# The Application of Neural Network and Spline Wavelet Models in the Electroencephalogram Analysis Automation Process

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***Abstract*—The article focuses on the use of synthesized wavelets in the electroencephalogram analysis automation process. It describes the procedures for obtaining neural network and spline models proposed by the author. The advantages and disadvantages of the method are shown. The paper proposes a system of electroencephalogram analysis automation process based on the use of two levels of continuous wavelet transform. A detailed description of its operation is given. The paper describes a software package developed on the basis of the system. During the tests, the software feature detection accuracy (eye artifacts and pathological components) in the signal was 81.5%. It suggests the main areas for the developed system and package application, as well as ways for their further improvement.**

## I. Introduction

Electroencephalogram (EEG) is a complex signal that may be obtained by recording the electrical activity of neurons in the human or animal brain [1]–[3]. As a general rule, EEG is recorded from a large number of electrodes (leads). It makes it possible to evaluate the physiological state of the human brain both generally and at the level of various brain departments.

In the analysis of the EEG, it is important to identify the main rhythms characteristic of a healthy state and the rhythms the presence of which in a significant amount can be interpreted as the evidence of pathology. Each rhythm corresponds to a specific frequency range which is easy to identify. For these purposes, standard methods based on the Fourier Transform can be applied.

Besides the basic EEG rhythms, it is important to identify the different kinds of special features. These features include: EEG fragment specific to a pathological condition of the human brain, as well as artifacts. Artifacts are phenomena which are not directly related to brain activity. The presence of artifacts in a recording may lead to its false interpretation. Therefore, it is very important to identify both pathological activity graphoelements and EEG fragments with artifacts. Artifacts can be divided into those associated with the activity of the patient's body and those signaling the violations of the rules of EEG procedure.

In rooms designed specifically for EEG registration, it is normally possible to avoid a large number of artifacts, especially those associated with disorders during the study.

When using a mobile unit, it is recommended to take additional measures aimed at artifact elimination. However, even in such difficult circumstances, the presence of an experienced physiologist helps to eliminate the artifacts in the analysis.

A much more difficult situation can arise when it is necessary to conduct EEG research in the absence of specialized professional or any healthcare professional.

The author proposes a system that can fully automate the process of EEG analysis. The system for detecting artifacts and pathological components in EEG uses mathematical apparatus of wavelets.

## II. Selection of the Mathematical Apparatus

Wavelets are special functions with zero integral value capable of scaling and shifting along the time axis [4], [5]. Wavelets are widely used in signal analysis.

As is known [6], the classical Fourier transform does not allow the time-frequency analysis. A step towards solving this problem was the use of Short Time Fourier Transform. However, the transform has its drawbacks that are associated with the complexity of bandwidth selection. The main advantage of wavelets compared to Fourier transform is the ability to perform the time-frequency signal analysis. In addition, wavelets are functions that have various, sometimes quite complex, shapes. Their diversity allows choosing the wavelet most suitable for the analysis of the specific type of signal [5].

Among wavelet signal analysis algorithms, the most widely used are those which use a continuous (CWT) or discrete (DWT) wavelet transform.

To identify the characteristics of the signal, the continuous wavelet transform is often used [6]. The formula of continuous wavelet transform function $f(t)$ is as follows [7]–[10]:

$$W(a,b) = \frac{1}{|a|^{1/2}} \int_{-\infty}^{\infty} f(t)\psi\left(\frac{t-b}{a}\right)dt, \quad (1)$$

where $\psi(t)$ is wavelet, $a$ is scale, $b$ is shift parameter.

The results of the continuous wavelet transform can be visualized. Usually a wavelet spectrogram is used for this purpose [11], [12]. Wavelet spectrogram is a three-dimensional graph, along the axes of which the following are plotted: time shift (x-axis), scale (y-axis) and the value of wavelet coefficients (z-axis). Often wavelet spectrogram is constructed as a two-dimensional graph. In this case, the wavelet coefficients are plotted in color. The paper uses the latter version of the wavelet spectrogram construction. This helps to avoid the redundancy of graphic information. Apart from wavelet spectrograms, it is possible to use wavelet coefficient graphs constructed for certain values of scale.

