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NOVELTIES IN EEG ANALYSIS OF PATIENTS WITH EPILEPSY

Abstract: Epilepsy is the second most prevalent neurological disorder in humans. Cause of epilepsy originates from chronic structural and functional abnormalities in cerebral cortex. Electroencephalogram (EEG) is essential for diagnosis of epilepsy and seizure type detection. Usually, neurologist manually detects specific epilepsy pattern on EEG record to confirm epilepsy diagnosis, so the diagnosis of epilepsy can be very strongly determined by the person who is analysing EEG findings. In the near future a patient's seizure may be detected and aborted before physical manifestations begin. There are many methods that have been investigated in context of EEG signal processing, and some of them are wavelet transform (WT), Hilbert-Huang transform etc. This paper presents the novelties in classification and analysis of intracranial EEG and epilepsy detection based on mathematical functions.

Key words: *EEG, Epilepsy, Wavelet transform, Hilbert Huang transform*

1. INTRODUCTION

Epilepsy is one of the most common neurogical diseases followed with frequent epileptic seizures. It is characterized by recurring seizures in which abnormal electrical activity in the brain causes altered perception or behavior. It has affected more than 40 million people worldwide. Epilepsy's hallmark symptom, seizure, is manifestations of epilepsy and can have a broad spectrum of debilitating medical and social consequences [1–6]. An area of great interest is the development of devices that incorporate algorithms capable of detecting an early onset of seizures or even predicting the hours before seizures occur. Intention is, in the near future, that a patient's seizure may be detected and aborted before physical manifestations begin. [1, 7, 8]

Information transfer through the brain has electrochemical nature, but electrical potentials created by individual neurons have extremely small amplitudes, and

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only synchronized activity of larger number of neurons creates a potential large enough to be measured with electrodes placed on the scalp. Signals collected with these electrodes represent the brain activity and are called electroencephalogram (EEG). Recorded electrical activity of the brain is based on postsynaptic potentials that last longer and occur on a larger neuron surface than action potentials and therefore have a higher detection probability. [7,8]

2. ELECTRICAL BRAIN SIGNALS

In terms of denoting individual EEG frequency bands, the commonly used classification contains: *delta* (0–4 Hz), *theta* (4–8 Hz), *alpha* (8–12 Hz), *beta* (13–30 Hz), and *gamma* (30–60 Hz) rhythms or signals. Activities or amplitudes of particular EEG signal components can have great benefits in terms of patient status identification or certain diagnosis establishment. Characteristics of EEG signal components can be shortly described as follows:

Alfa – centered in the frequency range from 8 to 12 Hz with 20 to 60 μV amplitudes, typically occurring in the occipital brain areas, and this rhytm is specific for a complete relaxation state: also, with the beginning of either mental or physical action, these waves disappear. *Beta*- in 13 to 30 Hz frequency range, amplitudes from 2 to 20 μV, characteristic of the state of normal, healthy vigilance, increased concentration and intense mental activity. *Delta*-oscillation with great amplitudes and low frequencies, with 20 to 200 μV, while *theta* components amplitudes are in the range from 20 to 100 μV. *Gamma* waves typically have higher frequencies, about 40 Hz.[1,8]

3. DIFFICULTIES IN EEG ANALYSIS

Electroencephalogram established itself in the past as an important means of identifying and analyzing epileptic seizure activity in humans. It serves as a valuable tool for clinicians and researchers to study the brain activity in a non-invasive manner. Careful analyses of the EEG records can provide valuable insight into and improved understanding of the mechanisms causing epileptic disorders. Detection of epileptiform discharges in the EEG is an important component in the diagnosis of epilepsy. In most cases, identification of the epileptic EEG signal is done manually by skilled professionals, who are small in number.[9–11] The diagnosis of an abnormal activity of the brain functionality is a vital issue.

A recently published study by Barkmeier et al., has sugested that human reviewers showed surprisingly poor inter-reviewer agreement, but did broadly agree on the ranking of channels for spike activity. The computer algorithm performed as well as the human reviewers and did especially well at ranking channels from highest to lowest spike frequency. Highly trained human reviewers were asked to manually mark individual spikes on each of an average of 96 channels from 10 different patients. Surprisingly, only 23.7% of these were marked by at least two reviewers and just 3.1% by all three reviewers. So, diagnosis of epilepsy in a classical way can be very strongly determined by the person who is analysing EEG record.[12]

