Quality improvement of diagnosis of the electromyography data based on statistical characteristics of the measured signals

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ABSTRACT

Research and systematization of motor disorders, taking into account the clinical and neurophysiologic phenomena, are important and actual problem of neurology. The article describes a technique for decomposing surface electromyography (EMG), using Principal Component Analysis. The decomposition is achieved by a set of algorithms that uses a specially developed for analyze EMG. The accuracy was verified by calculation of Mahalanobis distance and Probability error.

Keywords: EMG, tremor, decomposition of surface EMG signal, principal component analysis, Mahalanobis distance

1. INTRODUCTION

The electromyographic (EMG) signal measures electrical currents generated in muscles during its contraction representing neuromuscular activities[1]. EMG is composed of the action potentials from groups of muscle fibers organized into functional units called motor units (MUs)[2]. This signal can be detected with sensors placed on the surface of the skin or with needle or wire sensors introduced into the muscle tissue. It is a result of the summation of all Motor Unit Action Potentials (MUAP) in the region near the electrodes. The composition of a surface EMG signal from MUAPs results in a stochastic signal, because of the different firing rates and the large number of motor units that contribute[1,3]. Raw EMG offers valuable information in a particularly useless form. This information is useful only if it can be quantified. Analysis of EMG signals with powerful and advanced methodologies is becoming a very important requirement in biomedical engineering[4]. The main reason for the interest in EMG signal analysis is in clinical diagnosis and biomedical applications when only two or three MUs in the vicinity of the sensors are active, it is usually possible to visually identify most of the individual MU action potentials because the incidence of superposition among the individual MU action potentials is relatively low. However, when the EMG signal contains the activity of four or more MUs the individual action potentials become, in large part, indistinguishable to the naked eye because the incidence of superposition among two or more MU action potentials becomes numerous and the shapes of the MU action potentials may approach in similar[5,6].

2. EXPERIMENTAL

The initial data are EMG, which was recorded from muscle of the human right hand *Extensor digitorum Radialis* by surface electrodes without postural load. Input signals are interference curves. Biosignal is a multidimensional array that is stored in a file in text format. Number of columns of the array corresponds to the number of components of a random process, the number of rows equal to the number of counts.

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Clinical data for research of tremor phenomena were studied in department of neurology using hardware standard electromyograph Neuro-MVP-4 and software Neurosoft at Kharkiv Municipal Health Care "Medical Center Emergency and Disaster Medicine" (Regional Hospital). Research was conducted with group of 58 patients ranging in age from 18 to 75 years, 25 of them are healthy and 33 suffer from different forms of tremor disorders.

Fig. 1 shows examples of two signals for processing: the first curve in a norm (woman, 27 years); the second curve is a disorder that causes tremors and muscle rigidity (woman, 69 years), signal has 5-6 oscillations per second. EMG of norm it is an implementation of 46297 counts of multivariate random signal, sampling step in seconds is 10.8 ms. EMG of pathology (tremor) consists of 39685 counts with sampling frequency 25.2 ms. The results of the EMG analysis of pathology compare with similar curves in norm. Table 1 shows parameters of EMG, obtained with Thurn-amplitude analysis of Neurosoft, because amplitude and frequency of measured signals are some of the main characteristics.

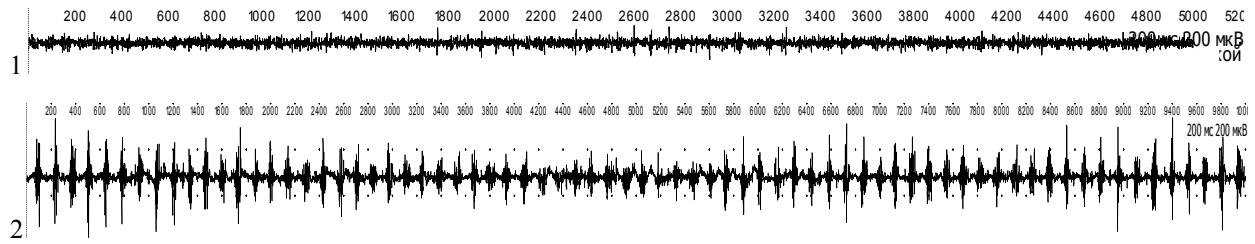


Figure 1. Samples of clinical interference EMG signals for processing: 1 – norm curve; 2 – tremor curve.