If we analyze the formula of CWT (1), it is possible to conclude that the choice of wavelet has a significant impact on the results of the continuous wavelet transform.

The studies [5] have shown that the traditional wavelet families as a rule do not allow us to obtain the necessary localization of EEG features on the wavelet spectrogram. To solve this problem, the wavelets synthesized on the basis of signal fragment (sample) can be used.

The author has developed two classes of wavelet models suitable for continuous wavelet transform: neural networks and splines [13], [14]. The advantage of these models is the possibility to obtain analytical wavelet recording adapted for detecting specific characteristics of the signal.

They will be considered further.

## III. Requirements for Wavelets in Continuous Wavelet Transform

In order to consider a function as wavelet, it is necessary for the function to meet certain requirements. For wavelets suitable for CWT, these conditions are rather weak:

1) It is necessary to fulfill the admissibility conditions:

$$C = \int_{-\infty}^{\infty} |\hat{\psi}|^2 |\omega|^{-1} d\omega < \infty .$$

In practice it is enough for wavelet to have zero integral value.

Meeting this condition ensures the possibility of performing an inverse continuous wavelet transform:

$$f(t) = C^{-1} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} W(a,b) \psi\left(\frac{t-b}{a}\right) \frac{1}{a^{1/2}} \frac{dadb}{a^2} .$$

2) Rationing.

Wavelet must be defined within the interval [0, 1]. Furthermore, it must be subjected to normalization in the space $L^2$.

3) To ensure regularity, wavelets at their extreme points should have the value of zero.

Apart from the basic requirements described above, it is important for wavelet to have formalized representation, which is necessary for computing CWT with the digital signal processor, as it is important to have the possibility to calculate the wavelet value for different scale values.

## IV. Neural Network Wavelet Models

The procedure for obtaining neural network wavelet models was described in detail in previous papers of the author [13]. This paper focuses on the main points without which further explanation will be impossible.

Artificial neural networks can be regarded as a universal system for approximating [15]. They can be used for obtaining neural network wavelet models for CWT.

Studies have shown [13] that among the most common types of neural networks for wavelet modeling, networks based on radial basis functions (RBF networks) are the most suitable. They allow us to get an accurate mathematical description of the sample.

The procedure for obtaining neural network wavelet models includes the following steps:

1) Selection of the sample: a fragment of the signal with a feature that should be detected in other implementations of the signal can be taken as a sample.

2) Setting the vector of the argument values over the interval [0, 1].

3) Sample approximation by an artificial neural network based on radial basis functions.

Fig. 1 shows an example of RBF network which was used in the construction of neural network wavelet model based on an eye artifact sample. It has 202 parameters. The fragment length is 100 samples.

4) Calculation of the integral value of the resulting function.

5) Calculation of the deviation from the integral of zero value.

6) Sample displacement on the y-axis by adding / subtracting the error value to / from each reading.

7) Obtaining a function with zero integral value.

8) Rationing in the space $L^2$.

9) Loading function in the bank of synthesized wavelets.

The advantages of neural network wavelet models are as follows:

1) The relative simplicity. To construct such a model, the 2($N$+1) parameter, where $N$ is a number of sample readings, is required.

2) The exact description of the sample at its short length and complexity.

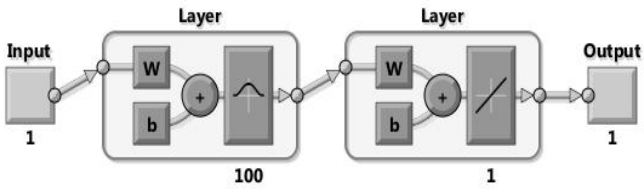


Fig. 1. Example of RBF network used in the wavelet synthesis based on an eye artifact sample

3) Formalized representation of the wavelet.

4) The model provides a wavelet adapted for the analysis of a specific signal.

5) The possibility to reduce the complexity of the model through the use of multi-layer perceptrons instead of RBF networks. However, this may reduce the accuracy of the sample description.