EEG is the recording of electrical activity along the scalp of head, produced by the firing of neurons within the brain. It refers to the recording of the brain's spontaneous electrical activity over a short period of time, usually 20–40 minutes, as recorded from multiple electrodes placed on the scalp. In neurology, the main diagnostic application of EEG is in the case of epilepsy, as epileptic activity can create clear abnormalities on a standard EEG study. [8,13,14] Well-known causes of epilepsy may include: genetic disorders, traumatic brain injury, metabolic disturbances, alcohol or drug abuse, brain tumor, stroke, infection, and cortical malformations (dysplasia). Therefore, EEG activity always reflects the summation of the synchronous activity of thousands or millions of neurons that have similar spatial orientation. Because voltage fields fall off with the square of the distance, activity from deep sources is more difficult to detect than currents near the skull. Scalp EEG activity shows oscillations at a variety of frequencies. Several of those oscillations have characteristic frequency ranges, spatial distributions, and are associated with the different states of brain functioning. These oscillations represent synchronized activity over a network of neurons.[8, 13]

EEG signals involve a great deal of information about the function of the brain. But classification and evaluation of those signals are limited. Since there is no definitive criteria established by experts, visual analysis of EEG signals in time domain may be insufficient. The routine clinical diagnosis needs the analysis of EEG signals. Therefore, some automation and computer techniques are used for this aim. Recent applications of the WT and Neural Network (NN) to engineering-medical problems can be found in several studies that refer primarily to signal processing and classification in different medical areas. It is important to emphasize the algorithm for classification of EEG signals based on WT and Patterns Recognize Techniques.[8, 15–18]

4. ENERGY DISTRIBUTION OF THE EEG SIGNAL COMPONENTS

Some results of our previous research, shown in this chapter, were published recently [1, 8, 11, 14, 18], and the datasets were originally selected from the Epilepsy Center in Bonn, Germany. [16] The datasets we particularly used and denoted consisting of three groups of EEG signals, were basically extracted from both normal subjects and epileptic patients. The first group was recorded from healthy subject (A set), the second group was recorded prior to a seizure (steady state) from part of the brain of the patient with epilepsy syndrome (C set) and the third group (E set) was recorded from the patient with the epilepsy syndrome during the seizure. As is well known, the EEG signal contains a several spectral components. The magnitude of a human brain surface EEG signal is in the range of 10 to 100 μV. The frequency range of the EEG has a fuzzy lower and upper limit, but the most important frequencies from the physiological viewpoint lie in the range of 0.1 to 30 Hz. The standard EEG clinical bands are the delta (0.1 to 3.5 Hz), theta (4 to 7.5 Hz), al-

pha (8 to 13 Hz), and beta (14 to 30 Hz) bands. EEG signals with frequencies greater than 30 Hz are called gamma waves.[6]
Generally, a wavelet is a function $\psi \in L^2(R)$ with a zero average

$$\int_{-\infty}^{+\infty} \psi(t)dt = 0. \tag{1}$$

The Continuous Wavelet Transformation (CWT) of a EEG signal *x(t)* is defined as:

$$CWT_{\psi}x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-b}{a}\right)dt \tag{2}$$

where $\psi(t)$ is called the 'mother wavelet', the asterisk denotes complex conjugate, while a and b $(a, b \in R)$are scaling parameters, respectively.[1,8,19] The scale parameter a determines the oscillatory frequency and the length of the wavelet, and the translation parameter b determines its shifting position. The scaling function is closely related with the low-pass filters (LPF), and the wavelet function is close-

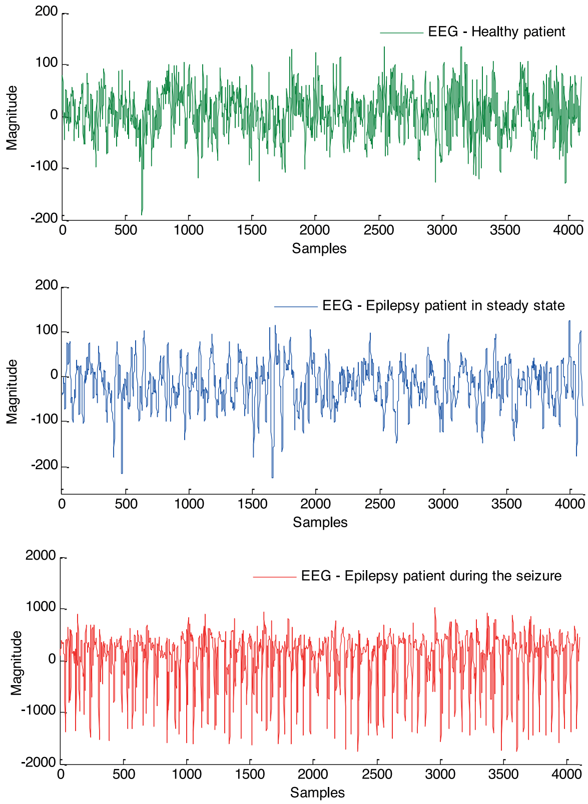

Fig. 1. The first EEG signal presents the EEG of a healthy patient, the second EEG signal presents the EEG of an epilepsy patient in steady state and the third EEG signal presents the EEG of an epilepsy patient during the seizure.

