

Blinking Artefact Recognition in EEG Signal Using Artificial Neural Network

Rafał Bogacz¹, Urszula Markowska-Kaczmar¹, Andrzej Kozik²

¹Computer Science and Management Department, Wrocław University of Technology

²Video-EEG Laboratory, Department of Child Neurology, T. Marciniak Hospital, Wrocław

Abstract

Artefacts are noises introduced to an EEG signal by patient's movements and sources of electric field outside the patient's body. The artefacts impede a doctor's expertise and an automatic analysis of the signal. The most common and characteristic kind of artefacts are blinking artefacts. This paper presents a neural based approach to finding artefacts in the signal. The inputs to the network are different coefficients computed for a window of the signal, expressing some characteristic properties of blinking artefacts. 41 coefficients were designed. Sensitivity and correlation analyses were used to choose 14 coefficients for the network's inputs. One used a large training set including coefficients for over 27000 windows, containing different kinds of EEG waves. Three classification algorithms were compared: *k*-neighbours, RBF networks and back propagation networks. The program was tested on the EEG signal and was highly evaluated by a domain expert.

1. INTRODUCTION

EEG signal is a bioelectric brain activity measured in a number of places on the scalp (the number of electrodes is equal to 19 in the presented work). The measured signals are digitised and stored on hard disk of a computer. Artefacts are noises introduced to an EEG signal by patient's movements and sources of electric field outside the patient's body. The most common and characteristic kind of artefacts are blinking artefacts.

The aim of the described work was to create a computer program finding blinking artefacts in the EEG signal. There is no a set of rules determining if the fragment of the signal does contain a blinking artefact, or does not. Hence, neural networks were chosen as a classification tool. For simplicity, in this paper a word "artefact" will refer to "blinking artefact".

An example of EEG signal with an artefact is presented in Figure 1. The artefact is the mostly visible in signals form the two most frontal electrodes: Fp1 and Fp2 and also from other frontal electrodes: F3, F4, F7 and F8.

Removing artefacts from EEG signal may aid the work of doctors, because artefacts disturb their attention. Removing artefacts is also important in automatic analysis of EEG signal. It may be used as a pre-processing in the systems giving a diagnosis. It is also necessary in

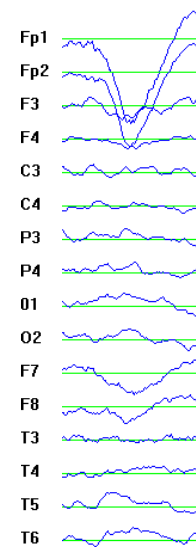


Figure 1. Artefact in an EEG signal

computer analyses helping doctors in making a decision, e.g. EEG-mapping (a new method of EEG signal presentation in a form of colour maps, giving additional information in comparison with the traditional method). Artefacts introduce noise and deform the shape of the maps.

The second section of the paper presents the related works. The next sections describe the preparing of the training set: selection of signals, coefficients computed for the windows of signal and selection of these coefficients. Section 6 compares three classification algorithms for finding artefacts. Finally section 7 concludes the paper and shows the direction of the future work.

2. RELATED WORKS

Very simple criteria of the artefact recognition are presented in [6]. According to them a 5-second's fragment of EEG signal includes an artefact when the following conditions are satisfied:

- High amplitude of delta rhythm (0.5-4 Hz) in channels Fp1 and Fp2.
- Symmetry of signals in channels Fp1 and Fp2.
- Rapid decline of delta rhythm posteriorly (the amplitude of delta rhythm in Fp1 and Fp2 is much higher than in other channels).

Using these simple methods, the authors achieved high classification accuracy: 94.9%. However, the algorithm was tested on small data set (330 windows, which 78 of them included artefacts).

In [3] authors used neural network with wavelet signal preprocessing to finding artefacts. This approach is very interesting, however very low generalisation ability was obtained. Neural networks may be also used to artefact correction [7] – filtering artefacts from EEG signal.

3. TRAINING DATA FOR THE NEURAL NETWORK

The input to the neural network, used in this work, is not a raw sampled signal, but different coefficients computed for a window of one second of the signal. The window moves by 0.25 second of the signal.

Artefacts differ in shape, amplitude and frequency. There are also some other waves, which are similar to artefacts. In order to handle all this cases by the network, a large training set for the network was created. 500 MB of EEG signal (equivalent of 14.5 hours of recording) from 86 patients was analysed. From this data one chose 27267 the most representative windows (from 55 patients), containing different kinds of blinking artefacts, pathological and proper waves, and artefacts caused by other sources (e.g. jaw, muscle).

Chosen windows were classified as containing artefact or not containing. In the case of 2 patients, this classification was performed on the ground of video-EEG recording of patients' faces. In the case of other patients, the classification was undertaken by a domain expert on the ground of the shape of the signal. Such a classification was not objective, because for some windows even the expert was not sure if the window contains an artefact.