## V. SPLINE WAVELET MODELS

Spline wavelet models for CWT, proposed by the author have already been described [14].

The principal difference of the spline wavelet models lies in the use of cubic spline in the mathematical description. The application of interpolation instead of approximation makes a positive effect on the accuracy of even the most complex samples of great length.

The rest of the procedure for obtaining spline wavelet model is similar to the procedure described for the neural network.

The main advantages of spline wavelet models are as follows:

1) Accuracy of sample representation.

2) Possibility to obtain a wavelet based on samples of complex shape.

3) Formalized representation of the wavelet.

4) The model provides a wavelet adapted for the analysis of a specific signal.

The disadvantages are the high complexity of such models. It includes $4N$ parameters where $N$ is a number of sample readings.

## VI. THE SYSTEM OF AUTOMATED EEG ANALYSIS

Fig. 2 is a bookkeeping scheme of the automated EEG analysis proposed by the author. The main idea lies in the use of two levels of continuous wavelet transform in the analysis of the EEG. On the first level "rough" signal analysis is made, the areas with special features are spotted and their initial classification is made. This information is used on the second level – a more "accurate" analysis of the selected areas with CWT and synthesized using wavelets. Selecting synthesized wavelet and scale according to primary data as well as providing repeated CWT help to get a reasonably "accurate" result for detecting special features in EEG.

Let us explain the principles of the system in more detail.

Electroencephalogram, represented as a matrix of discrete values (wherein a column corresponds to a specific lead, and the string corresponds to a set of samples from different channels selected in particular discrete time), arrives at the input of the channel division block. The procedure is reduced to separation of the matrix into vector columns. The separation of EEG into channels allows us to divide computational flows. This approach can significantly accelerate the processing of the recording. It is relevant if there is the possibility of parallelization of computational flows when using for example FPGA or multicore DSP.

Then the signal from each channel of EEG is sent to the input to the fragment separation block. At the block, the signal is separated into fragments of fixed length. Fragment length is determined by the computational power of the element base used. The separation into fragments helps to reduce the computational load. It is important because the analysis algorithm uses two levels of continuous wavelet transform, each of which requires high computational power.

In order to avoid the loss of important information on the edges of the analyzed signal fragments, partial overlap is required.

Next, each fragment is subjected to CWT using "general" wavelet. This procedure is performed in the CWT block using "general" wavelet. As a “general” wavelet one can use those wavelets suitable for EEG signal analysis (in view of its smoothness and other characteristics). According to the conducted research [5] "Mexican Hat" (Fig. 3) refers to this group of wavelets. Another advantage is that it has formalized performance:

$$\psi(t) = \left(\frac{2}{\sqrt{3}}\pi^{-1/4}\right)\left(1-x^2\right)e^{-x^2/2}.$$

The use of "general" wavelet for the whole recording provides a set of graphs for wavelet coefficients with localized features on them. Wavelet coefficients are calculated for certain values of the zoom ratio. The selection of scale is as follows. Each feature of the EEG has the so-called fundamental frequency. For example, for eye artifacts, this frequency is 5 Hz. Knowing the fundamental frequency, it is easy to determine the scale, that corresponds to this frequency:

$$a = \beta / \omega ,$$

where $a$ – scale, $\beta$ – proportionality factor, $\omega$ – frequency.

The values of the wavelet coefficients, calculated for a given scale, and their graphs will reflect the presence or absence of particular feature in the selected signal realization.

Fig. 4 shows graph of the signal fragment with eye artifact (Fig. 4, *a*), graph of wavelet coefficients for a given scale (Fig. 4, *b*) and wavelet spectrogram (Fig. 4, *c*). Both graph of wavelet coefficients and wavelet spectrogram are suitable for detecting the presence of the features in the signal and performing the primary classification. However, the construction of the wavelet spectrogram based on the complete set of scales leads to redundancy, which is the reason why it is not used in the system.

To identify features based on the graph of wavelet coefficients, it is enough to apply their thresholding which is performed in wavelet coefficient processing block I.