ly related with the high-pass filters (HPF). The decomposition of the signal starts by passing a signal through these filters. The approximations are the low-frequency components of the time series or signal and the details are the high-frequency components of the signal. The signal passes through a HPF and a LPF. Then, the outputs from filters are decimated by 2 to obtain the detail coefficients and the approximation coefficients at level 1 (A1 and D1). The approximation coefficients are then sent to the second stage to repeat the procedure. Finally, the signal is decomposed at the expected level. [18, 19]

Figure 1 shows the three signals from the analyzed database.

It is obvious (Fig. 1) that the magnitudes of the EEG signal of a patient with epilepsy and during the seizure are much larger than those of the other two EEG signals. Also, components of the EEG signal (δ, θ, α, β and γ) of a patient with epilepsy and during the seizure have much larger magnitudes than the other two EEG signals. The magnitude of the EEG signals of the healthy patient and the EEG signals of the epilepsy patient in steady state have approximately the same values.

Frequency bands corresponding to five decomposition levels for wavelet Db 4 used in this study, with sampling frequency of 173.6 Hz of EEG signals were listed in Table 1.

Table 1. Frequency bands corresponding to different decomposition levels.

Decomposed signals	Frequency bands (Hz)	Decomposition level
D1	43.4–86.8	1 (noises)
D2	21.7–43.4	2 (gama)
D3	10.8–21.7	3 (beta)
D4	5.40–10.8	4 (alpha)
D5	2.70–5.40	5 (theta)
A5	0.00–2.70	5 (delta)

The Db4 transform has four wavelet and scaling function coefficients. We could recognize different distribution of energy of the analyzed signals, which was generally quite similar for each group of EEG signals. The results showed that different groups of the analyzed signals (sets A, C and E) are obviously different in energy distribution of signals in the frequency bands of decomposition of EEG signals. Energy distribution of EEG signals where epileptic seizure was registered was significantly different from the first two cases. Energy activity of D 3, D 4 and D 5 components was dominant, while A 5 component was somewhat lower. [1,8,18]

5. EEG SIGNAL CLASSIFIER BASED ON PERCENTAGE OF ENERGY DISTRIBUTION

The percentage of energy distribution can be used for classification of EEG signals. One of the common tools used for classification are Artificial Neural Networks

(ANN). In the classifier based on percentage of energy distribution of EEG signals (Omerhodzic et al., 2010) the Feed-Forward Neural Network (FFNN) is used to classify different EEG signals. The classified accuracy rate of EEG signals of the proposed approach was 94.0%. A hundred percent correct classification rates were obtained for normal EEG signals. The results showed that different groups of the analyzed signals are obviously different in energy distribution of signals in the frequency bands of decomposition of EEG signals.[1,8]

6. THE POSIBILITY OF MAKING DIAGNOSIS OF EPILEPSY FROM EEG SIGNALS USING HILBERT HUANG TRANSFORM

In our recently published research Hilbert-Huang transform (HHT) was used for two groups of EEG signals: one representing EEG signals of healthy subjects and the other from patients with epileptic syndrome without seizure. Results presentation has been done through empirical mode decomposition (EMD) procedure and marginal Hilbert spectrum. Results obtained using this methodology indicate that the EEG signals from the subjects with epileptic syndrome contain components with significant amplitude values in the frequency range up to 10 Hz, which physically represents the area of delta and theta waves.

According to these results, clear differentiation between two signal groups is enabled, offering an excellent base for simple and efficient automated classifier development, which is reserved for further researche in this area. [20]

7. CONCLUSION

Wavelet transform and Hilbert-Huang transform, due to their advantages over the other techniques of analyzing and processing of signals, found its application in medicine. We believe that analysis of EEG signals using WT and HHT can be a suitable methods for precise and reliable identification of bioelectric state of the cerebral cortex, both in healthy and epilepsy patients. Finally, it can be quite a reliable indicator of epilepsy. Monitoring and analysis of the patient over a longer period of time can give us more information concerning the development of epilepsy.

REFERENCE

[1] I. Omerhodzic, S. Avdakovic, A. Nuhanovic, K. Dizdarevic: „Energy distribution of EEG signals: EEG signal wavelet-neural network classifier" World Academy of Science, Engineering and Technology, vol. 61, 2010. p. 1190–1195.

