيانات هذه الإشارات من ٣٩ مريضاً بالباركنسون و ٤١ مريضاً بالارتعاش الاضطرابي. هذه البيانات مقسمة إلى قسمين: ٤٠ لإجراء التجارب، والقسم الآخر لإجراء الاختبارات. وكل هذه البيانات أخذت من مستشفى جامعة كيل في ألمانيا. طبقت ثلاث طرق مختلفة في هذه الدراسة لتشخيص مرضى الباركنسون من مرضى الارتعاش الاضطرابي وهي: التقنية الأولى: تقنية تحويل الموجات والتي أعطت دقة تشخيص ٨٠٪ على بيانات التجارب و ٨٥٪ على بيانات الاختبار. التقنية الثانية: تقنية الوصف الإحصائي لتحويل فورير السريع والتي أعطت دقة تشخيص ٩٠٪ على بيانات التجارب و ٨٢،٥٪ على بيانات الاختبار. التقنية الثالثة: تقنية الوصف الإحصائي لمغير المقدار لتحويل هيربرت والتي أعطت دقة تشخيص ٨٧،٥٪ على بيانات التجارب و ٦٥،٥٪ على بيانات الاختبار. ثم بعد ذلك تطبيق نظام "التصويت" لعمل خلاصة لهذه النتائج من الطرق الثلاثة والنتيجة الأخيرة هي دقة تشخيص ٩٢،٥٪ على بيانات التجارب و ٨٥٪ على بيانات الاختبار و ٨٨،٧٥٪ على البيانات الكلية.

المفردات المفتاحية: تحويل الموجات، الوصف الإحصائي للإشارة، تحويل هيربرت، ارتعاش الباركنسون، الارتعاش الاضطرابي، كفاءة التمييز.

1. Introduction

The two most common disorders that cause involuntary muscle shaking movements are Parkinson's disease (PD) and essential tremor (ET). PD is a neurodegenerative disease caused by the loss of dopamine receptors which control and adjust the movement of the body (Mayo Clinic, Parkinson's Disease 2010). It was first described in 1817 by James Parkinson in an essay on the "shaking palsy" (We Move: Parkinson's disease). Nowadays, between 7 and 10 million people worldwide are living with PD (Parkinson's Disease Foundation 2012).

ET, on the other hand, is a benign neurological movement disorder that causes shaking of hands, head, voice and sometimes the legs and trunk (International Essential Tremor Foundation 2010; American Academy for Neurology 2011). In contrast to PD, which is characterized by a shortage of dopamine, ET does not seem to involve any neurological abnormalities. It is just a tremor with no associated health problems (We Move, Essential Tremor; Mayo Clinic, Essential Tremor 2010).

Although ET and PD are considered distinct disorders, there is an overlap in some clinical features (Shahed and Jankovic 2007; Bermejo *et al.* 2007). Therefore, an accurate diagnosis of either disease is

difficult and it can take years to receive a diagnosis (Parkinson's Disease Foundation 2012).

A differential diagnosis of PD or ET tremors is usually achieved clinically, but there is a certain overlap in the clinical presentation between the two diseases that can make the differentiation on purely clinical backgrounds difficult (Hossen *et al.* 2010). In such unclear cases, functional imaging of the dopaminergic deficit and a DAT-Scan are used for differentiation (Hossen *et al.* 2010). However, these are considered complex and expensive, and lack wider availability. Additionally, a considerable amount of time is necessary to make a differential diagnosis. Therefore, scientists are investigating the use of the spectral analysis of a tremor time series recorded by accelerometry and a surface electromyogram (EMG) as simpler and more efficient technique.

Hossen *et al.* (2010) adopted a wavelet decomposition with a soft decision algorithm to estimate an approximate power spectral density (PSD) of both accelerometer and EMG signals for discriminating 39 PD subjects from 41 ET subjects collected by the Hospital of Kiel University in Germany, with a total accuracy of 85%.

In (Hossen *et al.* 2013), the statistical signal characterization (SSC) technique, which is a time-domain

Table 1. Trial data-size, age, gender, and disease duration distribution of both groups.