The areas with special features are formed on the basis of the position of the feature in the signal within the featured area

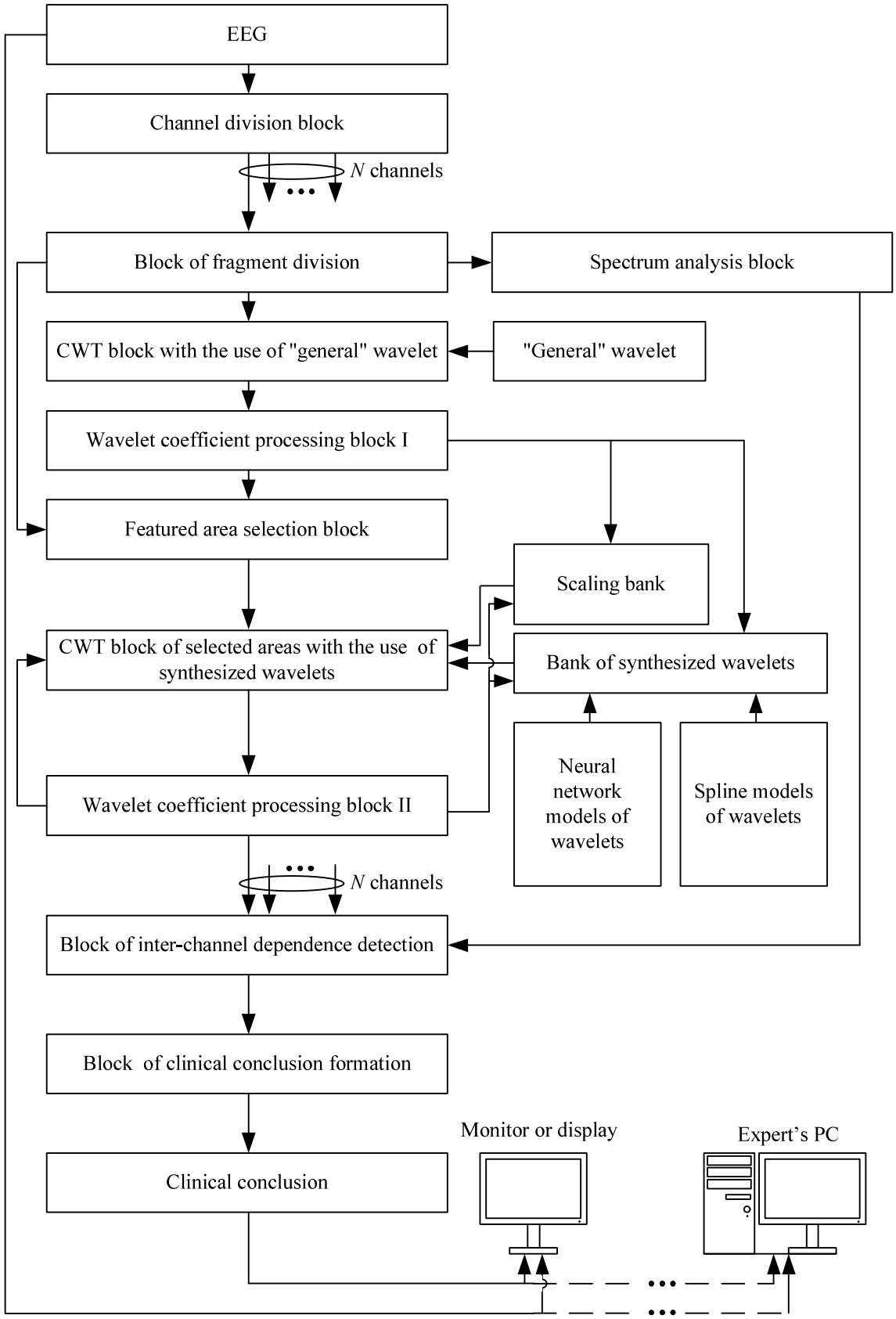


Fig. 2. Block diagram of the automated EEG analysis

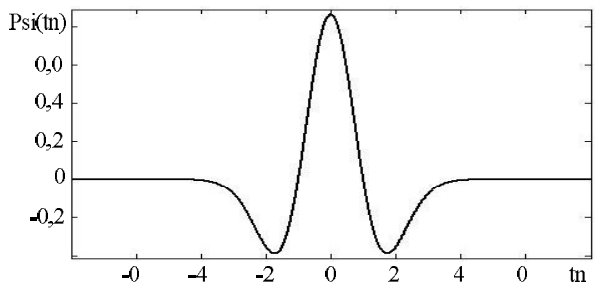


Fig. 3. Wavelet "Mexican hat"

