SOM Neural Networks in Detection of Characteristic Features of Brainstem Auditory Evoked Potentials (BAEP)

IZWORSKI A., WOCHLIK I., BUŁKA J., PASŁAWSKI A.
Department of Automatics
AGH University of Technology
Al. Mickiewicza 30, 30-059 Kraków,
POLAND

Abstract: - The Brainstem Auditory Evoked Potentials (BAEP) potentials provide an objective, electrophysiological diagnostic method, widely applied in examinations of auditory organs, in particular for such cases, when the application of traditional audiometric methods is difficult or impossible, e.g. in examination of little children and infants. The shape of the time-dependent signal, and its possible distortion, and particularly the presence or absence of characteristic waves are of great diagnostic importance. In the present work methods of preliminary processing and automated identification of wave V are presented, using the SOM type neural networks for determination of structure of the feature space and classification.

Key-Words: - Brainstem Auditory Evoked Potentials, Neural Networks, Self-Organizing Map

1. Introduction

Brainstem Auditory Evoked Potentials (BAEP) potentials present an objective, electrophysiological diagnostic method, widely applied in examinations of auditory organs, in particular in those cases, when the application of traditional[classical] audiometric methods is difficult or even impossible. A typical time dependence of BAEP potential consists of five to seven waves, registered within 10 ms from the application of the acoustic stimulus. In the clinical evaluation of auditory brainstem response the parameters related to wave V are taken into account, in particular its absence or presence.The present work contains a description of preliminary processing methods for the BAEP signal, which optimize the conditions for a subsequent recognition of wave V by the neural networks (Fig.1)

In the preliminary stage of the study the analysis applied to the set of BAEP signals to be recognized was oriented towards the detection of existing groups. Such analysis is able to determine the number of various classes in the input set.

2. Preliminary data processing

Every measured sample containing a recording of an BAEP potential for a given stimulation is a vector consisting of 1000 elements and is characterized by a huge data redundancy, considerable noise level and unfavourable statistical characteristics. The aim of the preliminary data processing is such a transformation of the multi-dimensional input vector to a vector of the dimension as small as possible, containing only the information relevant for the correct classification. Additionally it is required that the components of the output vector should not be correlated

Another problem, for which solution is required, is the construction of a data representation convenient for its processing and storage in the computer memory. In order to fulfill the above the signal has been initially filtered by a low-pass FIR filter with a cut-off frequency f_o=0.07 Hz [3], then the average value and linear trend have been extracted and finally every second element have been selected. Thus the number of datapoints was reduced to 500.

In order to verify the influence of applied procedures measurement of classification efficiency have been carried out for non-filtered signals containing both the average and linear trend and for the filtered signals with the average and linear trend removed. The analysis of the results leads to a conclusion, that too low cut-off frequency value results in decrease of the classification efficiency, and on the other hand filtration omitting also results in a little drop of the classificator efficiency.

The extraction of the average and linear trend is a meaningful procedure and improves the operation of the system. The neural network carrying out the classification later on is not burdened then with unnecessary information.

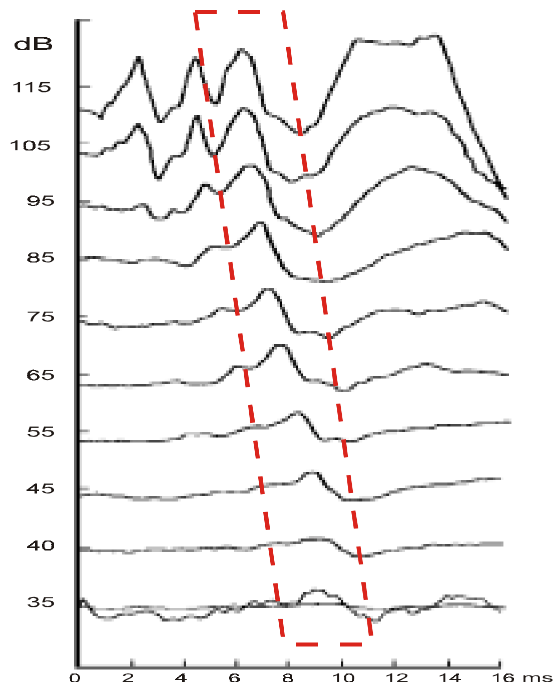

Fig.1 Typical recording of the BAEP signal obtained for a person with normal hearing abilities.

In the next step the effort was focused on the reduction of dimension of the vector fed to the network's input, and for that signal approximation has been used, in the basis consisting of 3-rd order spline functions [9].

As a result of the experiments carried out the number of basis function has been selected as N=36.

Thus the function approximation in the basis of spline functions, being a consecutive step of the preprocessing, enabled the reduction of the dimension of the vector fed to the network's input to only 36 components.

For realization of the analysis artificial neural networks, called selforganized feature maps (SOM - Self-Organizing Map) [2], have been applied.

The networks map the distribution of the input vectors from their original space to a space of reduced dimensionality, at the same time preserving the topology, i.e. the distance relations. Due to that property they are naturally fit for studies of input data ordering e.g. for grouping detection.

