

## **Increasing Effectiveness of Human Hand Tremor Separation Process by Using Higher-Order Statistics**

*Jacek Jakubowski, Stanisław Osowski\*, Augustyn Chwaleba*

Military University of Technology, Warsaw, Poland

\* also Warsaw University of Technology, Warsaw, Poland

**Abstract.** The paper presents an attempt to discriminate the most often observed three types of human tremor with objective techniques by measuring the acceleration of the hand and by calculating some characteristic features of these time series. Different mathematical descriptions have been adopted in order to generate the features. They have come from both second and higher-order statistics. A simple neural classifier has enabled the recognition of these three kinds of tremor with 3.6% error rate.

### **1. Introduction**

Tremor is a rhythmic involuntary oscillatory movement of body parts, with a relatively fixed frequency and amplitude. It can be observed in healthy subjects as well as in patients with various diseases. Among the pathological cases, essential and parkinsonian tremor are the most often observed types. Parkinson's disease is a growing problem, with 120-180 victims in each 100 000 people. Most patients are over 40 years old although the disease can appear in younger subjects. Essential tremor affects even up to 5000 people in each 100 000. The mean age at onset is 45 years, but the disorder may start in adolescence and early adulthood. Although investigators have uncovered many of the brain's mechanisms, the cause of the diseases is still unknown and the clinical distinction between them can be difficult. Even for an experienced neurologist, making an accurate diagnosis in the early stages may be a problem. There are, as yet, no sophisticated blood or laboratory tests available to diagnose the diseases and classical examinations are highly subjective. Since the cases have similar clinical features but require different treatments, making a precise diagnosis as soon as possible is essential for starting patients on proper medication. There have been attempts to separate these tremors with objective techniques by measuring the acceleration of hands and application simple features of conventional spectral description – peak value and peak frequency of power spectral density (PSD) [1]. However, no clear-cut separation has been found with these methods – none of the parameters helps to decide reliably which kind of pathological tremor is present [1][2][3]. The natural task is then twofold: to exploit other PSD features and to apply descriptions extracting new information from existing data.

### **2. Discussion of the problem of proper signal description**

One of the most fundamental and useful tools in digital signal processing is power spectral density. The measure is easy to implement and has straightforward interpretation as the distribution of power among frequency components. PSD is usually defined with the use of Wiener-Kinchine theorem as the Fourier transform of the 2<sup>nd</sup>-order moment, i.e. as the Fourier transform of autocorrelation sequence. However, in general, there are other functions considered in the theory of stochastic processes – higher-order moments, certain non-linear combinations of moments, called cumulants and their Fourier transforms. In such terms, PSD and autocorrelation functions are a subset of higher-order statistics (HOS) of the signal, which would suffice for the complete statistical description of Gaussian processes. However, there can be information in signal time series that does not show up in these 2<sup>nd</sup>-order measures. Then, practically any technique which has ever involved PSD should be reformulated and re-examined in terms of HOS, to see if better results emerges. There are several motivations to do so. First, all cumulants and their related spectra of order  $n > 2$  of any kind of Gaussian process are zero, be they colored or white (it also holds for symmetrically distributed random processes in the 3<sup>rd</sup>-order statistics). Secondly, the cumulant of two statistically independent random processes equals the sum of the cumulants of the individual ones [4]. These above two properties are of paramount importance when the acceleration based

methods and A/D converters in tremor acquisition are used because the quantization noise is assumed to be symmetrically distributed and we can then suppress the effect of additive noise when the signal is non-Gaussian. Thirdly, higher-order spectra are complex functions and enable to reconstruct magnitude and phase of a linear system operating under random non-Gaussian input (the 2<sup>nd</sup>-order statistics are “phase blind”) [5]. And eventually, HOS techniques can be used to reveal information about non-linearities which is simply not available with conventional spectral techniques [6][7]. However, using the above properties is limited to non-Gaussian signals.

### 3. Acquisition procedure and material

Time series of hand tremor have been collected by light-weight piezoresistive accelerometers and a simple data acquisition system [8]. During recordings subjects were sitting comfortably with forearms supported. Their hands were slightly raised. The sensors were fixed on subjects' fingers, one on each hand. The acceleration signals were digitized with a rate of 100Hz. The length of each record was 10s so that 1024 data points were obtained. The time series have been normalized to unity variance and zero mean value. The data set consisting of 339 time series of physiological, 139 time series of parkinsonian and 98 time series of essential tremor has been taken into account [9]. In subsequent neural classification 70% of all data in each class has been treated as a learning set.