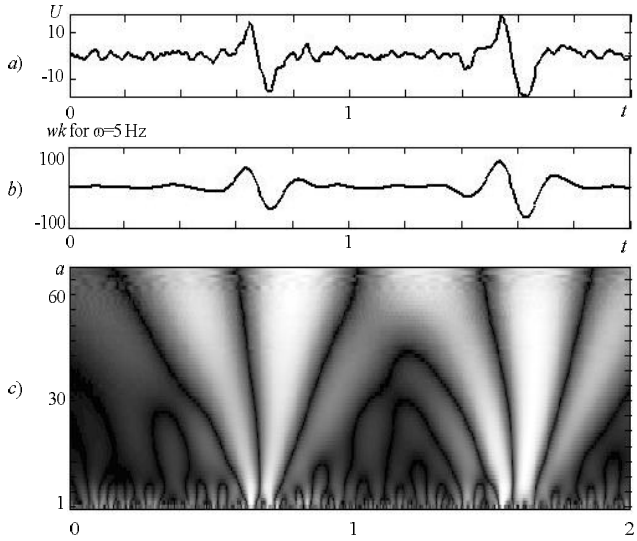


Fig. 4. Graph of the wavelet coefficients, constructed to scale, corresponding to eye artifact *b*) and wavelet spectrogram with a redundant set of scales *c*)

selection block. The procedure for their formation comprises the following steps (Fig. 5):

1) Selection of the central wavelet coefficient out of the wavelet coefficient group, which according to the results of the first CWT level presumably corresponds to the features.

2) Detection of the sample point (channel number, fragment number, its serial number in fragment) corresponding to a given wavelet coefficient.

3) Loading $k/2-1$ samples before and $k/2$ samples after the key sample, thus forming a length equal to $k$ samples.

This approach can significantly reduce the amount of processed data during the more accurate, or "fine" analysis.

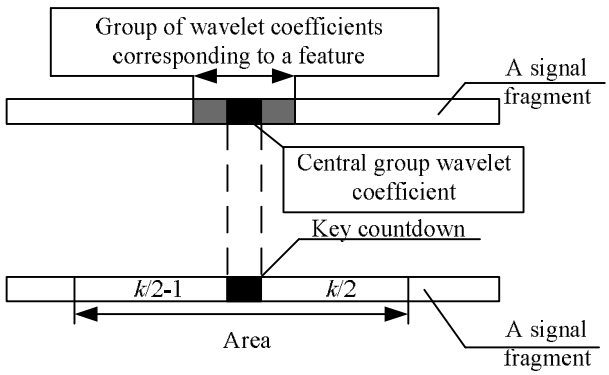


Fig. 5. Formation of featured fragments

Further, the selected areas undergo CWT using synthesized wavelets in the corresponding block. Neither the first nor the second stage of the CWT implies the necessity to build a wavelet spectrogram for all scale values. It is enough to calculate the values of wavelet coefficients for the scale and with the use of the synthesized wavelet which corresponds to the expected feature. Synthesized wavelets are loaded from the synthesized wavelets bank.

The obtained wavelet coefficients (Fig. 6) are processed. This procedure is performed in the wavelet coefficient processing block II.

The studies have shown that to identify eye artifacts and a number of pathological components thresholding of the wavelet coefficients is sufficient. For more complex features, it is necessary to use other methods, such as those based on the use of artificial neural networks.

