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EMG Signal Morphology in Essential Tremor and Parkinson's Disease

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Abstract— **The aim of this work was to differentiate patients with essential tremor from patients with Parkinson's disease. The electromyographic signal from the biceps brachii muscle was measured during isometric tension from 17 patients with essential tremor, 35 patients with Parkinson's disease, and 40 healthy controls. The EMG signals were high pass filtered and divided to smaller segments from which histograms were calculated using 200 histogram bins. EMG signal histogram shape was analysed with a feature dimension reduction method, the principal component analysis, and the shape parameters were used to differentiate between different patient groups. The height of the histogram and the side difference between left and right hand were the best discriminators between essential tremor and Parkinson's disease groups. With this method, it was possible to discriminate 13/17 patients with essential tremor from 26/35 patients with Parkinson's disease and 14/17 patients with essential tremor from 29/40 healthy controls.**

I. Introduction

Essential tremor (ET) and Parkinson's disease (PD) are progressive neuromotoric diseases. PD is mainly a disease among the old, and it has an estimated prevalence of 1 % in those over 60 years of age in industrialised countries [1]. For ET, the estimate is $4.6\,\%$ in people over 65 years old [2]. Their main symptoms, rest tremor in PD (4–6 Hz) and postural tremor in ET (5–10 Hz) [3], are different, but overlapping symptoms occur. Patients with PD usually have postural tremor in addition to rest tremor [4]. There is also evidence of rest tremor appearing in approximately 20 % of patients with ET [5]. Thus it can be difficult to differentiate between PD and ET tremor as both may occur under same circumstances. There is increasing clinical, pathological, genetic and neuroimaging evidence that ET and PD are related even though they are two different diseases [4].

The diseases are not curable and the treatment is mainly relieving the symptoms and increasing the life quality of patients. There is great interest in to being able to differentiate between the diseases since the treatments are different. While there is currently no reliable test for differential diagnosis of ET and PD, diagnosis is done mainly by clinical observation. However, in the early stages of the diseases, the rate of misdiagnosis can be as high as 20–30 % in PD and 33 % in ET [6].

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Tools that have been tried and have partially succeeded in discriminating between the two diseases include SPECT imaging [7], transcranial sonography [6] and combined sonography, olfactory and motor function assessment [8]. First two of these methods are costly and also demand advanced measurement settings. The combined method produced promising results.

There is a growing interest in methods based on surface EMG and kinematic measurements of patients with PD and patients with ET because they have certain benefits: complex measurement setup is not needed and the measurements are easy to produce, cost-efficient and non-invasive. Several EMG studies to differentiate PD from ET have been done: long-term EMG [9], wavelet-based [10], pattern [11], movement and force variability [12], and spectral power based [13] analysis. The discrimination efficiency varies between 85–100 % in these studies.

It has been shown that EMG signals of patients with PD contain more tonic background activity and rhythmic burst activations than healthy controls (CO) [14]. The signal morphology of EMG of patients with PD has been analysed and it has been successfully used to differentiate patients with PD from CO [14]. The method is easy to implement; it does not need extra equipment in addition to the measurement device and it is relatively quick. To our knowledge, this method has not been applied to discriminate between patients with PD and ET.

EMG signal morphology was studied by using sample histograms during isometric contraction of biceps brachii muscle with varying loads to observe differences between the diseases. The main aim of this study is to develop a method to differentiate patients with ET from patients with PD by EMG measurements. The secondary aim is to differentiate the morphology of EMG signal in patients with ET, patients with PD and in the CO.

II. Materials and methods

A. Subjects

The measurements consisted of EMG and movement measurement data of 17 patients with ET, 35 patients with PD and 40 CO measured in 2nd city outpatient clinics in Petrozavodsk after giving their informed consent. Clinical UPDRS data was available for patients with PD.

The average duration of the disease in patients with PD was (8 ± 8) years (mean$\pm$std) and the severity of the disease

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in UPDRS scale was (32 ± 12). The patients had a diagnosis of idiopathic PD and they were taking medication for the condition. The duration of disease varied plenty in patients with ET, the average duration was (12 ± 12) years at the time of measurement. The patients had a diagnosis of ET and some of them had medication for the condition. The control group was recruited from generally healthy Russian citizens. No group had other medical conditions affecting the motor functions. This study was approved by the human ethics committee of Petrozavodsk State University.