	PD	ET
Number of Patients	19	21
Mean Age (Range)	64.54 (40-90) Years	63.24 (27-94) Years
Gender (Male/Female)	11/8	12/9
Mean Disease Duration	16.4 Years	34 Years

Table 2. Test data-size, age, gender, and disease duration distribution of both groups.

	PD	ET
Number of Patients	20	20
Mean Age (Range)	68.22 (52-85) Years	64.52 (32-86) Years
Gender (Male/Female)	12/8	11/9
Mean Disease Duration	15.3 Years	29 Years

approach and has been applied in many areas (Hirsch 1992), was applied on the spectrum of the accelerometer signal using the same data as that used by Hossen *et al.* (2010).

The aim of this study is to apply the statistical signal characterization on both accelerometer and EMG signals in both the frequency domain and Hilbert domain and to combine the results with that of the soft decision wavelet-based PSD estimation technique to discriminate between the same data used by Hossen *et al.* (2010; 2013). A voting technique is suggested to improve the final discrimination efficiency.

Section 2 presents the data used in the work. The different analysis methods are included in section 3. Section 4 contains the results. Discussions and concluding remarks are given in section 5.

2. Subjects and Data Recording

2.1 Subjects

In this study, subjects were recruited from the Hospital of Kiel University in Germany, 39 of whom were patients with PD and 41 were patients with ET movement disorder. All the patients were suffering from a moderate to severe postural tremor that could not be differentiated easily through clinical background.

The data were divided into two groups: one set was used for training (trial data) and the other was used for the testing (test data). The trial data consisted of 19 PD subjects and 21 ET subjects. The test data consist of 20 PD subjects and 20 ET subjects.

Table 1 shows details of the trial data: size, age, and gender, and disease duration for both PD and ET subjects. Table 2 shows the same details in relation to information about test data.

2.2 Data Recording

Both PD and ET patients were comfortably seated in an armchair with their forearms supported by arm rests. Postural tremor frequency was recorded from the

more affected side while subjects extended their hands and fingers actively to a 0° position with the resting forearm. This posture was held against gravity and, in this condition, tremors were recorded for a period of 30 seconds. A piezoelectric accelerometer of about 2 grams was fixed to the dorsum of the more affected hand in the middle of the third metacarpal bone, and bipolar surface-EMG recordings with silver-silver-chloride electrodes from forearm flexors (EMG1) and extensors (EMG2) were taken.

EMG electrodes were fixed close to the motor points of the ulnar part of the hand extensor and flexor muscles of the forearm, thereby preferentially recording the extensor and flexor carpi-ulnaris muscles.

The EMG read out was later band-pass filtered between (50 and 350 Hz) and full-wave rectified. All data were sampled at 800 Hz.

3. Methodologies

Three methods will be discussed in this section in brief:

The soft decision wavelet decomposition (SD-WDEC) (Hossen *et al.* 2010), the statistical signal characterization (SSC) applied on the spectrum of the accelerometer signal (Hossen *et al.* 2013), and the statistical signal characterization (SSC) applied on the amplitude variation of the Hilbert transform of EMG2 signal.

3.1 The Soft Decision Wavelet Decomposition Algorithm (SD-WDEC)

The soft decision wavelet decomposition algorithm can be used to estimate the power spectral density of the signal using the following steps (Hossen 2004):

- The wavelet-decompositions (low-pass and high-pass filtering) are computed with all branches up to a certain stage m to obtain 2^m sub-bands.

- All estimator results up to stage m are stored, and a probability measure is assigned to each path (*ie.* frequency band) to bear the primary information.
- If $J(L)$ is the assigned probability of the input signal being primarily low-pass, the number $J(H) = 1 - J(L)$ is the probability that the signal is primarily high-pass. The probability $J(L)$ is assigned as the ratio of the number of positive comparisons between the low-pass filtered sequence and the high-pass filtered sequence to the total number of comparisons for a given stage.
- At the next stage, the resulting estimate can be interpreted as the conditional probability of the new input sequence containing primarily low (high) frequency components, given that the previous branch was of predominantly low (high)-pass character.
- The probabilities $P(B_i)$ derived from the estimator outputs, where i is the index of the band, may be interpreted themselves as a coarse measurement of the PSD. The higher the probability value of any band, the higher its power-spectral content.