Table 1. Parameters of clinical EMG signals

Curve	Max amplitude, μV	Mean amplitude, μV	Σ amplitude, mV/s	Mean frequency, 1/s	Amplitude/frequency, μV·s
1 norm	124	105	0,04	0,4	262
2 tremor	509	165	6,2	37,5	4,41

3. RESULTS AND DISCUSSION

Generally, the amplitude of the signal can range between 0 to 10 mV (peak-to-peak) and 0 to 1.5 mV. The frequency of EMG signal is between 0 to 500 Hz[7-10]. In this paper we explain most popular technique is Principal Component Analysis (PCA), which applied for signal classification and decomposition. PCA is a useful statistical procedure that has found importance in many fields, and is a well known technique for finding patterns in high dimensional data. It is a way of identifying pattern in data, and expressing the data in such a way to highlight their similarities and differences[4]. The other main advantage of PCA is that once these patterns are found, the data can be compressed by reducing the number of dimensions, without much loss of information[11-18]. Using PCA allows identifying the structural features of EMG signals and determining its quantitative changes. Also, this method conducts a multilevel decomposition and choice of the number of basic components of EMG in automatic mode. It consists of 6 main stages:

Step 1 – representation of the initial data vector in the form of a rectangular table tensor.

Step 2 – diagonalization of the covariance matrix.

Step 3 – the construction of the orthogonal projection of the main components of initial sample data (Fig. 3, 4).

Step 4 – singular value decomposition signal level 32 (Fig. 5).

Step 5 – reconstruction of the decomposed signal by all levels of (Fig. 6).

Step 6 – classification of the main components for the establishment of norm and pathology.

Eigenvectors of the dataset (Fig. 2) $U_1, U_2 ... U_n$ will correspond to the principal components of variation in the data. The covariance matrix of the data, which is given by:

$$\sum = \frac{1}{m} X^T X \ , \tag{1}$$

where X is the data matrix with examples in rows, and m is the number of examples.

Note that $\sum$ is a size matrix $n \times n$ and not the summation operator. After computing the covariance matrix, compute the principal components.

The length of each signal was detailed on the level of 32. Also, these same signals were reconstructed on all 32 levels, but this operation is better coped with by low-frequency components.

Fig. 2 shows input signals for processing of PCA method, where (Fig. 2a) was selected fragment of increase the amplitude in postural load in norm, and in Fig. 2b also was selected fragment of example of oscillations (tremor).

Quality improvement of diagnosis of the EMG confirmed the accuracy of the calculation of discriminant characteristics. Initial data for verification of diagnosis consists of 58 signals: 25 in norm (condition Θ_0) and 38 in tremor (condition Θ_1). For each set of average values of the EMG parameters was calculated the statistical characteristics: the mean values $m_i^{(0)}$, $m_i^{(1)}$ and standard deviations $\sigma_i^{(0)}, \sigma_i^{(1)}$. Then compute the Mahalanobis distance:

$$\delta = \sqrt{\sum_{i=1}^{n} \left(\frac{m_i^{(0)} - m_i^{(1)}}{\sigma_i} \right)^2} \ , \tag{2}$$

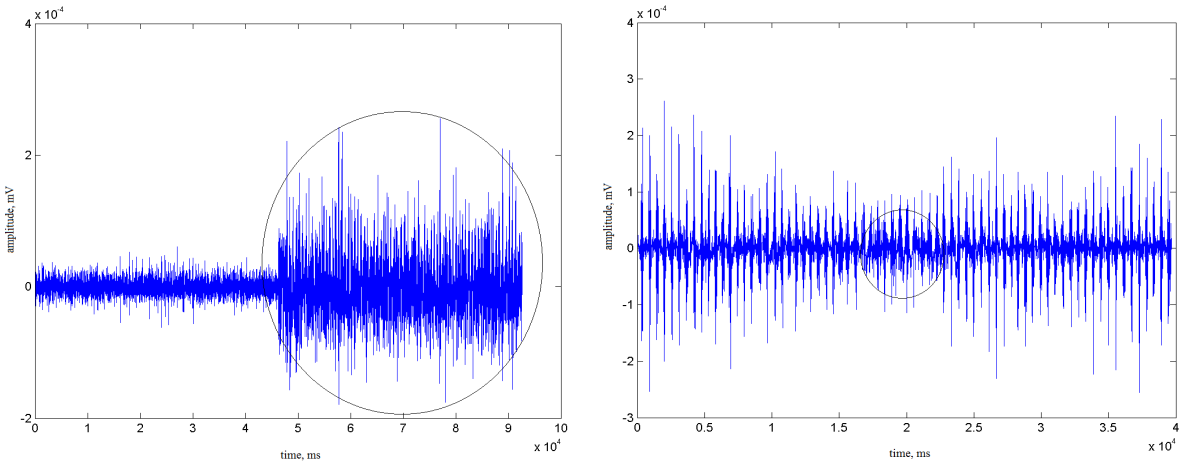
$$\sigma_i = \max\left(\sigma_i^{(0)}, \sigma_i^{(1)}\right). \tag{3}$$

