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Classification of EEG Signals with Artifacts, Based on Fractal Dimension Analysis, Wavelet Transform and Neural Network

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ABSTRACT

Several examples of artifacts in real EEG signals are detected, analyzed and classified using wavelet transform for feature extraction and neural network as a classifier. Combination of this method with the analysis of fractal dimension dynamics makes the artifact detection in experimental EEG more efficient.

KEYWORDS: EEG, artifacts, fractals, wavelet, neural networks.

1. INTRODUCTION

Electroencephalogram (EEG) is one of the most important diagnostic tools in neurophysiology. EEG signals are the electrical activities in the cortex or on the surface of scalp caused by the physiological activities of the brain. Nowadays modern techniques such as CT, MRI and others are widely used for investigating the brain, but electroencephalography, being discovered in 1929, still remains one of the best nondestructive testing methods in the analysis of brain functioning, identification of cerebral injuries and patients treatment.

Various signal processing techniques have been applied to the analysis of clinical EEG signals. Fourier transform, resulting in the spectral decomposition of EEG signals to α, β, γ, δ and θ rhythms, is a conventional method, widely used for the standard quantitative analysis and clinical applications (Niedermeyer and da Silva, 1993; Da Silva et al., 1986; Borel and Hanley, 1985).

Recently a number of research groups have proposed several methods to quantify the information of the EEG. Among these are the Wavelet Transform, Chaos, Entropy, Subband Wavelet Entropy and EEG signal modeling (Rosso, 2001; Bai et al., 2000; Al-Nashash et al., 2002). Analyzing energy distribution over frequency subbands or statistical properties of the signal, different authors are trying to overcome difficulties connected with the multivariable and non-stationary character of EEG signals. Additional difficulty comes from the fact that EEG is mixed with non-brain signals (artifacts) caused by small movements of the patient, electrical or mechanical interference Vasserman et al., 1997; Van de Velde et al., 1998; Vande Velde et al., 1999; Liu et al., 2002; Shen et al., 2001; Hoppe et al., 2001; Britton et al., 2000). Sometimes sudden abnormality in brain activity (paroxysm) is considered as an artifact to separate it from the regular activity. Generally automatic methods of artifact recognition do not stand in comparison with traditional visual EEG analysis by trained EEG experts (Vasserman et al., 1997). In the paper (Shen et al., 2001) a wavelet packet decomposition method is successfully used for classification of transient time-varying EEG signals, but artifact rejection was performed by an EEG expert visual inspection of the recording. In our opinion wavelet or other time-frequency transforms analyze energy distribution but fail to detect the main feature of artifacts - abrupt change of the signal statistical properties. On the other side in the past two decades we have seen multiple examples in the biophysics and physiological literature with regard to the identification of phenomena having long-term memory and probability densities that extend far beyond the typical tail region of Gaussian distributions. These processes have been classified as 1/f-phenomena, since their time series have spectra that are inverse power law in frequency or their probabilities have an inverse power-law distribution. In any case the underlying structure is fractal, either in space, time or both (West et al., 2003). Analysis of fractal dimension can help to classify artifacts with different statistical properties but corresponding models like fractal Brownian motion are developed for time-invariant processes (Mandelbrot and Van Ness, 1968; Cronover, 2000; Al-Kasasbeh, 2004; Mandelbrot, 1983). In the present paper we are trying to

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combine advantages of both approaches plotting first the dynamic of fractal dimension and applying wavelet transform to it.

2. Wavelet transform and artifact feature extraction

Wavelet transform allows to decompose signal on localized in both time and frequency basis functions. Wavelet transform has variable time and frequency resolution while Short Time Fourier transform has constant resolution. Wavelet transform has high resolution in time and low resolution in frequency in high frequencies area and high resolution in frequency and low resolution in time in low frequencies area. This approach produces especially good results when high frequency signal components have short duration, while low frequency components – long enough, EEG signal as well as the most of biological signals has an exactly this structure (Da Silva et al., 1986).

Fig.1shows a regular EEG signal for comparison with examples of some artifact signals given in Figs.2-5. Artifacts in EEG signals are often very similar to some phenomena caused for example by paroxysmal activity (see Fig.6). The task of classification allocated "suspicious" parts of EEG signals consists of 2 parts: feature description of the object and construction of a decision making algorithm.

From the digital filtering point of view wavelet transform can be implemented by using two FIR filters and decimation: original signal passing through high-pass and low-pass filters H(z) and G(z). Then the high-frequency component is stored, while the low-frequency component is filtered again. Such scheme is known as subband coding scheme (Fig.7).

$$c_{j,k} = 2^{1/2} \sum_n c_{j-1,n} h_{n+2k},$$

$$d_{j,k} = 2^{1/2} \sum_n c_{j-1,n} g_{n+2k},$$

Since FIR-filters are not ideal, filter outputs are always aliased. However, filters are constructed in such a way that information about aliased signals in one channel is available in other channels. Hence, it is possible to obtain perfect reconstruction.