For m decomposition stages, 2^m bands result. Each band covers $(F_s/2^{m+1})$ Hz of the spectrum, where F_s is the sampling frequency. So with level 8, 256 frequency bands result. Each band covers $(400/256)$ Hz of the signal-spectrum range between 0 and 400 Hz.

Most of the researchers found that the peak in the EMG tremor spectrum is at a frequency of 5 to 6 Hz. It may differ between each type of tremor (Rissanen *et al.* 2007; Wang *et al.* 2006). Researchers noticed also that at the double of those frequencies (first harmonic), there was also a peak in the spectrum, so it was better to investigate the tremor spectrum up to 18-20 Hz. We used 20 bands up to 30 Hz to detect all of the peaks that may have relations to the tremors.

3.2 Statistical Signal Characterization (SSC) on the Spectrum of the Signal

The SSC is a method that characterizes a waveform not only as a function of the frequency component amplitudes but also as a function of the relative phases of the frequency components. In SSC, there are four parameters that could be extracted from the amplitude, frequency, and phase of the signal waveform. The four waveform parameters are the amplitude mean, amplitude deviation, period mean, and period deviation.

In this technique, the waveform is divided into segments with each segment bounded by two extrema: maxima and minima. The absolute difference of both extrema amplitudes is called segment amplitude, and the difference in their time is called the segment period.

The segment amplitude and period are calculated for each segment of the waveform as shown in Fig. 1. The result would be two vectors: an amplitude vector and a period vector whose lengths are equal to the number of segments.

Where,

$$\text{Number of segments, } N_s = n_e - 1$$

Where, n_e = number of extrema.

$$\text{Segments Amplitude vector, } A_n = |a_n - a_{n-1}|$$

A_n = amplitude of the n th segment,

a_n = waveform amplitude at the concluding extremum of the segment,

a_{n-1} = waveform amplitude at the beginning extremum of the segment.

$$\text{Segments period vector, } T_n = t_n - t_{n-1}$$

T_n = period of the n th segment,

t_n = waveform elapsed time at the concluding extremum of the segment,

t_{n-1} = waveform elapsed time at the beginning extremum of the segment.

The main SSC vectors are:

$$ma = \sum_{i=1}^{N_s} \frac{A_i}{N_s} \quad (1)$$

$$mt = \sum_{i=1}^{N_s} \frac{T_i}{N_s} \quad (2)$$

$$da = \sum_{i=1}^{N_s} \frac{|A_i - ma|}{N_s} \quad (3)$$

$$dt = \sum_{i=1}^{N_s} \frac{|T_i - mt|}{N_s} \quad (4)$$

Where,

ma = amplitude mean,

mt = period (time) mean,

da = amplitude mean deviation,

dt = period mean deviation.

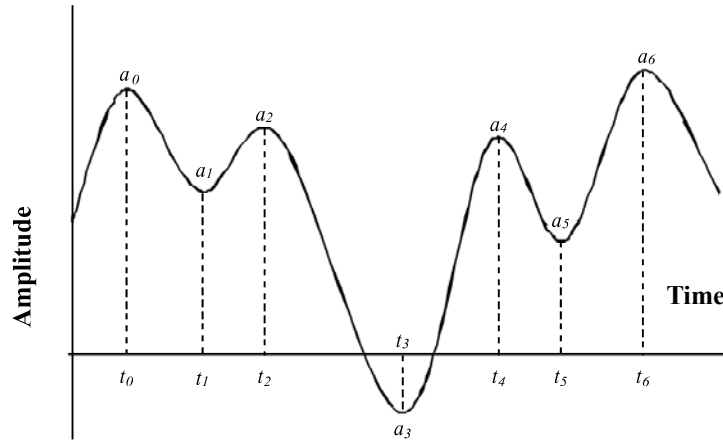


Figure 1. SSC segments amplitudes and time characteristics.