Probability error for decision diagnosis:

$$P \le 1 - \Phi\left(\delta / 2\right), \tag{4}$$

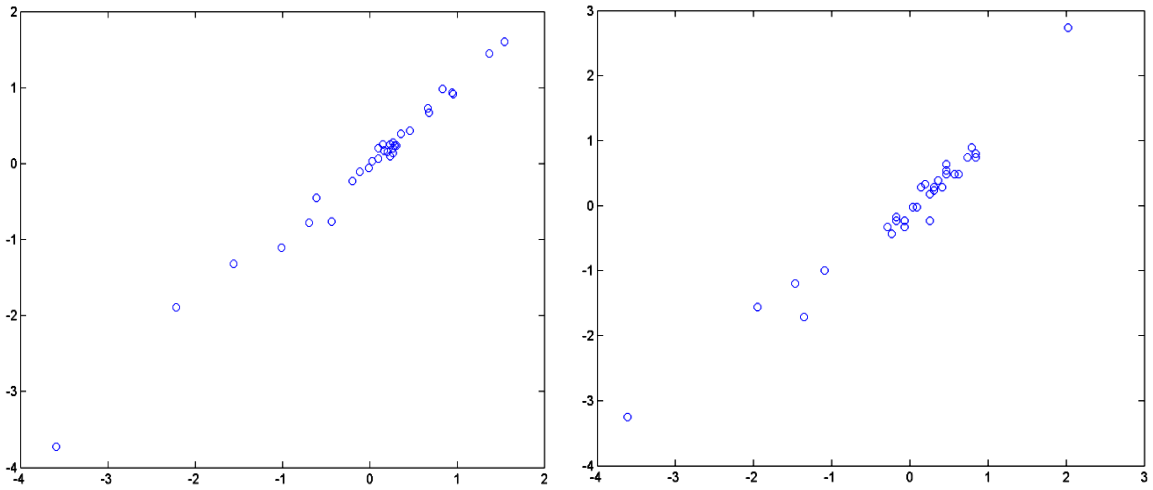
From (2) and (4) it is obvious that the smaller Probability error, the greater the dispersion of normalized squared distance between the vectors of averages. The subscript "0" indicates norm, "1" is equal to different types of tremor. Thus, the calculation includes six informative parameters. Table 2 shows the results of calculations of the characteristics of the signal parameters for frequency. When ranking of values in order of decreasing Mahalanobis distance, it is possible to analyze the influence of the number of parameters in the discriminant characteristics for the diagnosis method. Fig. 7 shows the cumulative increase in the characteristics of Mahalanobis distance and the reduce of the Probability error, as a function of space and dimension j informative parameters.

The resulting graphs demonstrate that the maximum value of Probability error is not more than the value 0,59 for calculated parameters, therefore, it has a greater influence on the diagnosis process. Less important parameters on the probability of making diagnosis almost no effect and can be excluded from the calculations.