If the results of the processing of the wavelet coefficients do not allow to confirm that the area contains the expected feature, it undergoes CWT with the use of another synthesized wavelet and another scale. For this purpose, there is extra connection provided between the wavelet coefficient processing block II, the block performing CWT, banks of synthesized wavelets and scale values.

The bank of synthesized wavelets can contain wavelets obtained by using neural network models or splines. The choice of a specific model is based on the requirements of the analysis accuracy and the element base power.

Neural network models have fewer parameters, respectively, less complexity. Their use is preferable if it is necessary to have high system performance (for example, in the analysis of large EEG records) or in the absence of the necessary computational power. They allow us to get wavelets, quite accurately approximate to the sample.

Spline models allow us to get the wavelets with guaranteed accuracy of approximation to the model of even the most complex shapes. This is promising, but the greater complexity of spline models may restrain their use in the development of mobile version of the automated EEG analysis.

The information about all the features is collected in the block of inter-channel dependence detection where comparison and analysis of the relationships between the channels and refinement of feature type take place. For example, if the eye artifacts are present in the EEG, they will be most evident in the frontal leads, but their presence will be found in other channels. This comparison allows you to get more accurate

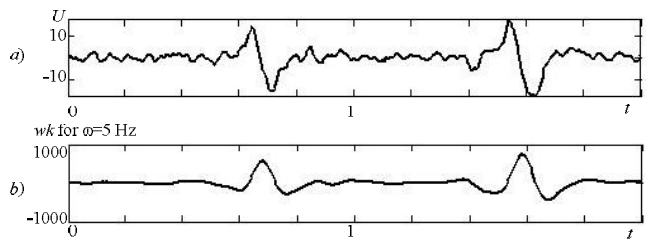


Fig. 6. Signal area with eye artifacts a) and its corresponding graph of wavelet coefficients b), obtained with a synthesized wavelet

results and localize the feature source. Additionally, the block receives information about spectrum analysis result. This makes it possible to assess not only the presence or absence of a particular feature, but also to assess the main EEG rhythms.

Summarized information is sent to the block of clinical conclusion. Clinical conclusion can be shown on the display of the device or its monitor, it can also be sent as a message to an expert (if necessary). Apart from sending a report, the system is capable of sending EEG to an expert or displaying it on the monitor of the device for an additional on-site analysis by an expert.

## VII. Software package

The author offers a software package for automated EEG analysis (Fig. 7). Its code name is "Katyusha SAB-03". This package has been developed on the basis of the proposed system described above. It has been developed in MATLAB, and has an interactive graphical user interface; it is designed to be used on a desktop PC or a laptop. The package is capable of detecting eye artifacts in EEG and some types of graphoelements with pathological activity, including those typical of absentia.

The graphical interface contains:

1) The information fields about the patient:

- Surname of the patient.
- First name.
- Patronymic.
- Date of birth.
- Sex.
- Address.
- The date of the first treatment.

2) Setting the channel selection and the time range to display EEG graphs. It helps, if necessary, to view the fragments of recording which are of interest.

3) Indicator graph located below the EEG output field allows us to graphically mark a featured area. If the indicator is at zero, the fragment has no features if indicator shows one, then the fragment has a feature (pathology or artifact).

4) In the clinical conclusion field clinical conclusion is formed. In the figure it is also indicated as a report. The package is being tested, so clinical conclusion is currently a form of report. It is planned to improve the package to get full-scale clinical conclusion in a form that a physiologist can read.

### *A. Software package testing*

During test trials, 119 EEG were analyzed. The selection of recordings was performed randomly. In parallel with the diagnostic work carried out by means of the software package, visual analysis was performed by an expert. After completing the analysis, the results were compared. The number of error-free replies of the software package reached 81.5%. The analysis took into account eye artifacts and some types of pathological activity.