During inverse transform low-frequency component $c_{j+}2j$ and high-frequency component $d_{i+}2j$ pass through FIR-filters H*(z) and G*(z) defined via H(z) and G(z). As a result we have a low-frequency signal component c_{i+1j} etc. The output of this procedure is a perfectly reconstructed original signal c.

$$c_{j-1,n} = 2^{1/2} \sum_k c_{j,k} h_{n+2k} + 2^{1/2} \sum_k d_{j,k} g_{n+2k}.$$

For the perfect reconstruction, coefficients $\{h_j\}$ and $\{g_j\}$ of filters H(z) and G(z), correspondingly, should satisfy the following conditions:

$$2\sum_k \left(h_{n+2k} h_{p+2k} + g_{n+2k} g_{p+2k}\right) = \delta_{n,p}$$

$$2\sum_n h_{n+2k} h_{n+2p} = 2\sum_n g_{n+2k} g_{n+2p} = \delta_{k,p}$$

$$2\sum_n h_{n+2k} h_{n+2p} = 0$$

Using wavelet transform, one can decorrelize nonstationary signal for more effective classification. But for some signals that classical wavelet-decomposition is far from being ideal. Meyer and Coifman (Daubechies, 1992) proposed wavelet-packet decomposition scheme.

At each level not only the low-frequency components but also the high-frequency ones are filtered. General filtering scheme can be represented as a binary tree (Fig. 8).

Wavelet packet is defined as subgraph G of full decomposition graph, which is satisfying the following conditions:

1. Tree root belongs to G.
2. At each vertex graph G either splits into two parts or terminates.

The signal at each node of wavelet packets decomposition tree can be interpreted as output of some band-pass filter. Computational complexity of this decomposition is O(NlogN).

It is common to distinguish the following spectral rhythms of EEG signals: α,β,γ,θ,δ. Rhythms distribution over frequencies is well matched with subband coding scheme bandwidth decreasing at each level twice. In EEG signals without pathology rhythms are distributed over frequencies as shown in Table 1.

Table 1. EEG rhythms frequency distribution.

Rhythm	Frequency range (Hz)
δ-rhythm	0.5 – 3
θ-rhythm	4 – 6
α-rhythm	8 – 13
β-rhythm	13 – 40
γ-rhythm	> 40

Since every node in wavelet-packets corresponds to a certain frequency band, so subband coding scheme gives a good EEG decomposition on rhythms.

Taking into account all rhythms, it is enough to decompose the signal till level 5. The full wavelet-packets decomposition tree of the signal contains 62 nodes.

Since discrete wavelet-transform unlike continuous is not time invariant we use as features the normalized energy density of wavelet-coefficients at wavelet-tree nodes $p_{i,j}$.

$$p_{i,j} = \frac{\sum_{n=N/2^j} c_{i,j}(n)^2}{N/2^j} \quad ;$$

where

i = 1 ... K – class number,

j = 1 ... 62 – feature number

$c_{i,j}(n)$ – wavelet-coefficients for class i at node j.

N- signal length.

Since features quantity is redundant, the stepwise discriminant analysis based procedure was used for features number reduction (Van de Velde et al., 1998). A feature is used only if it is uncluded by stepwise discriminant analysis and there are no direct descendants of this node in the model.

Figure 9 shows the sum of wavelet coefficients of different levels for various artifacts. As one can see from the figure wavelet coefficients at resolution level r=5 have similar values for different artifacts and for regular activity while they become strongly different as r decreases. This indicates the importance of coefficients at low r for classification purposes. But at the same time the figure illustrates the difficulties of classification as the difference between regular activity (solid line) and various artifacts is small and has different sign for different levels and different artifacts. The classification under the circumstances is not efficient, the fact being confirmed by other publications (Shen et al., 2001; Hoppe et al., 2001).

3. Analysis of fractal dimension dynamics

Theoretically the most important difference between regular EEG signal and artifact is in their statistical properties. Typical duration of a short artifact is close to the minimum time of a human reaction that is to 0.1…0.3 ms. Within this time artifact signals should show higher level of correlation than a normal EEG signal with a set of high frequency and low frequency rhythms.