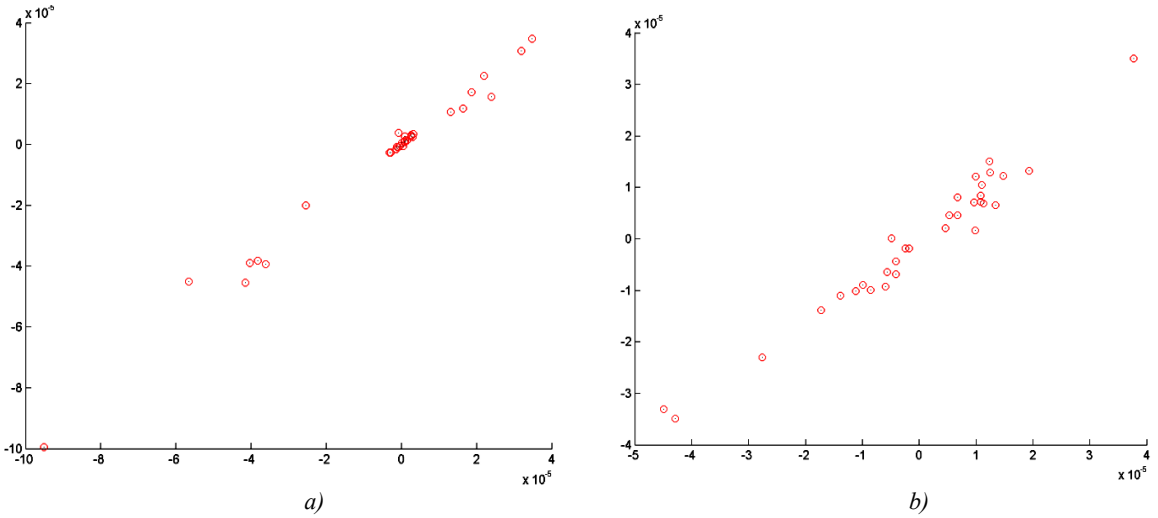
a) *b)*

Figure 2. Input EMG signal for processing of PCA method: (a) norm; (b) tremor.



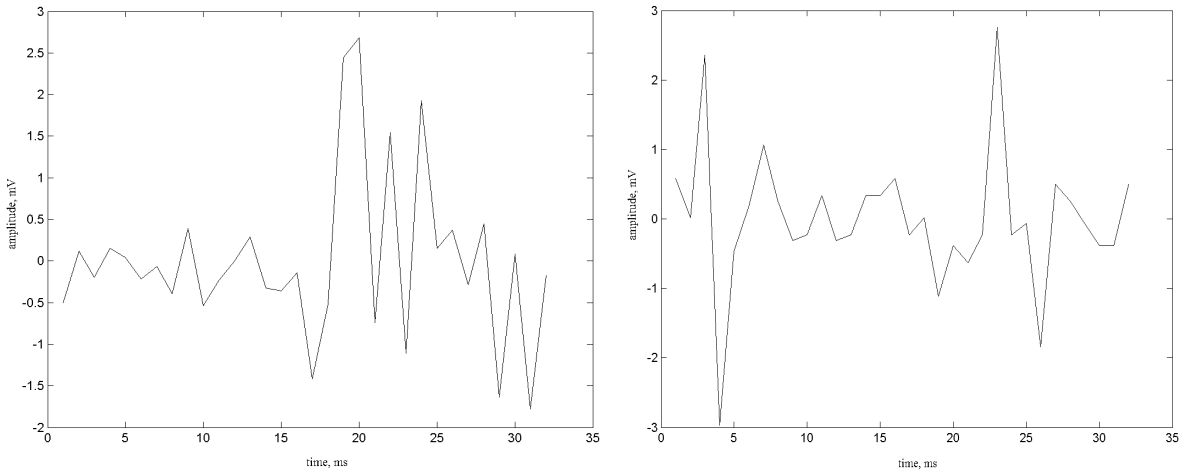
a) *b)*

Figure 3. Computed eigenvectors of the dataset: (a) norm; (b) tremor.