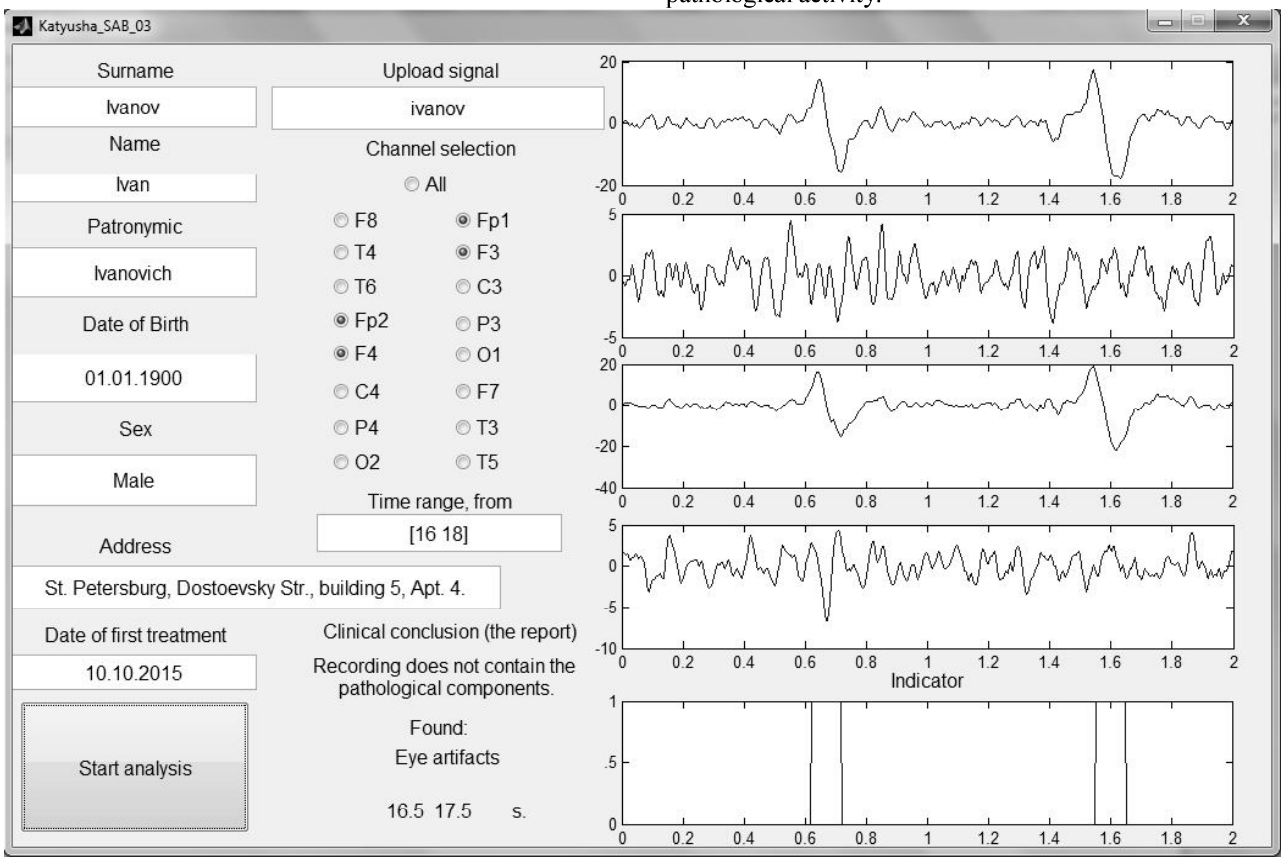


Fig. 7. Graphical interface of the software package for automated EEG analysis

*B. Application area*

Despite common, well-established principles of EEG analysis which can be the basis for any new method or approach to EEG analysis, one needs to clearly understand the role of biomedical signal automated analysis systems. When the results of examination are of critical importance, for example, prior to surgery, such systems can only be used as an auxiliary tool. In this regard, the author suggests the following areas of application for the developed system and software package:

1) Further development and refinement of the proposed software package should allow for its use in environments where there is no possibility to provide medical assistance by specialized professionals or in the absence of medical personnel.

2) The application for the express analysis of EEG in terms of patient turnover during routine examinations of company staff engaged in work that requires high level of attention.