B. Measurements

The skin beneath electrodes was cleaned with cotton pad wetted with ethanol prior to electrode placement. Disposable Ag/AgCl surface electrodes (Medicotest M-00-S) were placed bilaterally to the belly of the biceps brachii muscle and beneath the belly with inter-electrode spacing of 3 cm. The measurements were done with bipolar connection the reference electrode being 6–7 cm laterally from the recording electrodes, and recorded with ME6000 biosignal monitor (Mega Electronics Ltd., Kuopio, Finland) with sampling rate 1000 Hz.

All measurements were done while the patient being on medication. During the measurements the subjects were standing and holding their elbows in $90\,^\circ$ angle and their palms were directing upwards. This isometric tension lasted at least 15 s and was firstly done without additional load, and then with loads of 1 kg and 2 kg in both hands.

C. Analysis

After the measurements 7-second segments were chosen from EMG signals of each subject from both hands and with 3 different loads: 0, 1 and 2 kg. The segment was chosen from the middle of the isometric trial and was visually checked for possible artefacts. Smoothness priors detrending method [15] was used to remove low frequency trends from the signal. The method resembles high pass filter with a cut-off frequency approximately 10 Hz. The filtered segments were then divided to overlapping epochs with epoch length 2048 ms and overlap 75%.

The EMG signal is a sum of individual motor unit action potentials and therefore its pattern is impulse like. The morphology of impulse patterns includes information about pathologies such as PD and ET. Because of the spiky nature of EMG signal, the morphological analyses can be more efficient for extracting signal properties than traditional amplitude and spectral based methods. The morphology was analysed using sample histogram which was calculated with 200 bins for each epoch in one segment. Then the histograms of one segment were averaged to decrease deviation in histogram shape.

The shape of the histogram contains different features of the signal. To assess these features more rigorously, feature dimension reduction techniques, as principal component analysis (PCA) can be used. In this approach the data dimension is reduced to present as much as possible information with as few as possible components. After the reduction it is possible to visualise the histogram properties with only few components. These components serve as new parameters and can be used to differentiate the signals.

In the PCA approach (partially presented in [14]), feature vectors are formed from single patient (CO, ET and PD) histograms. Even though the histogram is calculated separately for right and left hand, the histograms are concatenated to create feature vector. One of the main characteristics of PD is the side differences of symptoms and this method possibly reveals them when applying PCA.

The PCA begins from modelling the feature vectors with a linear model to obtain basis vectors ϕ_j. With this model jth feature vector can be expressed as

$$z_j = H\theta_j + v_j, \tag{1}$$

where H is the model matrix containing the basis vectors $\phi_1 \dots \phi_K$ as columns. The parameter θ_j contains the weights and v_j the model error for the jth feature vector. The feature vector z_j can be expressed as the sum of basis vectors $\phi_1 \dots \phi_K$ with weights $\theta_j(1 \dots K)$ as

$$z_j = \phi_1\theta_j(1) + \phi_2\theta_j(2) + \cdots + \phi_K\theta_j(K) + v_j. \tag{2}$$

The linear model can be presented in matrix form where feature matrix Z is concatenated from vectors z_j if the data set consists of feature vectors from multiple subjects

$$(z_1 \cdots z_M) = Z = H\theta + v. \tag{3}$$

The selection of basis vectors can be done in several ways. In this approach basis vectors are chosen to be the eigenvectors of experimental correlation matrix

$$R = \frac{1}{M}\sum_{j=1}^{M} z_j z_j^T = \frac{1}{M} ZZ^T. \tag{4}$$

By this selection it can be shown that first basis vector ϕ_1 is the best mean-square fit for the feature matrix Z, basis vector ϕ_2 is the best mean-square fit for the residual of the first fit and further, choosing K' eigenvectors which have the largest eigenvalues is the best K'-dimensional orthogonal approximation for the data set. In this work 6 basis vectors of largest eigenvalues were chosen to represent the original feature vectors. The principal components $\theta_j(i)$ correspond to the weights for the basis vectors in the Eq. 2 and they can be solved in the least-squares sense from the linear model as

$$\hat{\theta} = (H^T H)^{-1} H^T Z = H^T Z, \tag{5}$$

where $H^T H = I$ because of the orthonormal eigenvectors of R. The principal components are now parameters of the histogram shape and can be considered as signal properties.