To test the data for non-Gaussianity the procedure developed by Hinich has been used [10]. The basic idea is that if the 3<sup>rd</sup>-order cumulant of a process is zero, then its bispectrum and bicoherence  $bic_{3y}$ ,

$$bic_{3y} := \frac{S_{3y}(f_1, f_2)}{\sqrt{S_{2y}(f_1)S_{2y}(f_2)S_{2y}(f_1 + f_2)}} \quad (1)$$

are also zero ( $S_{2x}$  is PSD and  $S_{3x}$  is the 3<sup>rd</sup>-order spectrum, bispectrum). If the bispectrum is not zero, then the process is non-Gaussian. The test result for non-Gaussianity is reported as probability of false alarm, the so called PFA, i.e., the probability that one will be wrong in assuming that the data have a non-zero bispectrum. If this value is small, say 0.05, we accept the assumption of non-zero bispectrum which means that the data are non-Gaussian. Care must be taken if the PFA is high since it means that the process is symmetrically distributed and may be Gaussian but does not have to be. Fig. 1 presents the results of the test from Hinich. As it can be seen the percentage of tremor signals with non-Gaussian distributions equals about 98 for parkinsonian, 70 for essential and 60 for physiological tremor. Thus using the 2<sup>nd</sup>-order statistics alone is far insufficient for proper mathematical description of the majority of tremor processes.

### 4. Initial preprocessing and neural classifier

Several statistical processing methods have been adopted for the description of tremor signals in as many ways as possible [9]. They have taken into account linear and nonlinear properties of statistical processes. In particular they included: non-parametric classical estimation (Welch's method) of PSD, the fourth-order cumulant based method estimation of PSD [4], parametric estimation of transfer function of linear time invariant system whose output is assumed to be the acquired tremor signal (HOS measure) [5], non-parametric bispectrum magnitude and diagonal part of non-parametric bispectrum and trispectrum magnitudes. Features discriminating the three classes of tremor signals have been deduced from the above descriptions with the use of defined eleven different number parameters (e.g. spectral moments [9]). Since the set of features achieved in that way was very numerous, their ability to discriminate among two each classes  $A$  and  $B$  has been initially verified with simple measure

$$fom_{A-B} = \frac{\left| \bar{c}_A - \bar{c}_B \right|}{\sigma_A + \sigma_B}, \quad (2)$$

where  $\bar{c}_A, \bar{c}_B$  are mean values of feature  $c$  in class  $A$  and  $B$  respectively. Values  $\sigma_A, \sigma_B$  are standard deviations of the feature in both classes. High values of the  $fom$  indicate good discrimination ability of feature  $c$ .

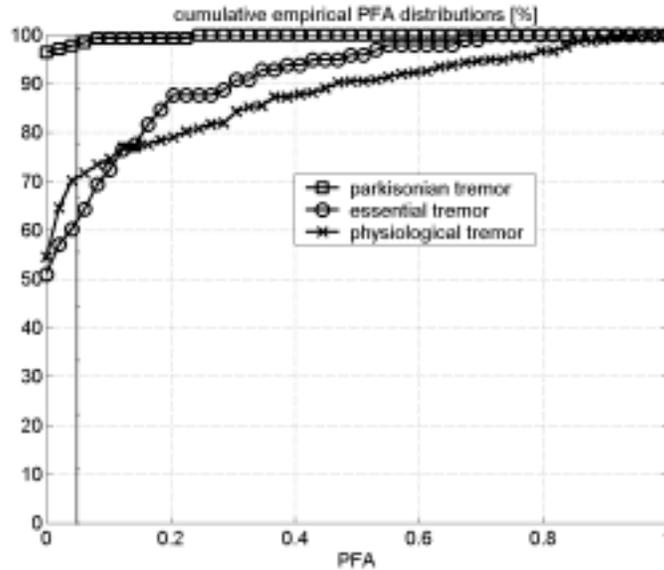


Fig.1. Results of the test for non-Gaussianity.

The mapping from the set of 30 features chosen with the use of the  $fom$  to the three groups of tremor has been conducted with the use of MLP neural network (multi-layer perceptron). The applied program uses the algorithm of directional minimization and adaptive method in the training process [11][12]. In order to achieve high generalization ability of the network, single layer structure of hidden neurons has been used.