3. The chosen methods and assumptions

For purpose of the present study two sets of BAEP signals have been constructed: the learning and test set, each consisting of 75 brainstem responses. The parameters of BAEP recordings selected for the study were as follows: the triggering stimulus took the form of a cracking sound of intensity between 70[1] and 20dB, the signal size included 100 values (equivalent to 10ms period of the BAEP signal). The task, that the neural network was expected to perform, i.e. the classification of auditory brainstem response signals, consisted of the detection of presence of wave V in a single signal recording. Thus both the class of signals with wave V visible and the class of signal with wave V absent have been taken for the analysis. The SOM neural network consists of a two dimensional layer of neurons, for which the concept of vicinity[neighborhood] is introduced. The input of each neuron is provided with the input signal and a constant value (Bias). The network's output is given by the signal from that neuron, for which the answer is the strongest (thus its vector of weights W is the most similar to the input vector X) The SOM network's learning algorithm was a modified Kohonen algorithm - autolearning with competition. The number of presentations of the learning set is determined at the beginning of the learning process. In each learning step the weights are corrected for all the neurons, with varying intensity of the correction, depending on the distance from the winner-neuron. Let's assume that the winner of the competition is the j-th neuron. The correction of the i-th weight of the j-th neuron in a single learning step is given by the formula:

$$\Delta w^{j}_{i} = \eta(t)h(j,j^{*})(x_{i} - w^{j}_{i})$$

The h function determines the weights correction intensity for j-th neuron, if the winner is the vector j*:

$$h(j,j^{*}) = exp(-d(j,j^{*}) / 2\sigma^{2})$$

[1] the signals of higher intensities have not been taken into consideretion , because from automated classiffication's point of view they were not interesting. All the signals with intensities higher than 70dB clearly contained wave V and were easily classfied. On the other hand their including into the data sets would certainly spoil the ratio of number of signals with wave V present to the number of signals with wave V absent.

where d(j,j*) is the distance of the j-th neuron from the winner-neuron, calculated using the Lf measure. The learning coefficient η and the σ parameter are adjusted during the whole process:

$$\eta(t) = \eta_i(\eta_f / \eta_i)^{t/t_f}$$

$$\sigma(t) = \sigma_i(\sigma_f / \sigma_i)^{t/t_f}$$

The SOM network's learning algorithm was a modified Kohonen algorithm – selflearning with competition. Detailed information on that problem can be found in work [2].

4. Analysis of auditory brainstem response potentials using som networks

As a result of the learning process the SOM neural network maps the set of BAEP signals onto a two-dimensional lattice of neurons, preserving the distance relations from the original space of the input signals. It means that the signals which activate the same neuron are more alike than the signals activating different neurons. On the other hand for signals activating different neurons the closer neurons the signals activate the more similar they are themselves. Such property of the SOM networks can be used for detection of grouping in the set of BAEP signals.

After completion of the neural network's learning process its particular neurons should be labelled (calibrated), i.e. it should be determined which class of signals they can represent. The network's neurons which have not been activated for any signal of the learning set are eliminated. If the network's neurons have been the winners only for signals containing the wave V, or only for signals with wave V absent then their labelling is an obvious consequence. On the other hand the neurons winning for signals belonging to both classes are labelled according to the type of predominant signals (in case of equal number of signals the distances of neural weights vectors and BAEP signal vectors are studied).

Let's now consider for a particular example, what type of information about the set of BAEP signals can be provided by the neural network. The results of learning for a network containing 36 neurons (6x6 neurons lattice) are presented in Fig. 2. It is easily noticed that 23 neurons have been activated in the learning process, and 6 of them recognized the signals not containing the wave V, 10 of them recognized the signals containing the wave V, and 7 reacted to signals belonging to both classes. After an additional calibration of the latter neurons finally 8 neurons recognized signals not containing wave V, and 15 neurons the signals in which wave V was visible.

The obtained distribution of network's neurons (Fig.2) is very interesting. The number of active neurons can be treated as the estimate number of groups in the set of BAEP signals. This is obviously a certain approximation, as in many simulation somewhat different results have been obtained, and even for the network analyzed here after measuring of mutual distances between neighboring neurons it turned out that connection of some of them is possible, what resulted in reduction of the number of detected groups. However the number of obtained groups was in accordance with predictions estimating that the number of various groups of signals should not be less than:

*number of classes * number of stimulating intensities = 12*

The division into groups did not take place exactly according to the intensity of triggering stimulus, but anyway it has shown that the above considerations are correct, because in most cases the signals atrributed to a given neuron were signals of identical values of the stimulus intensity or signals with neighbouring intensity values, e.g. for the neuron at (5,6) they were three signals of the stimulation intensity 60dB and three signals of 70dB.