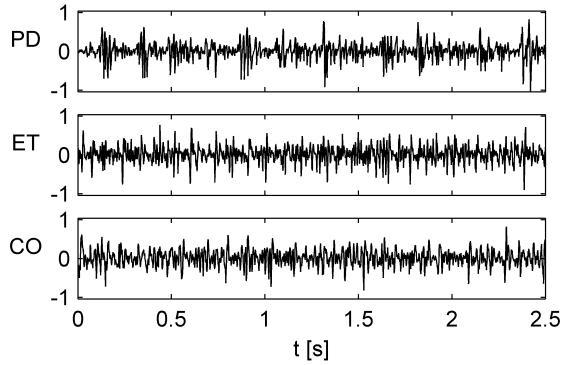

Fig. 1. EMG signal from a single patient with PD, patient with ET and CO without load in hand.

III. Results

Differences in signal morphology between the CO and the patients with ET and PD without load in hands can be seen in Fig. 1. The EMG signal in the patient with PD is uneven and contains lot of bursts compared to the control signal. The difference between the EMG of the patient with ET and the CO is not as clear, but there is still slight difference in the spikiness of the signals.

EMG histograms were calculated for all subjects with different loads. Fig. 2 shows histograms for the same control and patients with ET and PD. There are two major parameters which differ in these histograms: the side differences between left and right side and the steepness of the histogram peak. On the right hand side, the steepness of the histogram increases when comparing between ET and CO and between PD and ET. On the left hand side, the ET and the CO histograms are similar to the right hand side histograms of ET and CO, but the PD histogram is more similar to the CO histogram than to the PD histogram on the right hand side. According to the histograms, the symptoms of this patient with PD are greater on the right hand side which is also confirmed by the UPDRS scores for hand tremor. The sharper histogram peak indicates higher spikiness of the signal of the patient with PD and is one of the main differences in the signal morphology.

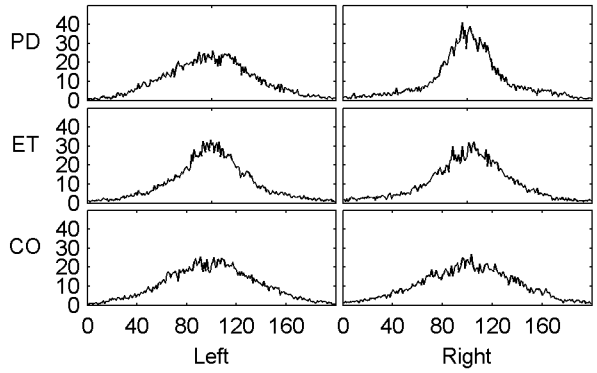

Fig. 2. Histograms for the patients in Fig.1.

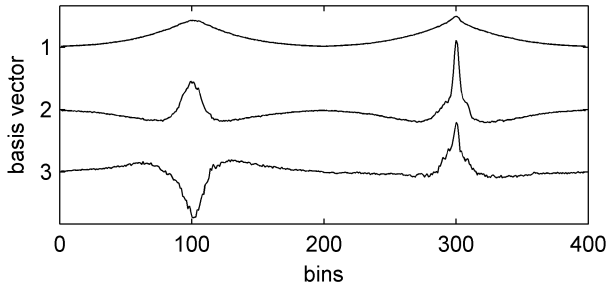

Fig. 3. The first three basis vectors calculated from the histograms.

The first three basis vectors of the data are shown in Fig. 3. The basis vectors describe the different properties of the histograms. The first basis vector corresponds to the height of the histogram, the second to the sharpness of the peak and the third to the side differences. The analysis was done by comparing every combination of two basis vectors and evaluating their ability to discriminate between the PD, CO and ET groups. It was found that the first and the third basis vector are best for differentiating between PD, ET and CO.

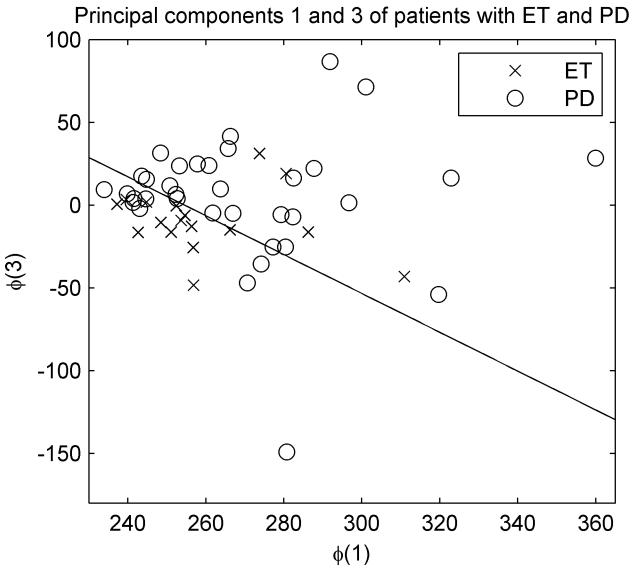

Fig. 4. Principal components $\theta(1)$ and $\theta(3)$ of ET($\times$) and PD($\bigcirc$) group without load in hands.