The time domain signal of length 10000 samples is divided into 40 sections of length 250 each. The four SSC parameters are used to derive 12 new parameters, computed as an average, maximum, or minimum of the main SSC parameters of the 40 sections.

1. Average of amplitude mean: Mean (ma)
2. Maximum amplitude mean: Max (ma)
3. Minimum amplitude mean: Min (ma)
4. Average of amplitude mean Deviation: Mean (da)
5. Maximum amplitude mean deviation: Max (da)
6. Minimum amplitude mean deviation: Min (da)
7. Average of period mean: Mean (mt)
8. Maximum period mean: Max (mt)
9. Minimum period mean: Min (mt)
10. Average of period mean deviation: Mean (dt)
11. Maximum period mean deviation: Max (dt)
12. Minimum period mean deviation: Min (dt)

In Hossen *et al.* (2013), the SSC was applied on the spectrum of the accelerometer signal, (*ie.* on the FFT of the accelerometer signal). The 12 parameters were obtained for the trial data. For each parameter, a threshold was assigned using receiver operating characteristics (ROC) (Provost and Fawcett 2000) for the best results for discriminating the trial data. The results of the test data were also obtained using the same threshold.

3.3 SSC after the Hilbert Transform of the Signal

A real time function and its Hilbert transform relate to each other in such a way that they together create what is called an analytical signal. The analytical signal has a real part, which is the original signal, and an imaginary part, which is the Hilbert transform; it is a 90° phase shifted version of the original signal. The instantaneous amplitude is the amplitude of the com-

plex Hilbert transform and the instantaneous frequency is the time rate of change of the instantaneous phase angle.

In this study, the SSC was applied on the amplitude deviation of the Hilbert transform of the signal. The 12 parameters were obtained for the trial data. For each parameter, a threshold was assigned using ROC for the best results in discriminating the trial data. The results of the test data were also obtained using the same threshold. The results were also shown in terms of specificity, sensitivity, and accuracy (Rangayyan 2001).

4. Results

4.1 SD-WDEC

The SD-WDEC method was applied on each of the three different signals (Acc, EMG1, EMG2) using Daubechies 4 (db4) wavelet filter. The results (number of correct PD and ET subjects) of test data are listed in Table 3 with the results of voting. Table 4 shows the same results obtained through trial group data using the features obtained from the test group data. Figs. 2 and 3 show the results of classification using EMG1 signal of test data and trial data respectively.

4.2 Application of SSC on the Spectrum of the Signal

Table 5 shows the results (number of correct PD and ET subjects) using all SSC parameters and the accelerometer signal on the trial and test data. The best result obtained is with parameter Min (da): 85% (17/20) sensitivity, 95% (19/20) specificity and 90% (36/40) accuracy. Figure 4 shows the classification of PD and ET subjects according to the trial data (19 PD; 21 ET). Figure 5 shows the implementation of ROC on the results of Fig. 4 to find the correct threshold to be used with test data. Figure 6 shows the classifica-

Table 3. Results of SD-WDEC (classify test data using trial data).

Classification based on	Correct PD subjects	Correct ET subjects	Correct PD/ 20	Correct ET/20
Acc. Signal	2, 4, 6, 7, 8, 11, 14, 16, 17, 18, 19, 20	4, 5, 6, 7, 8, 9, 11, 14, 15, 17, 18	12	11
EMG1	2, 3, 4, 5, 8, 9, 10, 11, 14, 15, 17, 18, 20	1, 2, 3, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20	13	17
EMG2	2, 3, 4, 5, 6, 8, 9, 11, 14, 15, 16, 17, 18, 19, 20	1, 2, 3, 4, 5, 6, 9, 10, 13, 14, 15, 16, 17, 18, 19, 20	15	16
Voting	2, 3, 4, 5, 6, 8, 9, 11, 14, 15, 16, 17, 18, 19, 20	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20	15	19

Table 4. Results of SD-WDEC (classify trial data using test data).