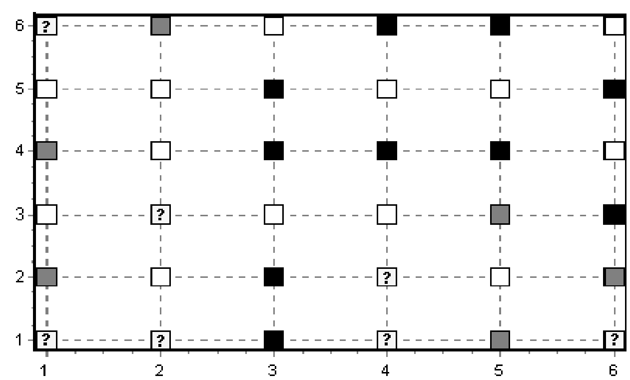

Fig.2 Exemplary neural network after completion of the learning process. The non-active neurons are denoted as white, the neurons activated by signals containing wave V - black, the neurons activated by signals not containing the wave V - grey, and the neurons reacting to both types of signals are labelled by '?'.

The analysis of the way in which the set of signals is divided between particular neurons can also provide different information. There were 1 to 10 signals per one neuron, or average 3.3 signals per neuron. Only four neuron recognized single signals, and what's more in three cases they were signals not containing the wave V. For the latter signals there were 1.7 signals per neuron on the average. The above facts may lead to a conclusion that the class of signals not containing the wave V is more diversified than the class of signals containing it. Also that result is in accordance with common sense conclusions, because to the class of signals with the wave V absent belong all the signals registered for low intensities of the activating stimulus, the signals which are distorted as a result of defects of the brainstem auditory centers or the occurrence of various disturbances during the measurements, e.g. muscular artefacts.

Due to the analysis of the signals division into groups another type of signals can be detected: the signals which with high probability were classified incorrectly. For example the neuron at (1,4) has been activated for 8 signals, including only one denoted as a signal containing wave V, so most probably incorrectly.

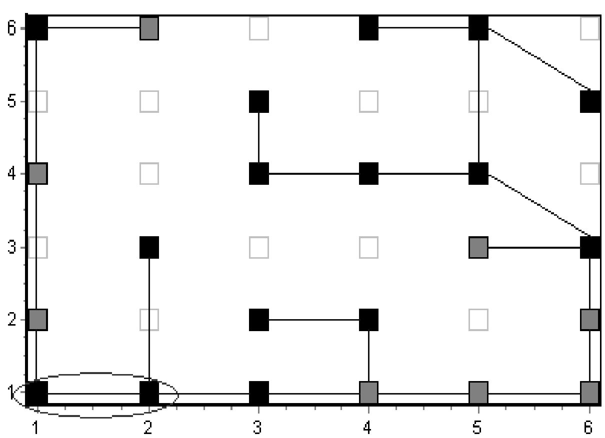

Fig.3 The tree with the minimal span, connecting the active neurons of the network. An exemplary group of neurons has been denoted, which can be replaced by one neuron placed at (2,1). Selected distances between the neuron weights vectors, expressed in Euclidean metric, are also shown in the picture.

5. Simulation parameters

During the completed simulations the influence of the neural network size and learning parameters η, σ and t_f on the quality of BAEP signals classification has been studied. With the increasing number of the network's neurons the value of RMS error has decreased while the number of activated neurons has increased. At the same time the networks classified the signals of the learning set better and better. However, excluding the 4x4 networks, for which the results were much worse then for the other, the rest of the networks achieved comparable results in recognition of the test set signals. Thus increasing the number of neurons did not improve the network's generalization abilities.

As for the values of the learning coefficient η and the σ parameter, on which the intensity of the weight corrections in the winner-neuron neighborhood depend (Fig.3), the obtained result prove that the values of these parameters should not be simultaneously too low or simultaneously too high. The values of the σ parameter have been mostly taken form the [5;1] range and the values of η parameter from the [1; 0.05] range. (Table 1: Selected classification results).

6. Conclusions

Summarizing the above considerations it should be concluded that the SOM neural networks can be successfully applied for the preliminary analysis of the set of BAEP potentials, and in particular for the studies of the signal grouping, what can be useful for the construction of architectures for multilayer backpropagattion networks used for the recognition. Additionally the analysis of sets of BAEP signals enables the detection of signals which are particularly difficult for classification, and signals which have been labelled incorrectly.

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Table 1
Selected classification results

Nr	Network architecture	Number of active neurons	Learning parameters			RMS error	Correct classifications[%]	
			t_f	η_f	σ_f		Learn.set	Test set
1	4×4	12	1000	0,1	1	11,42	73,68	75,32
2	4×4	11	16000	0,25	2,5	12,09	76,32	72,73
3	5×5	23	32000	0,25	2,5	6,61	86,84	75,25
4	5×5	20	8000	0,5	5	7,32	85,53	77,92
5	6×6	25	2000	0,1	2,5	6,26	89,47	80,52
6	6×6	21	2000	0,1	5	6,68	85,53	76,62
7	6×6	22	1000	0,25	2,5	6,99	84,21	76,62
8	7×7	32	2000	0,1	5	5,03	85,53	80,52
9	7×7	28	2000	0,5	1	5,11	88,16	79,29
10	8×8	33	2000	0,2	2,5	4,29	88,16	76,62