

UDC 621.924

T. V. Prybalovets,

N. V. Kresyun, MD,

K. A. Bidnyuk, candidate of medical sciences,

O. M. Nenova, candidate of medical sciences, professor assistant,

T. M. Muratova, candidate of medical sciences, professor assistant,

G. V. Chernetska, candidate of medical sciences

## APPLICATION OF THE CONTINUOUS WAVELET TRANSFORMATION (CWT) FOR THE AUTOMATIC DETECTION OF INTERICTAL EPILEPTIC DISCHARGES

*The Odessa National Medical University*

### Introduction

Wavelet-based methods for the automatic detection of EEG epileptic phenomena is preferred last time as a method for identification of certain type of shape of electrographic signals, especially when the effectiveness is compared with the Fourier method of EEG data analysis. Namely, ability to identify of signals with not-stationary characteristics is in favor for wavelet analysis advantages [1–4].

The net preference of WT for the automatic detection of epileptiform discharges have been shown on absence — like EEG pattern of activity (spike — wave bursts) [5–8]. Different types of wavelets with the fixed mother properties, which are identified by researches logically, such as Mexican hat, Daubechies 2 and similar are used successfully [1; 8]. Meanwhile, it is of great importance is to detect appearance of single spike of sharp wave, which is happened during interictal period [9–11]. Unpredictable character of the precipitation of such phenomena is in favor for the preferable usage of CWT as a main technology.

Hence, the aim of work was to develop CWT for detection of single spikes or/ and sharp waves in patients EEG during interictal period.

### Materials and Methods of Investigation

Hence in this work we present the further development of idea on marginal recalculation of wavelet coefficient with known scale. Some principles of automatic parameters of algorithm for the

usage of mother wavelets recalculations are also worked out.

The process of conversion of the initially continuous signal which is registered by one EEG lead  $\xi(t)$  into discrete form and  $x(i)$  might be described by equation:

$$x(i) = [\xi(i \cdot \Delta_D)] = [\xi(t) \cdot \delta(t - i\Delta_D)] \quad (1)$$

where  $[\ ]$  — operator of the sampling,  $\Delta_D$  — sampling frequency,  $\delta(t)$  — Dirac delta function.

Wavelet function, which is determined in space  $L^2(R)$  also is satisfactorily localized both time and frequency coordinates. Continuous wavelet transform (CWT)  $W(a, b)$  of discrete signal which is made on the basis mother wavelet  $\psi_0(t)$  is performed in accordance to the equation:

$$W(a, b) = a^{-1/2} \sum_i \left( x(i) \cdot \psi_0^* \left( \frac{i-b}{a} \right) \right) \quad (2)$$

where  $a$  — the scale of analysis,  $b$  — time,  $\psi_0^*(t)$  — complex conjugate function of  $\psi_0(t)$ .

The central part of wavelet function  $\psi_0(t)$  is possessed by a certain frequency value  $f_{center}^\psi$ , when the amplitude of signal is maximal:

$$|\hat{\psi}_0(f)| \rightarrow \max \quad (3)$$

where  $\hat{\psi}_0(f)$  — the result of Fourier transformation of function  $\psi_0(t)$ .

The central frequency determines the frequency component of data, which causes the maximal influence upon the wavelet coefficients. Hence, inclusion of the sampling of the initial signal as well as

changes of wavelet scale permits to identify frequency components of data which causes maximal influence upon the wavelet coefficients of certain scale.

Let us take that epileptic manifestations are observed at certain frequency bandwidth  $[f_{low}; f_{high}]$ . In this case the corresponded bandwidth of scales of wavelet transformation will be described by equation:

$$\begin{aligned} & [a_{low}; a_{high}] = \\ & = \left[ (f_{center}^{\Psi} \cdot f_{\Delta} / f_{high}); (f_{center}^{\Psi} \cdot f_{\Delta} / f_{low}) \right] \end{aligned} \quad (4)$$

where  $f_{\Delta} = 1 / \Delta$  — frequency of sampling of the initial data.

It is necessary to create the *descriptive sequence*  $E(i)$  on the basis of calculated bandwidth of scales, which permits to identify the presence or absence of proper phenomena and their location in accordance to time-schedule.

The presence of local phenomena with the even well defined local frequency in the row of data is expected to have effect upon wavelet coefficients in rather high bandwidth of scales; despite wavelet function is well localized in frequency zone. Taking into consideration this fact, it is reasonable to substitute relatively small bandwidth of scales with the logically accepted one, such as averaged scale as an example.