Classification based on	Correct PD subjects	Correct ET subjects	Correct PD/19	Correct ET/21
Acc Signal	1, 6, 7, 8, 9, 11, 12, 13, 15, 16, 17, 19	2, 3, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 19, 20, 21	12	17
EMG1	1, 3, 4, 6, 8, 9, 10, 11, 13, 16, 17	1, 2, 3, 4, 5, 6, 7, 8, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21	11	18
EMG2	1, 3, 4, 6, 8, 9, 10, 11, 13, 17, 19	1, 2, 3, 4, 5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 17, 18, 20, 21	11	18
Voting	1, 3, 4, 6, 8, 9, 10, 11, 13, 16, 17, 19	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21	12	20

tion of PD and ET subjects according to the test data (20 ET; 20 PD). The final result of discrimination is 90% accuracy obtained on trial data and 82.5% obtained on test data.

4.3 Application of SSC on the Amplitude Deviation of the Hilbert Transform of the Signal

The SSC was implemented on the amplitude deviation of the Hilbert transform of the signal. The highest results were obtained using EMG2 signal with the Mean (dt) parameter on the trial data with 80% (16/20) sensitivity, 95% (19/20) specificity and 87.5% (35/40) accuracy. The result obtained on the test data was 65.5%. Table 6 shows the results of all parameters

using EMG2 signal. Figure 7 shows the results of classification of trial data using EMG2 with the Mean (dt) parameter. Figure 8 shows the results of the classification of test data using the same parameter and signal as used in Fig. 7.

4.4 Voting Results

Voting is a technique used to combine three results of different methods or versions, or the results of application of the same method on three different signals. For each data under test, if the data is classified in any category (ET or PD) two times or more, it is considered as belonging to that category. A voting can be useful to enhance the evaluation efficiency. A last voting is applied on the best results obtained. The

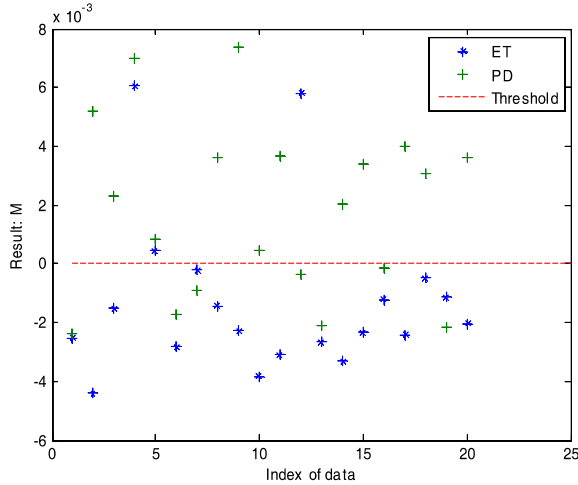


Figure 2. Results of classification of test data using EMG1 signal.

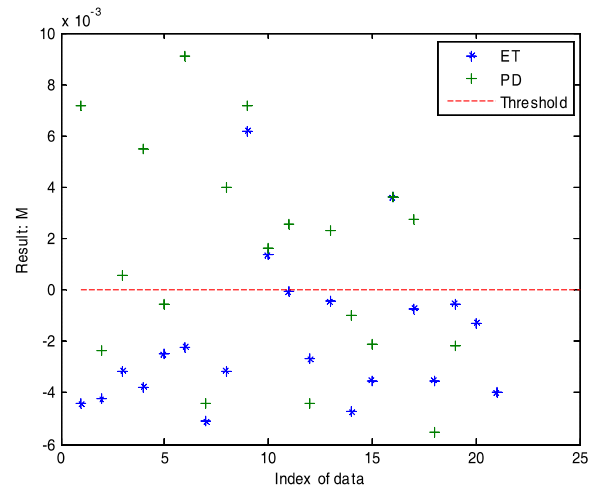


Figure 3. Results of classification of trial data using EMG1 signal.