3) Application in the EEG analysis of long duration. For example, EEG that take more than 24 hours to complete. This will help to detect the position of artifacts and pathological activity areas. Later the featured fragments may optionally be subjected to further analysis by an expert.

4) Applications for medical staff training in the creation of specialized simulators.

*C. Further improvement*

Further improvement of the system and the package includes:

1) Improvement of the mathematical apparatus of wavelets in order to improve the accuracy of the EEG analysis.

2) Development of methods for the wavelet coefficients analysis with a view to the possibility of identifying and classifying more complex EEG features.

3) Improving the interface and clinical conclusion formation technology.

4) The development of a mobile version of the system as a compact device. The author is currently engaged in relevant work. The priorities are: low cost, simplicity, rapid deployment, mobility.

## VIII. CONCLUSION

Here are the main results obtained:

1) The possibility to use synthesized wavelets in the process of electroencephalogram analysis automation.

2) Comparative analysis of neural network and spline models has showed that both classes of models can be applied for EEG analysis. However, the neural network models have less complexity than the spline models. The advantage of spline models is that they provide guaranteed accuracy of the sample. Their use can be promising in detecting complex features, but requires higher computational costs.

3) After further development and refinement, the proposed system of automated EEG analysis should be capable of detecting features of the EEG without being controlled by a physiologist.

4) The proposed software package is implemented on the basis of the described system. In the future, it should allow getting clinical conclusion based on the EEG without the participation of a physician. Testing for detecting eye artifacts and a series of pathological components resulted in 81.5% accuracy which is acceptable for such systems, with the total of 119 EEG signals tested.

5) Further improvement of the system and the package will be focused on:

- Improvement of the mathematical apparatus of wavelets;
- Improvement of methods of CWT result analysis;
- Expansion of the number of detected features;
- Improving the performance and convenience of a graphic interface;
- The creation of mobile package in the form of an independent device or on the basis of a smartphone or tablet computer.

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## REFERENCES

[1] V.V. Gnezditsky, *The inverse objective of EEG and Clinical electroencephalography (mapping and localization of sources of electrical activity in the brain)*. Moscow: MEDpress-inform, 2004.

[2] Y.D. Kropotov, *Quantitative EEG, cognitive evoked potentials of the human brain and neurotherapy*. Donetsk: Publisher Zaslavsky A.Y., 2010.

[3] L.R. Zenkov, M.A. Ronkin, *Functional diagnosis of neurological diseases: a guide for doctors*. Moscow: MEDpress-inform, 2011.

[4] *A.I. Solonina, S.M. Arbuzov, Digital Signal Processing. Modeling in MATLAB*. St. Petersburg: BHV-Petersburg, 2008.

[5] S.M. Arbuzov, A.B. Stepanov, *Application of wavelet analysis in electroencephalography*. St. Petersburg: Link, 2009.

[6] V.V. Vityazev, *Wavelet analysis of time series*. St. Petersburg: Publishing St. Petersburg State University, 2001.

[7] C. Blatter, *Wavelets - Eine Einfuhrung*. A.K. Peters, Ltd., 1998.

[8] I. Daubechies, *Ten Lectures on Wavelets*. SIAM, 1992.

[9] C.K. Chui, *An Introduction to Wavelets*. Academic Press, 1992.

[10] H.-G. Stark, *Wavelets and Signal Processing*. Berlin: Springer, 2005.

[11] N.K. Smolentsev, *Fundamentals of the theory of wavelets. Wavelets in MATLAB*. Moscow: DMK Press, 2014.

[12] N.K. Smolentsev, *Introduction to the theory of wavelets*. Moscow-Izhevsk: "Regular and Chaotic Dynamics", 2010.

[13] A.B. Stepanov, "Neural network model of wavelets for the continuous wavelet transform", *in Proc.* ICCTPEA *Conf.,* Jun.-Jul. 2014, pp. 177-178.

[14] A.B. Stepanov, "On the use of splines for wavelet construction for solving the problem of biomedical signal analysis process automation", *in Proc.* FRUCT *Conf.,* Apr. 2015, pp. 216-221.

[15] S. Haykin, *Neural networks*, New Jersey, 1999.