The data were divided into two sets: the training set containing 21040 windows (1531 with artefacts) and the testing set containing 6227 windows (660 with artefacts).

4. COEFFICIENTS COMPUTED FOR A WINDOW OF A SIGNAL

For each window, 41 coefficients expressing some characteristic properties of blinking artefacts were computed. Some of the coefficients were designed by the authors and were based on their knowledge about the artefact recognition. Then the network was trained. Other coefficients, which were introduced, were based on an analysis of the signal's fragments, which were incorrectly classified by the network. All the coefficients are listed below (detailed description of the coefficients can be found in [1]):

- Parameters of the wave with the highest amplitude in the window in averaged signal from channels Fp1 and Fp2 (such average signal will be mark AVFp12 in the rest of the paper). If there is an artefact in the window of AVFp12, it is the wave with the highest amplitude. The parameters are marked by letters in Figure 2.

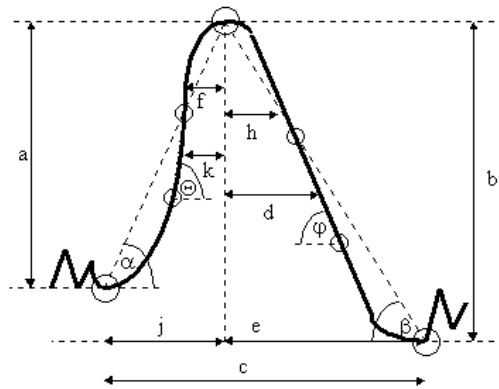


Figure 2. Parameters of the wave with the highest amplitude in the window

- Coefficients expressing criteria from [6] (presented in section 2):
 - Amplitude of delta rhythm (0.5 – 4Hz) in AVFp12.
 - Symmetry between Fp1 and Fp2 (correlation between Fp1 and Fp2, similarity of amplitudes of the waves with the highest amplitudes in Fp1 and Fp2).
 - Decline of delta rhythm posteriorly (quotient of delta amplitude in Fp1 and in F3, quotient of delta amplitude in Fp1 and C3).
- Covariance between AVFp12 and other channels. In EEG signal artefacts are visible not only in Fp1 and Fp2 but also in other channels.
- Quotient of standard deviation of the signal AVFp12 inside the wave with the highest amplitude, and standard deviation outside the wave with the highest amplitude. This coefficient expresses the fact that an artefact is always a single wave. It was introduced because one kind of epileptic waves has very similar shape but they are periodic waves.
- Quotient of standard deviation of AVFp12 and average of deviations of signals in other channels. This coefficient expresses the feature of artefacts that they are the mostly visible in channels Fp1 and Fp2.

- Bipolar coefficients. Another two coefficient are based on bipolar visualisation of EEG signal (signals are presented as differences between some two electrodes) and express characteristic features of artefacts in bipolar visualisation
- Coefficients describing a spike-slow-wave complex (SSW). SSW is briefly presented in Figure 3 and it is the most characteristic for epilepsy. SSW can be present in any EEG channel (also only in Fp1 and Fp2), therefore it can be very similar to artefacts. The coefficients express the following features of SSW:
 - High amplitude waves on the left and right side of the wave with the highest amplitude.
 - Characteristic spike before the wave with the highest amplitude.



Figure 3. Spike slow wave complex

The above-presented coefficients encode a large amount of expert knowledge. Therefore, the classification method presented in this paper can be considered as a hybrid neural-expert approach rather than a pure neural approach.

5. SELECTION OF INPUTS FOR THE NEURAL NETWORK

Some of presented coefficients bring similar or irrelevant information. Large number of inputs to the network increases number of weights, hence it decreases the generalisation ability of the network [4]. To reduce the number of inputs and choose the most suitable coefficients, the sensitivity analysis [4] was used to compute the sensitivity of coefficients – the measure of information bringing by each coefficient about existence of an artefact. The sensitivity analysis gives different results in different runs, because the results depend on the starting values of weights, which are initialised randomly. Therefore, in this work the sensitivities of coefficients were averaged over 70 runs of the analysis.

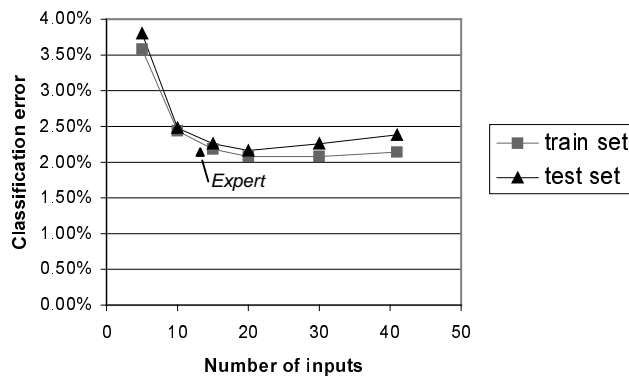


Chart 1. The classification error of the neural network depending on the number of inputs

The coefficients were sorted by sensitivity and then the error of back propagation network was testing depending on the number of inputs. Chart 1 shows the classification error of the back propagation network with 3 hidden units after 200 epochs of learning. The most left points show the error of the network with 5 inputs having the highest sensibility, the next points – with 10 inputs, etc.