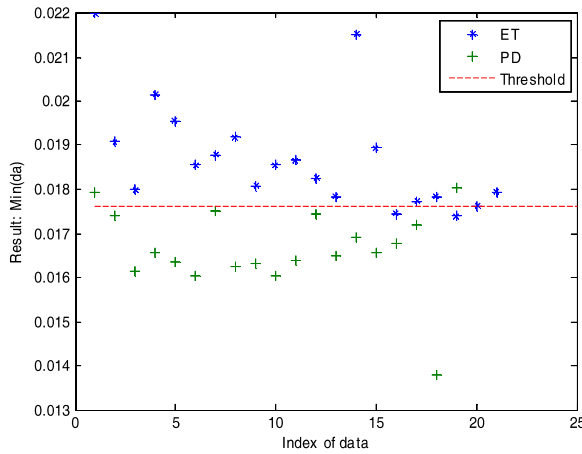


Figure 4. Results of classification of trial data using the spectrum of accelerometer signal and parameter Min(da).

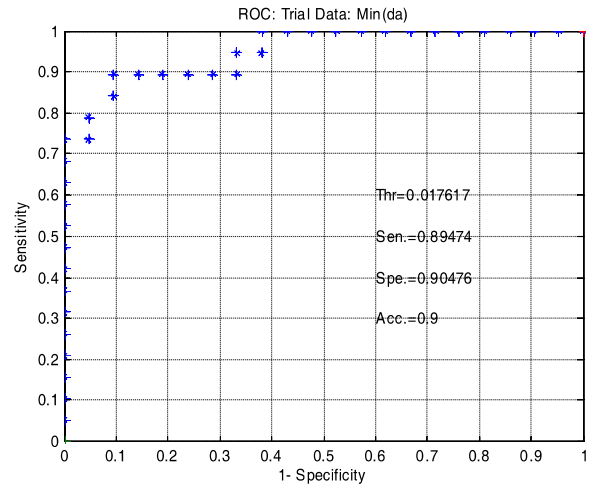


Figure 5. ROC results to find the threshold of Fig. 4.

accuracy was raised using the voting to 92.5% on trial data and 85% on test data. Table 7 shows the results of the trial data using a voting between the three mean methods applied in this paper: the soft-decision wavelet-decomposition voting result of all three signals (accelerometer, EMG1, and EMG2); SSC on the spectrum of the accelerometer signal with the Min (da) parameter, and SSC on amplitude deviation of the Hilbert transform of the EMG2 signal using the Mean (dt) parameter. Table 8 shows the voting results of test data. Tables 9 through 11 show the efficiency (specificity, sensitivity, and accuracy) results of all methods on trial data, test data, and overall data, respectively.

5. Discussion and Conclusions

An automatic system for discriminating between ET and PT based on voting between three different meth-

ods is investigated in this paper. The three methods were:

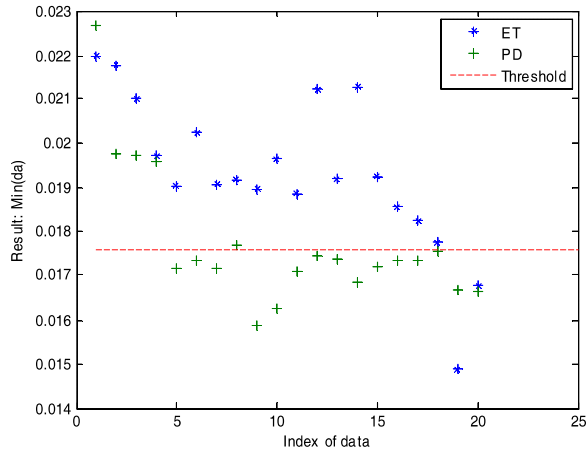
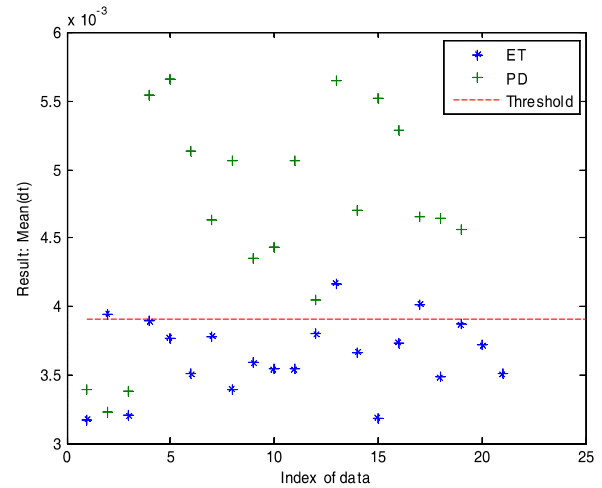
1. Method of computation of power entropy of wavelet-decomposed spectra using the fast approximate soft-decision technique, which is implemented on accelerometer and EMG signals (flexors (EMG1) and extensors (EMG2)). This method uses the sum of the power entropy of the frequency bands B6 (between 7.8125 and 9.375 Hz) and B11 (between 15.625 and 17.1875 Hz) that allowed for the best separation between the two common tremors. These bands are very close to the frequency regions in which the first and second harmonic peaks at double and triple the tremor frequency are found. It is a common observation that PD patients more regularly show peaks at harmonics of the basic tremor frequency than ET patients.