Statistical properties of a signal can be estimated using different tools (Al-Kasasbeh, 2004; Afifi and Azen, 1979) like correlation analysis, Kullback algorithm, fractal dimension definition… etc. One of the ways is to present the signal as a fractal Brownian movement. Looking at the plot of a typical EEG signal, one can see a chain of mountains and valleys and the smoothness of that "landscape" is different depending on the level of signal correlation. Quantitative estimation of that difference can be done as follows (Cronover, 2000). We choose a part of the signal (window) with the length L and make a linear regression presenting the signal inside the window as a straight line using the least square approximation. Next we estimate fluctuations of the signal from that straight line. Then we increase the length of the window and repeat the procedure. Plotting root mean square fluctuation Y as a function of the window length X in logarithmic scale should give us a straight line

$$\mathbf{Y = B + Hx}$$

For a noncorrelated sequence H=1/2. And deviation of H from ½ shows the level of the sequence correlation. It can be explained with the aid of the model of fractal Brownian movement developed in the works of Mandelbrot, Van Ness and others (West et al., 2003; Mandelbrot and Van Ness, 1968;Cronover, 2000; Al-Kasasbeh, 2004).

Fractal Brownian movement with parameter H is a process with the following properties:

1. X(t) is a continuous function
2. $\Delta X = X(t_2) - X(t_1)$ is a random Gaussian sequence with the dispersion

$$\sigma^2 (t_2 - t_1)^{2H},$$

where $t_2 > t_1$, σ is a positive constant, that is

$$P(\Delta X < x) = \frac{1}{\sqrt{2\pi}\sigma(t_2 - t_1)^H} \int_{-\infty}^{x} \exp\left(-\tfrac{1}{2}\left(\frac{u}{\sigma(t_2 - t_1)^H}\right)^2\right) du$$

Fractal Brownian movement with H=1/2 coincides with the classical Brownian movement (Cronover, 2000; Al-Kasasbeh, 2004).

From the property 2 we find that the dispersion of the fractal Brownian movement

$$E[(X(t_2) - X(t_1))^2] = \sigma^2 |t_2 - t_1|^{2H}$$

As the dispersion depends only on the difference t_2 - t_1, then the increments Δ X do not depend on the time of observation. At H=1/2 dispersion is equal zero, and increments are independent (Markov process). If H≠1/2, then the increments are correlated, but still they are scale invariant, that is

$$\frac{1}{\sqrt{2\pi}\sigma r^H (t_2-t_1)^H}\int_{-\infty}^{xr^H}\exp(-\tfrac{1}{2}(\frac{u}{\sigma r^H (t_2-t_1)^H})^2)du = \frac{1}{\sqrt{2\pi}\sigma (t_2-t_1)^H}\int_{-\infty}^{x}\exp(-\tfrac{1}{2}(\frac{s}{\sigma (t_2-t_1)^H})^2)ds, \quad s = u/r^H,$$

and the distributions

$$X(t+\Delta t) - X(t) \quad \text{and} \quad \frac{1}{r^H}(X(t+r\Delta t) - X(t))$$

have the same mean value and dispersion; that is they are statistically equivalent.

Simple expression

d = 2 - H

shows the connection between the parameter H and the fractal dimension d (Cronover, 2000).

In reality, neither EEG signal nor EEG plus artifacts are Gaussian sequences. χ - square test applied to the experimental EEG records showed that they can be considered as approximately scale invariant processes only over a short period close to a typical time of human reaction 100… 300 ms. We cut the experimental EEG record into 300 ms sections and applied the above described procedure to every section increasing the window length from the minimum length 1ms to the maximum length 100ms, plotting H parameter as a function of the section initial point. The resulting plot was submitted to wavelet transform instead of the original EEG signal. Figure 10 shows the sum of wavelet coefficients of different levels for various artifacts. One can compare the plots with similar plots from Fig.9. The main improvement is the visible gap between artifacts plots and regular activity plot. It helps to detect artifacts clearly though difference among various types of artifacts and difference between regular ad paroxysmal activities are small.

4. Classification of artifacts

Among other classification methods such as expert systems, fuzzy logic and Bayesian, Artificial Neural Networks (ANN) is considered as a satisfactory classifier (Majani, 1994). Using this method we follow the procedure which we described in details in (Al-Nashash, 2001). Its main advantage over other classifiers is the ability to learn by training. Furthermore, its complexity (i.e. number of free parameters in the classifier) does not grow with the dimension of the input or the size of the training set (Mallat and Zhong, 1992). Although there are various types and structures of neural networks found in the literature, Multilayer Feedforward Networks with the backpropagation training algorithm are the most successful and popular (Majani, 1994). When used in this application, the processing units can be one of three types: input layer units that accept the wavelets coefficients, output layer units that generate outputs (classes) and hidden layers units that do not interact directly with the inputs or outputs parameters. Collectively the hidden layers perform the classification objectives.

The backpropagation training algorithm is commonly used to iteratively minimize the following cost function with respect to the interconnection weights and neurons thresholds:

$$E = \frac{1}{2}\sum_{1}^{P}\sum_{i=1}^{N}(d_i - z_i)^2$$

Where P is the number of training patterns and N is the number of output nodes. d_i and z_i are the desired and actual responses for output node ***i***, respectively.