[2] R. L. Aylward: Epilepsy: a review of reports, guidelines, recommendations and models for the provision of care for patients with epilepsy. Clin Med, 2008, Vol. 4, p. 433–438.

[3] S. Lefter, O. O'Toole, B. Sweeney: Epilepsy and driving: new European Union guidelines. Ir Med J, 2010, Vol. 103, No. 3, p. 86–88.

[4] J. C. McHugh, N. Delanty: Epidemiology and classification of epilepsy: gender comparisons. Int Rev Neurobiol, 2008, Vol. 83, p. 11–26.

[5] A. K. Ngugi, S. M. Kariuki, C. Bottomley, I. Kleinschmidt, J. W. Sander, C. R. Newton: Incidence of epilepsy: A systematic review and meta-analysis. Neurology, 2010, Vol. 77, No. 10, p. 1005–1012.
[6] S. Tong, N. V. Thacor: Engineering in Medicine & Biology – Quantitative EEG Analysis Methods and Clinical Applications, Boston/London: Artech House, 2009.
[7] R. A. Saiz Díaz, A. Martínez Bermejo, J. Gómez Alonso: Diagnosis of epilepsy over the course of the disease. Neurologist, 2007, Vol. 13, No. 6 (Suppl 1), p. S 11–19.
[8] I. Omerhodzic, S. Avdakovic, A. Nuhanovic, K. Dizdarevic, K. Rotim: Energy Distribution of EEG Signal Components by Wavelet Transform. In: Wavelet Transforms and Their Recent Applications in Biology and Geoscience, Dumitru Baleanu (Ed.), ISBN: 978–953–51–0212–0, InTech, 2010.
[9] L. M. Patnaik, O. K. Manyamb: Epileptic EEG detection using neural networks and post-classification". Comput Methods Programs Biomed, 2008, Vol. 91, p. 100–109.
[10] J. Wang, G. Xu: Some Highlights on Epileptic EEG Processing. Recent Pat Biomed Eng, 2009, Vol. 2, pp. 48–57.
[11] I. Omerhodzic, S. Avdakovic, K. Dizdarevic, A. Nuhanovic: Wavelet transform based analysis of EEG signals and indicators of epilepsy. Acta Clin Croat 2011; 50(suppl 1): p. 42.
[12] D. T. Barkmeier, A. K. Shah, D. Flanagan, M. D. Atkinson, R. Agarwal, D. R. Fuerst, K. Jafari-Khouzani, J. A. Loeb: High inter-reviewer variability of spike detection on intracranial EEG addressed by an automated multi-channel algorithm. Clin Neurophysiol. 2012 Jun; 123(6): p. 1088–1095.
[13] S. Klein, B. M. Thorne: Biological psychology. New York: Worth, 2007.
[14] I. Omerhodzic, E. Causevic, K. Dizdarevic, S. Avdakovic, M. Music, M. Kusljugic, E. Hajdarpasic, N. Kadic: First neurosurgical expirience with the wavelet based EEG in diagnostic of concussion. 11th Congress of Neurosurgeons of Serbia with International participation. Nais, Serbia, Oct. 2008. Abstract book, p. 118.
[15] S. Motamedi-Fakhret et al: Signal processing techniques applied to human sleep EEG signals – A review. Biomedical Signal Processing and Control, 2014, vol. 10: p. 21–23.
[16] R. G. Andrzejak, K. Lehnertz, C. Rieke, F. Mormann, P. David, C. E. Elger: Indications of nonlinear deterministic and finite dimensional structures in time series of brain electrical activity: Dependence on recording region and brain state. Phys Rev E Stat Nonlin Soft Matter Phys 2001; 64(6 Pt 1): 061907.
[17] H. Adeli, S. Ghosh-Dastidar, H. Dadmehr: A wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy. IEEE Trans Biomed Eng., 2007, vol. 54(2): p. 205–211.
[18] S. Avdakovic, I. Omerhodzic, A. Badnjevic, D. Boskovic: Diagnosis of Epilepsy from EEG Signals Using Global Wavelet Power Spectrum. 6th European Conference of the International Federation for Medical and Biological Engineering IFMBE. Proceedings Volume 45, 2015, p. 481–484.
[19] H. He, J. A. Starzyk: A self-organizing learning array system for power quality classification based on wavelet transform. IEEE Transaction On Power Delivery, 2006, Vol. 21, No. 1, p. 286–295, ISSN 0885–8977.
[20] S. Ibric, S. Avdakovic, I. Omerhodzic, N. Suljanovic, A. Mujcic: EEG verified diagnosis of epilepsy using Hilbert Huang transform. The 1st Conference of Medical and Biological Engineering in Bosnia and Herzegovina – CMBEBIH 2015. Sarajevo, March 13–15, 2015.