When the number of inputs grows, the error on the train set decreases and then stabilises, while the error on the test set has the lowest value for 20 inputs. One computed the correlation matrix between coefficients. After the elimination of correlated coefficients from the set of 20 coefficients with the highest sensibility, the set of 14 inputs (called *Expert*) was chosen. It gives even lower error on the test set (also shown in Chart 1).

6. RESULTS OF CLASSIFICATION

Three classification algorithms: k -neighbours [5], RBF networks [2] and back propagation networks [4] were tested for the problem of artefact recognition. Table 1 shows the classification error on the test set of the algorithms with the *Expert* set of inputs. The errors are presented for different values of algorithms' parameters (k in the k -neighbours and number of hidden units for the neural networks). The lowest error for each algorithm is bolded.

Table 1 – Classification error for three algorithms

k -neighbours		RBF networks		Back propagation network	
k	Error on test set	Number of hidden units	Error on test set	Number of hidden units	Error on test set
1	2.15%	40	2.49%	3	1.80%
5	2.20%	60	2.59%	4	1.91%
7	1.98%	80	1.82%	5	1.40%
9	1.94%	100	1.80%	6	1.85%
11	1.98%	120	1.97%	7	1.69%

The lowest classification error (1.40%) was obtained for the back propagation network with 5 hidden units after 2000 epochs of learning. The obtained error for the back propagation networks was lower than for k -neighbours and RBF networks, because in the case of data used in this work, different inputs bring different amount of information about presence of an artefact. K -neighbours and RBF networks algorithms compute the Euclid distances between classified vector and some other vectors. Therefore, these algorithms cannot take into consideration the fact that different inputs bring different amount of information, what is the natural feature of the back propagation network.

Table 2 compares classification times of the test set for the Pentium 166 processor, for the classification algorithms. The differences are large and the shortest time was obtained for the back propagation network.

Table 2 – Times of classification of the test set for three algorithms

Algorithm	k -neighbours	RBF network (100 hidden units)	Back propagation net. (5 hidden units)
Classification time for the test set	about 15 minutes	about 1 minute	about 2 seconds

The performance of the network was tested on EEG signal and was highly evaluated by the domain expert. The answer of the network differed with the opinion of the expert only in untypical situation or when the expert was not sure.

The executable codes (for MS-Windows) of the program which finds artefacts in the EEG signal using the back propagation algorithm, may be download from <http://www.ci.pwr.wroc.pl/~bogacz/artefact>. The program has very friendly user interface.

7. SUMMARY

This paper presents a neural-based approach to finding artefacts in EEG signal. Very low classification error was obtain thanks to two factors:

- Large training set containing different kinds of EEG waves.
- Coefficients computed for the windows of signal, delivered to the network's inputs. The coefficients express the characteristic features of artefacts, which distinguish them from a clear signal. They encoded large amount of domain expert's knowledge.

The presented approach is going to be implemented in software for EEG signal analysis by the Elmiko Company from Warsaw. Before the implementation the program will be tested on other EEG signals. There is a possibility of existence of some pathological wave or artefacts for which the system gives the wrong answer. In such a case these waves must be added to the training set. It may be even a need of designing new coefficients to express some characteristic features of these waves.

REFERENCES

- [1] R. Bogacz: Wykrywanie artefaktów związanych z mruganiem w sygnale EEG za pomocą sieci neuronowej, Master Thesis, Wrocław University of Technology, <http://www.ci.pwr.wroc.pl/~bogacz/artefact> , (1998)
- [2] R. Bogacz, C. Giraud-Carrier: Supervised competitive learning for finding positions of radial basis functions, In Proc. of Third Conference on Neural Networks and Their Applications, Kule, pp 701-706 (1997)
- [3] P. Durka, R. Księżyk, K. Blinowska: Neural networks and wavelets analysis in EEG artefact recognition. In Proc. of Second Conference on Neural Networks and Their Applications, Szczyrk, pp 167-172 (1996)
- [4] S. Osowski: Sieci neuronowe w ujęciu algorytmicznym. Wydawnictwo Naukowo-Techniczne, Warszawa (1996)
- [5] T. Mitchell: Machine learning, The McGraw-Hill Companies Inc, New York (1997)
- [6] M. Nakamura, T. Sugi, A. Ikeda, R. Kakigi, H. Shibasaki: Clinical application of automatic integrative interpretation of awake background EEG: quantitative interpretation, report making, and detection of artifacts and reduced vigilance level. *Electroenceph. Clin. Neurophysiol.*, vol 98, pp.103-112 (1996)
- [7] R. Vigarío: Extraction of ocular artefacts from EEG using independent component analysis. *Electroenceph. Clin. Neurophysiol.*, vol 103, pp.395-404 (1997)