But in the case of wide bandwidth of scales it is possible to attract more complicated methods of creation of descriptive sequence, which also serves for the heightening of the effectiveness of analysis. For example, the weighted sum of wavelet coefficients determined at different scales as well as their minimal and maximal values might used with such a purpose.

In our case the descriptive sequence is created in accordance to the equation:

$$E(i) = \frac{W^2 \left( \frac{a_{low} + a_{high}}{2}, i \right)}{\sigma_{epoch}^2}. \quad (5)$$

The calculation of second degree of wavelet coefficients permits to increase the contrast of descriptive sequence while dividing by the dispersion of the epoch of analysis  $\sigma_{epoch}^2$  — provides invariant state of algorithm with regard to the scale of initial data and partially increase the resistance to perturbations.

#### Comparative analysis of the algorithm

With the aim of verification of the developed algorithm it was used for the analysis of the same test data, which have been used by other authors [9,10]. Taking into consideration that single spikes and

sharp waves correlates with alpha rhythm, the bandwidth which was under analysis was restricted by 8 and 13 Hz.

Effectiveness of algorithm was estimated via calculation of sensitivity and specificity coefficients:

$$R_{sensitivity} = \frac{TP}{TP + FN}, \quad (6)$$

$$R_{specificity} = 1 - \frac{TN}{(TP + FN) + TN} = \frac{TP + FN}{(TP + FN) + TN}$$

where  $TP$  — number of true phenomena which have been correctly identified,  $FN$  — number of missed phenomena,  $TN$  — number of false marked segments which does not contain phenomenon which is under seeking.

Unusual type of equation for the coefficient of specificity  $R_{specificity}$  is explained by the fact of the absence of possibility of correct determination of  $FP$  in case of identification of missed EEG elements of analysis, which are not phenomena. That is why proposed approach for  $R_{specificity}$  calculation is proper for the free from errors algorithm work.

## Results and Discussion

The results of identification of spikes and sharp waves in the group of 30 EEG segments, which contain 52 phenomena and 40 segments which contain different type of artifacts are presented in table 1.

Results revealed some sort of difference between theoretically based equation — calculated and artificially identified values which was made for each wavelet separately, but they are rather similar (see Table 1). The undulation of the effectiveness of algorithm with the usage of different parameters to poor and better results is clear as well.

The example of automatic calculation of the effectiveness of the usage of wavelet Symlet of third order for the identification of epileptic phenomena (Fig. 1).

Table 1

Comparative Effectiveness of Automatic Analysis of Data

Parameters	Type of work with parameters	
	Manual	Automatic
Value of scale		
mexhat	7	6
db2	20	16
Sensitivity		
mexhat	0.83	0.83
db2	0.83	0.69
Specificity		
mexhat	0.93	0.98
db2	1	1

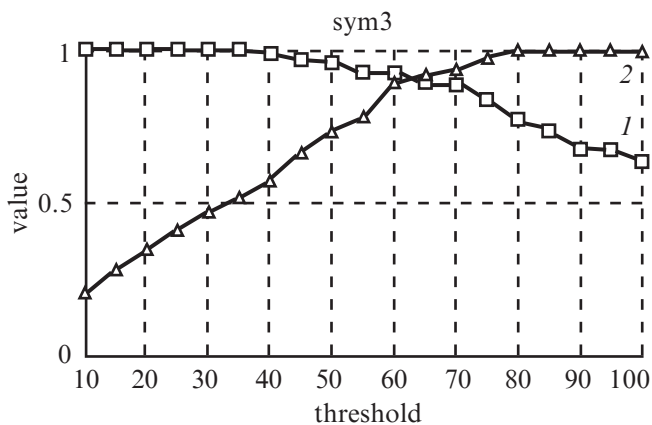


Fig. 1. Example of effectiveness of algorithm: 1 — sensitivity; 2 — specificity

Presented results show the effective usage of CWT for the automatic detection of spikes and sharp waves in EEG and might be useful for more precise interpretation of gained data on their characteristics [1; 4]. Hence, gained data are in favor that the automatization of the recalculation of parameters in accordance to proposed algorithm reveals the way for easy testing of different types of wavelets with the consequent identification most proper one(s) for effective analysis of EEG.

### Conclusions

CWT which converts frequency — time coordinates into scale-time one proved to be effective for the automatic detection of interictal epileptic phenomena, effectiveness of which is comparable with that one which might be achieved by expert analysis of EEG.

### REFERENCES

1. Geerts A.J.E. Detection of interictal epileptiform discharges in EEG M. Applied Mathematics thesis, University of Twente, Enschede, The Netherlands, Sept. 2012.