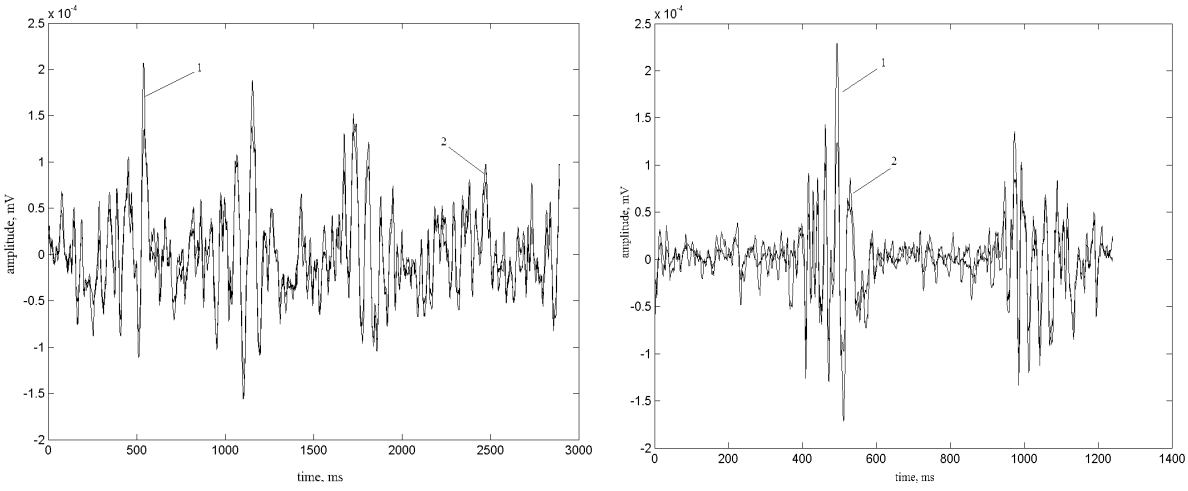
a) *b)*

Figure 4. The normalized and projected data after PCA: (a) norm; (b) tremor.



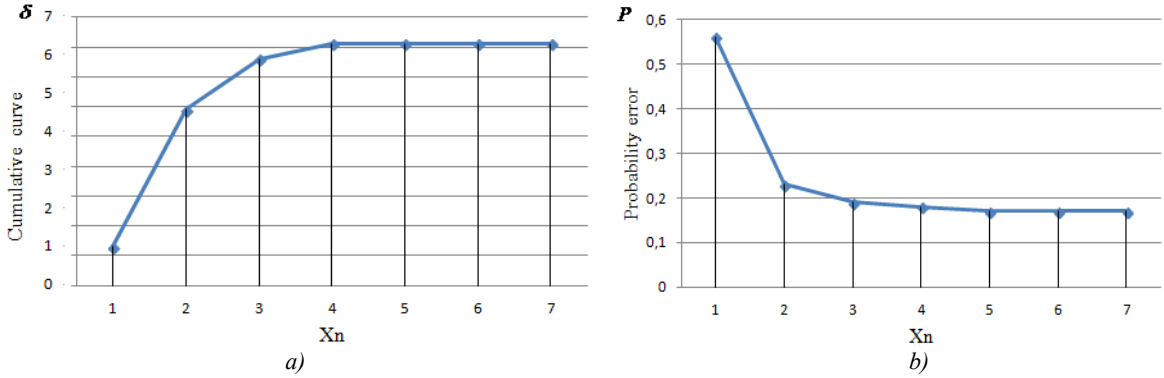
a) *b)*

Figure 5. Example of 32th level of singular decomposition of signal: (a) norm; (b) tremor.



a) *b)*

Figure 6. Example of 32th level of signal reconstruction: 1 (blue) original and 2 (red) reconstructed; (a) norm; (b) tremor.



a) *b)*

Figure 7. Graphs of cumulative increase in the characteristics of Mahalanobis distance (a) and reduce of the Probability error (b) for the parameter frequency.

Table 2. Calculation of characteristics for frequency EMG

Parameter		Control condition Θ_0	Control condition Θ_1	Mahalanobis Distance δ	Probability error P
X_1	$m^{(1)}$	10,1	3,2	0,56	≤ 0,59
	$\sigma^{(1)}$	9,2	3,8		
X_2	$m^{(1)}$	8,2	4,2	0,48	≤ 0,26
	$\sigma^{(1)}$	9,3	4,9		
X_3	$m^{(1)}$	11,5	6,0	0,35	≤ 0,19
	$\sigma^{(1)}$	9,2	5,4		
X_4	$m^{(1)}$	12	5,4	0,34	≤ 0,18
	$\sigma^{(1)}$	11,3	5,1		
X_5	$m^{(1)}$	12	4,3	0,82	≤ 0,17
	$\sigma^{(1)}$	8,1	5,9		
X_6	$m^{(1)}$	10,1	3,11	0,44	≤ 0,17
	$\sigma^{(1)}$	9,1	7,11		
$\{X_i\}^6$	δ_Σ			2,99	≤ 0,17

4. CONCLUSIONS

The method PCA identifies structural features of interference EMG signal and determines its quantitative changes in dynamics, and establishes factors influence that cause non-stationary oscillations. PCA is a powerful technique that identifies common temporal patterns across large datasets of time series like EMG signals and defines a low-dimensional space on which the original signals could be represented as vectors and classified. Graphs shows the characteristics of the cumulative increase in the Mahalanobis distance and reduce the probability of diagnostic error as a function of the dimension of space and informative parameters of amplitude and frequency. Using for frequency analysis just average value of the maximum values of the signals, can obtain probability error diagnostic solutions less than 0.17, which is quality improvement of diagnosis.

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