## 5. Results and conclusions

To evaluate chosen mathematical descriptions of tremor signals, four different vectors of features have been checked with the use of the neural classifier. They have contained: *vector 1* – classical PSD features, i.e. maximum value and its frequency (they have been treated as a reference vector), *vector 2* – other defined PSD features, *vector 3* – features coming from higher-order statistics only and *vector 4* – containing all the thirty features. The examinations have been conducted in the range from 10 to 0 hidden neurons. The results are depicted in Fig. 2. As it can be seen the common features from PSD are not sufficient for good recognition rates – the error equals 23% at 10 hidden neurons. Application of other PSD features has brought about considerable decrease in the error rate down to 6% at 6 hidden neurons. Taking into account only HOS features has caused further decrease of the error to the level of 4%. And eventually all the features has reduced the error to 3.6% at 4 hidden neurons. As a result one should notice that different types of information included in tremor signals (coming from the 2<sup>nd</sup>- and higher-order statistics) should be taken into account for the process of recognition to be efficient.

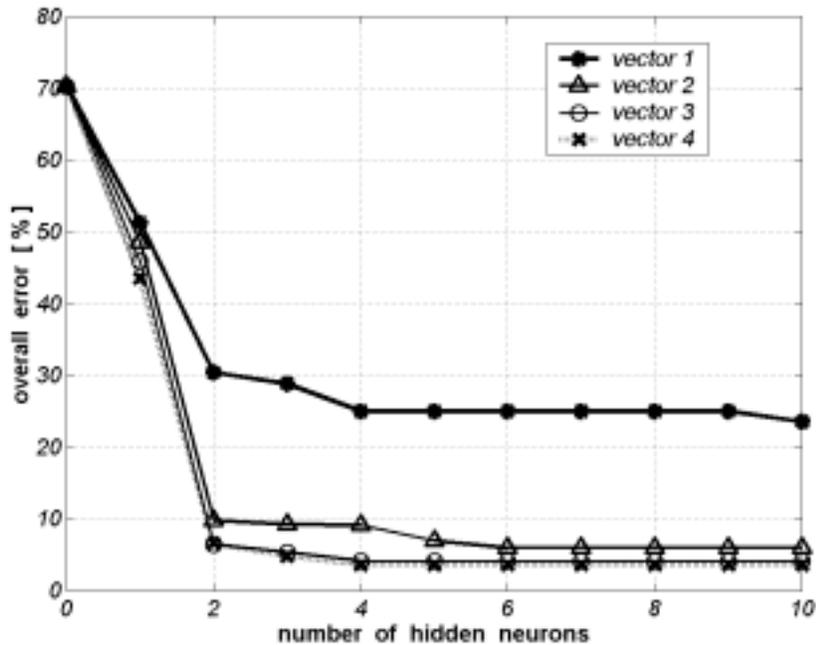


Fig. 2. The overall error of neural recognition of three groups of tremor at different input vectors vs. the number of hidden neurons.

## Literature

- [1] R. J. Elble, W. C. Koller, „Tremor”, John Hopkins University Press, Baltimore 1990.
- [2] J. Timmer, C. Gantert, G. Deuschl, J. Honerkamp, „Characteristics of hand tremor time series”, *Biological Cybernetics*, vol. 70, 1993, 75-80.
- [3] C. Gantert, J. Honerkamp, J. Timmer, „Analyzing the dynamics of hand tremor time series”, *Biological Cybernetics*, vol. 66, 1992, 479-484.
- [4] C. L. Nikias, A. P. Petropulu, “Higher-Order Spectral Analysis – A Nonlinear Signal Processing Framework”, Prentice Hall, N. J., 1993.
- [5] A. Swami, J. M. Mendel, “ARMA Parameter Estimation Using Only Output Cumulants”, *IEEE Trans. ASSP*, vol. 38, no7, 1990, pp. 1257-1264.
- [6] Y. C. Kim, E. J. Powers, “Digital Bispectral Analysis and Its Applications to Nonlinear Wave Interactions”, *IEEE Trans. Plasma Sci.*, vol. PS-7, no 2, pp. 120-131, 1979.
- [7] J. W. A. Fackrell, S. McLaughlin, “Non-linearity Detection for Condition Monitoring Using Higher-Order Statistics”, *Proceedings of COMADEM96*, Sheffield, 1996, pp. 519-528.
- [8] K. Kwiatos, “Measurements and analysis of human tremor”, Ph. D., Military University of Technology, Warsaw, Poland (in Polish).
- [9] J. Jakubowski, “Application of higher order-statistics for characterization of the human tremor”, Ph. D., Military University of Technology, Warsaw, Poland (in Polish).
- [10] M. J. Hinich, “Testing for Gaussianity and Linearity of a Stationary Time Series”, *J. Time Series Analysis*, vol. 3, nr 3, 1982, pp. 169-176.
- [11] S. Osowski, “Algorithm approach to neural networks”, WNT, Warsaw, Poland, 1996 (in Polish).
- [12] S. Haykin, “Neural networks, a comprehensive approach”, Macmillan Publishing Company, 1994, New York.