2. Zandi A.S., Dumont G.A., Javidan M., Tafreshi R. Detection of epileptic seizures in scalp electroencephalogram: an automated real-time wavelet-based approach. *J Clin Neurophysiol* 2012 Feb; 29: 1-16.

3. Acharya U.R., Sree S.V., Avin A.P., Yanti R., Suri J.S. Application of non-linear and wavelet based features for the automated identification of epileptic EEG signals. *Int J Neural Syst.* 2012 Apr; 22. doi: 10.1142/S0129065712500025.

4. Hamanen M.B., Chitravas N., Kaiboriboon K., Lhatoo S.D., Loparo K.A. Automated removal of EKG artifact from EEG data using independent component analysis and continuous wavelet transformation. *IEEE Trans. Biomed. Eng* 2014 Jun.; 61: 1634-1641.

5. Bosnyakova D., Gabova A., Kuznetsova G., Obukhov Yu., Midzyanovskaya I., Salonin D., Van Rijn C., Coenen A., Tuomisto L., Van Luijelaar G. Time-frequency analysis of spike-wave discharges using a modified wavelet transform. *J. Neurosci. Methods* 2006 Jul; 154: 80-88.

6. Ovchinnikov A., Lutjohann A., Hramov A., Van Luijelaar G. An algorithm for real-time detection of spike-wave discharges in rodents. *J. Neurosci. Methods* 2010; 194: 172-178.

7. Sitnikova E., Hramov A. E., Grubov V., Koronovsky A. A. Time-frequency characteristics and dynamics of sleep spindles in WAG/Rij rats with absence epilepsy. *Brain Res* 2014 Jan.; 1543: 290-299.

8. Pavlov A.N., Hramov A.E., Koronovsky A.A., Sitnikova E.Yu., Makarov V. A., Ovchinnikov A.A. Wavelet analysis in neurodynamics. Review, Achievements of Physic's Sciences (Russian) 2012; 182: 905-939.

9. Argoud F. I., De Azevedo F. M., Neto J. M., Grillo E. SADE3: an effective system for automated detection of epileptiform events in long-term EEG-based on context information. *Med. Biol. Eng. Comput* 2006 Jun.; 124: 459-470.

10. Lodder S. S., Askamp J., van Putten M. J. Inter-ictal spike detection using a database of smart templates, *Clin Neurophysiol* 2013 Jun.; 124: 2328-2335.

11. Liu Y.C., Lin C.C., Tsai J.J., Sun Y.N. Model-based spike detection of epileptic EEG data. *Sensors (Basel)* 2013 Sept.; 13: 12536-12547.

Submitted 18.10.2016

Reviewer L. S. Godlevsky, MD, PhD, prof.

УДК 621.924

Т. В. Прибаловець, Н. В. Кресюн, К. А. Біднюк, О. М. Ненова, Т. М. Муратова, Г. В. Чернецька

### ЗАСТОСУВАННЯ БЕЗПЕРЕРВНОГО ВЕЙВЛЕТ-АНАЛІЗУ ДЛЯ АВТОМАТИЧНОЇ ДІАГНОСТИКИ ІНТЕРІКТАЛЬНИХ ЕПІЛЕПТИЧНИХ РОЗРЯДІВ

У статті розглянуто приклад застосування апарату безперервного вейвлет-перетворювання для автоматичного виявлення епілептичних проявів на міжнападівій електроенцефалограмі. Був розроблений принцип автоматичного обчислення діапазону масштабів вейвлет-кофіцієнтів та формування описової послідовності для аналізу епілептичних проявів. Представлено порівняння результативності роботи алгоритму з ручним та автоматичним визначенням параметрів аналізу.

**Ключові слова:** епілептичні розряди, вейвлет-аналіз.

UDC 621.924

T. V. Prybalovets, N. V. Kresyun, K. A. Bidnyuk, O. M. Nenova, T. M. Muratova, G. V. Chernetska

### APPLICATION OF THE CONTINUOUS WAVELET TRANSFORMATION (CWT) FOR THE AUTOMATIC DETECTION OF INTERICTAL EPILEPTIC DISCHARGES

This article describes an example of using continuous wavelet-transforming for automatic detection of epileptic events on interictal EEG data. The principle of automatic calculation of wavelet-coefficients band and forming of the descriptive sequence for the analysis of the epileptic events was developed. The effectiveness comparison of algorithm working with the hand-set and automatically calculated parameters of analysis was presented.

**Key words:** epileptic discharges, wavelet analysis.