Table 5. Results of SSC on the spectrum of accelerometer signal.

<u>Parameter</u>	<u>Trial</u>		<u>Test</u>		<u>Threshold</u>
	PD/19	ET/21	PD/20	ET/20	
Mean(ma)	9	15	10	8	0.0160
Max(ma)	9	15	7	10	0.0300
Min(ma)	9	15	13	4	0.01190
Mean(da)	9	13	9	5	0.0218
Max(da)	11	10	10	14	0.0360
Min(da)	17	19	15	18	0.0176
Mean(mt)	8	13	8	18	0.0066
Max(mt)	12	9	15	6	0.0088
Min(mt)	15	13	13	14	0.0053
Mean(dt)	12	13	13	18	0.0034
Max(dt)	13	12	14	6	0.0055
Min(dt)	15	15	12	15	0.0021

Table 6. Results of SSC on the amplitude deviation of the Hilbert transform of EMG2 signal.

<u>Parameter</u>	<u>Trial</u>		<u>Test</u>		<u>Threshold</u>
	PD/19	ET/21	PD/20	ET/20	
Mean(ma)	11	16	6	16	0.3000
Max(ma)	16	11	11	11	0.4700
Min(ma)	11	12	10	12	0.2000
Mean(da)	10	15	7	15	0.2200
Max(da)	10	14	7	13	0.3000
Min(da)	12	10	11	9	0.1500
Mean(mt)	13	18	11	16	0.0075
Max(mt)	14	17	7	13	0.0088
Min(mt)	13	17	11	17	0.0065
Mean(dt)	16	19	11	15	0.0040
Max(dt)	15	18	7	13	0.0054
Min(dt)	16	16	16	16	0.0030

**Figure 6.** Results of classification of test data using the spectrum of accelerometer signal and parameter Min(da).**Figure 7.** SSC on the amplitude deviation on the EMG2 signal (classification of trial data), with parameter Mean(dt).

- Method of computation of the statistical signal characterization of the spectrum of the accelerometer signal. In this method, the SSC technique,

which is a time-domain approach, has been modified to be implemented on the spectrum of the accelerometer signal, resulting in a combination

Table 7. Results of voting (trial data).

Method	Correct PD subjects	PD /19	Correct ET subjects	ET /21
Soft-decision wavelet decomposition: voting on three signals	1, 3, 4, 6, 8, 9, 10, 11, 13, 16, 17, 19	12	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21	20
SSC on Spectrum of Acc. signal with parameter Min(da)	2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18	17	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 20, 21	19
SSC on Amplitude Deviation of Hilbert transform of EMG2 signal with parameter Mean(dt)	4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	16	1, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 14, 15, 16, 18, 19, 20, 21	18
Voting	3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19	17	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17, 18, 19, 20, 21	20

Table 8. Results of the voting (test data).