The update of the network weights is calculated as:

$$w_{ji}(t+1) = \alpha w_{ji}(t) + \eta x_i f^{'}\left(net_j^k\right)\sum_{l=1}^{N}(d_l - z_l) f^{'}(net_l^0) w_{lj}$$

Where α is a momentum constant, η is the learning rate, x_i is the input pattern at the iterative sample t, net_N^0 is the input to node N at the output layer and net_j^k is the input to node j in the kth layer.

The training process is terminated either when the Mean-Square Error (MSE) between the observed data and the ANN outcomes for all elements in the training set has reached a prespecified threshold or after the completion of a prespecified number of learning epochs.

Artifact classification was performed using Multilayer Feedforward Networks with the backpropgation training algorithm. Binary outputs were used for classification, however, in this application, the neural network was trained to give desired output values of 0.1 and 0.9 to represent 0 and 1. This was done to decrease the training time by preventing saturation of the sigmoid function and allowing the output units to continue to adapt. Classification performance was further enhanced by interpreting the output in excess of 0.8 as 0.9 and less than 0.2 as 0.1. The

Neurosolution software (Neurosolution Software, 1999) was used for constructing, training and testing the neural network.

5. Experimental results

Experimental results were received from the Institute of Neurophysiology of child, St. Petersburg and from King Hussein Military Medical Centre, Jordan

For experiments the EEG records from 18 patients without stable rough brain's bioelectrical activity disfunctions were used. The total time of recording exceeds 50 hours. The patients were placed in an acoustically and electrically shielded room where they were sitting in rest with open eyes. The EEG signals were recorded from electrodes placed on the scalp according to the international 10-20 system (Hughes, 1994). During the recording and in the course of the eye-witness study of the records a team of experts tried to mark artifacts. Small pieces of records 300ms long with artifacts were separated from the EEG signal. 80% of those samples after processing (denoising and detrending) were submitted to wavelet packet decomposition up to level 5. Wavelet function was Daubechies 8 and discriminant algorithm from Statistica 5.5 program was used for node selection . Then the dynamics of fractal dimension was plotted for every sample according to the above mentioned procedure. The received plots passed the same wavelet packet decomposition. For each type of artifacts the wavelet coefficients were averaged over the group of samples and after that the sum of wavelet coefficients at levels from 1 to 5 formed 5 features used for training of the neural network classifier. Then full EEG records including 100% of samples with different artifacts were used for recognition.

For analysis all 4 classes of the marked artifacts were used:

- "winking";
- "eyes movement";
- "swallowing ";
- "faulty contact".

One class of EEG phenomena "paroxysmal activity" was specially added;

The total amount of artifacts and phenomena selected by experts was 208.

Numbers of signals for each class is given in table 2:

Table 2.

Artifact and phenomena	Quantity
Winking	71
Eyes movement	63
Swallowing	23
Faulty contact	18
Paroxysmal activity	33

According to the described algorithm the nodes depicted in Fig.8 were included into the model. Selected nodes correspond to following frequency bands: 0-32 Hz, 48-50 Hz, 50-52 Hz and completely pass all EEG rhythms.

The average percent of correct classification is 96.15%.

Table 3 shows distribution of classification results over artifacts.

Table 3. Distribution of classification results

	Results distribution on classes					
Names of a'priori classes	% right answers	Winking	Eyes movement	Swallowing	Faulty contact	Paroxysm
Winking	97.18	69		2		
Eyes movement	95.23		60	3		
Swallowing	91.3		2	21		
Faulty contact	100				18	
Paroxysm	96.97			1		32

6. Conclusion

Numerical analysis of EEG showed that its fractal dimension dynamics makes the difference between a regular brain activity and artifacts more visible. Fractal dimension was calculated every 300 ms. This time is close to the minimum time of human reaction, which can be a reason of some abrupt change in the properties of EEG signals.

Experimental check showed efficiency of proposed approach to automatic artifact classification based on fractal dimension dynamics and wavelet transform.

Limited number of artifact samples was not representative enough and the a priori marking of artifacts could improve the results of recognition. However, compared with simple wavelet transform of the EEG, the transform of the fractal dimension plot makes the artifact detection more efficient.

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تصنيف الإشارات الكهربائية لدماغ الإنسان

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ملخـص

هنالك عدة أمثلة للاختلالات الحقيقية لإشارات فروق الجهد الكهربائية لدماغ الإنسان EEG تكتشف وتحلل وتصنف باستخدام نظريات التحويل الموجي وخصائص الشبكة العصبية لاستخلاص ميزات تلك الاختلالات والأسباب المؤدية إلى ذلك وتصنيفها.

إن ائتلافية هذه الطريقة مع التحليل الجزئي النمطي الديناميكي تجعل اكتشاف الاختلالات الحقيقية لإشارات فروق الجهد الكهربائية لدماغ الإنسان EEG أكثر فاعلية.

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