The principal components for the patients with ET, the patients with PD and the controls were calculated with 0, 1 and 2 kg load. The components of basis vectors $\phi(1)$ and $\phi(3)$ with 0 kg load are shown in Fig 4 for the patients with ET and the patients with PD, and in Fig 5 for the patients with ET and the controls. Most of the patients with ET are tightly stacked and only few patients are scattered away from the main group. The deviation in the components is larger on the patients with PD and they are distributed to larger area. Even though the larger scattering, the points are focused more to the vicinity of the ET cluster. It is possible to draw a linear discriminator which separates 13/17 (76 %) patients with ET and 9 patients with PD to the lower side and 4

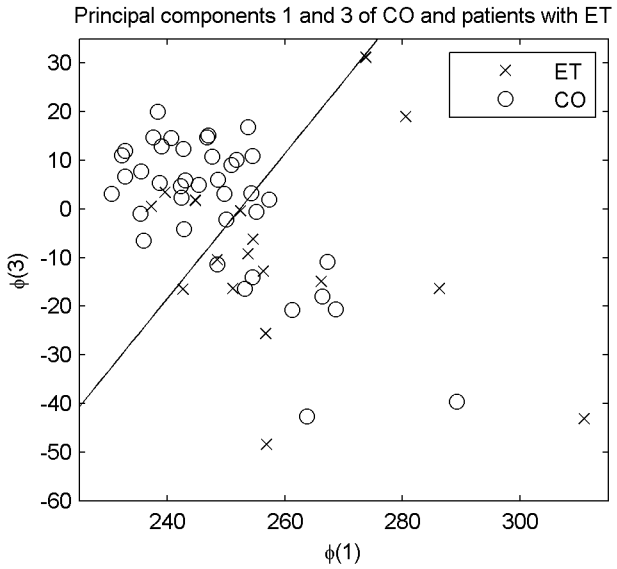

Fig. 5. Principal components $\theta(1)$ and $\theta(3)$ of ET($\times$) and CO($\bigcirc$) group without load in hands.

patients with ET and 26/35 (74 %) patients with PD to the upper side of the discriminator. It was noted in this study that increasing the load to 1 or 2 kg decreases the discrimination; the signal features become more similar between ET and PD.

Fig. 5 shows the components $\theta(1)$ and $\theta(3)$ for the patients with ET and the CO. The controls are divided into two subgroups which of the main cluster is centred around upper left corner of the figure. The rest of the controls overlap the patients with ET and decrease the differentiation accuracy. Regardless of the deviation of the controls it is possible to draw a linear discriminator so that 14/17 (82 %) of patients with ET are on one side, and 29/40 (74 %) controls on the other.

IV. Discussion

The properties of EMG signals of the CO and the patients with ET and PD were studied using EMG morphological analysis. The major finding was that the method that analyses the histogram morphology can discriminate patients with ET and patients with PD. However, absolute clear differentiation was not achieved due to non-uniformity of ET patients. The secondary finding was that ET occupies a position between PD and CO, thus revealing the dual nature of ET (physiological and pathological state). The best discrimination between ET and PD was achieved when there was no load in the subjects' hands. This is in concordance with an earlier study where the Parkinsonian EMG moved towards normalcy when the muscle was under load [16].

Though the ET group is in between the PD and the CO, it was noted that the patients with ET can be discriminated also from the CO with slightly higher efficiency than from the PD. The principal components of the patients with ET did not show as much variation as the components of the patients with PD. The reason for the variation in PD parameters is most likely caused by the inhomogeneous backgrounds of the patients: the group contained patients of different age, leading symptom, severity and duration of the disease. However, reason for the variation of parameters in the CO was not solved.

In conclusion, the results indicate that signal morphology of ET is different compared to to those of PD and CO, and this difference can be used in discrimination analysis. The morphologies also share some characteristics which can be seen as overlapping histogram parameters.

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