Method	Correct PD subjects	PD /20	Correct ET subjects	ET /20
Soft-decision wavelet decomposition: voting on three signals	2, 3, 4, 5, 6, 8, 9, 11, 14, 15, 16, 17, 18, 19, 20	15	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 19, 20	19
SSC on Spectrum of Acc. signal with parameter Min(da)	5, 6, 7, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20	15	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18	18
SSC on Amplitude Deviation of Hilbert transform of EMG2 signal with parameter Mean(dt)	2, 3, 6, 7, 8, 9, 13, 14, 15, 16, 18	11	1, 2, 3, 4, 5, 7, 8, 9, 13, 14, 15, 16, 17, 18, 20	15
Voting	2, 3, 5, 6, 7, 8, 9, 11, 13, 14, 15, 16, 17, 18, 19, 20	16	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 13, 14, 15, 16, 17, 18, 20	18

between time-domain and frequency-domain analysis. This method also can be interpreted as a technique investigating the morphology of the spectrum of the signal and concentrating on the amplitude and location of the peaks in frequency domain. The best parameter was found to be the minimum amplitude mean deviation [Min (da)].

3. Method of computation of the statistical signal

characterization of the amplitude variation of the Hilbert transform of the EMG2 signal. This method is based on the time-domain signal; the best parameter was found to be the average of period mean deviation [mean (dt)].

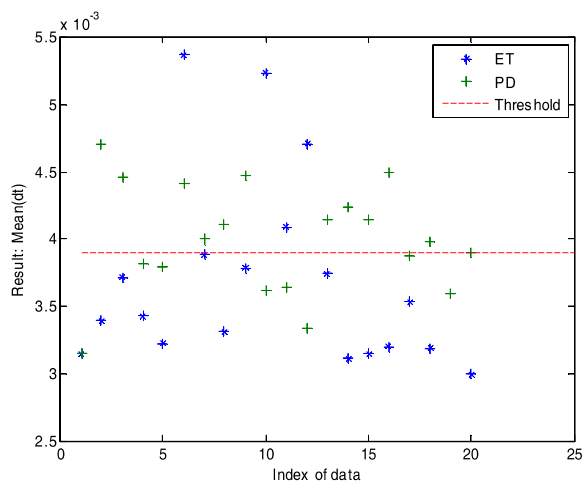
The discrimination results obtained on trial data of the above three methods were 80%, 90%, and 85%, respectively. The discrimination results of the test data

Table 9. Results of the voting (trial data), efficiency evaluation.

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Soft-decision wavelet decomposition: voting on three signals	63.2	95.2	80
SSC on Spectrum of Acc. signal with parameter Min(da)	89.5	90.5	90
SSC on Amplitude Deviation of Hilbert transform of EMG2 signal with parameter Mean(dt)	84.2	85.7	85
Voting	89.5	95.2	92.5

Table 10. Results of the voting (test data), efficiency evaluation.

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Soft-decision wavelet decomposition: voting on three signals	75	95	85
SSC on Spectrum of Acc. signal with parameter Min(da)	75	90	82.5
SSC on Amplitude Deviation of Hilbert transform of EMG2 signal with parameter Mean(dt)	55	75	65
Voting	80	90	85

**Figure 8.** SSC on the amplitude deviation on the EMG2 signal (classification of test data), with parameter mean(dt).

using the three methods were 85%, 82.5%, and 65%, respectively.

The voting between the three methods resulted in

discrimination efficiency of 92.5% and 85% on trial data and test data, respectively. The discrimination result on overall data was 88.75%.

A combination of those methods implemented on all three signals with all features fed as inputs to a neural network may result in better discrimination between ET and PD. Extension of the work is possible by including other tremors such as orthostatic tremor (OT), physiological tremor, and psychogenic tremor. In all cases, the collection of data from a larger group is recommended in order to facilitate more consistent results.

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Table 11. Results of the voting (overall data), efficiency evaluation.

Method	Sensitivity (%)	Specificity (%)	Accuracy (%)
Soft-decision wavelet decomposition: voting on three signals	69.23	95.12	82.5
SSC on Spectrum of Acc. signal with parameter Min (da)	82.05	90.25	86.25
SSC on Amplitude Deviation of Hilbert transform of EMG2 signal with parameter Mean (dt)	69.23	82.5	75
Voting	84.62	92.68	88.75

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