Classification of Event-Related Potentials using Multivariate Autoregressive Modeling combined with Simulated Annealing

C.E. Vasios, G.K. Matsopoulos, K.S. Nikita and N. Uzunoglu

Abstract - In the present work, a new method for the classification of Event Related Potentials (ERPs) is proposed. The proposed method consists of two modules: the feature extraction module and the classification module. The feature extraction module comprises the implementation of the Multivariate Autoregressive model in conjunction with the Simulated Annealing technique, for the selection of optimum features from ERPs. The classification module is implemented with a single three-layer neural network, trained with the back-propagation algorithm and classifies the data into two classes: patients and control subjects. The method, in the form of a Decision Support System (DSS), has been thoroughly tested to a number of patient data (OCD, FES, depressives and drug users), resulting successful classification up to 100%.

Keywords - Multivariate Autoregressive, Simulated Annealing, Neural Network, Back propagation, ERP

I. INTRODUCTION

Various techniques have been used for implementing EEG/ERP classification systems and a large part of the research has been devoted to the selection of the optimum features to be extracted from the biosignal. Particularly, Tsoi et al 1994 [1], differentiated normal subjects and subjects diagnosed as suffering from severe obsessive-compulsive disorder (OCD) and from severe schizophrenia. By recording one channel of EEG, they estimated the autoregressive model coefficients, as feature vector, and by using a multilayer neural network classifier, they correctly classified all normal cases, while missing one each from the obsessive compulsive and schizophrenia cases.

In an other paper, Roberts and Tarassenko [2] recorded one channel of data to cluster sleep stages using AR model coefficients. The purpose was to quantitatively investigate the number of different human sleep states. The parameterisation was performed using a 10° order Kalman filter and the coefficients were averaged over one second of time. These 10-dimensional feature vectors were then clustered with a Kohonen self-organizing neural network. It was found that there are eight different primary clusters and three types of transition trajectories among these eight clusters, which correspond to states of wake-fulness, dreaming sleep (REM) and deep sleep.

Nevertheless, there are cases were extracted information is required not from a single waveform but from a number of waveforms that have been simultaneously recorded. In these cases, the aforementioned AR model can be replaced by the Multivariate Autoregressive model [3]. According to this model, features are extracted from a number of input signals implementing the multivariate analogue of the AR model.

Anderson et al. [3] explored the use of scalar and multivariate autoregressive models to extract features from the EEG in order to discriminate different mental tasks. Order 3 was found to be the optimum using the Akaike Information Criterion. These features were then classified with a standard feedforward neural network trained via the back-propagation algorithm, resulting an average classification accuracy of 91.4% on novel EEG signals.

Also Franaszczuk, Blinowska and Kowalczyk [4] constructed a multivariate AR model to study the synchronization of brain structures. An order of 6 was found to be acceptable for parameterizing four channels of data recorded at 205 Hz. Auto- and cross- spectra were estimated from the multivariate AR model, and from these, coherence values were calculated. Partial coherences were found to be the proper measure of synchronization, because they remove the effects of other channels. Analysis of the multichannel EEG with this method could be used in researching the synchronization of brain structures, the degree of coupling between channels, the estimation of phase delays and eventually the direction of spreading of brain activity.

Rappelsberger and Perche [5] constructed a multivariate AR model from rabbit EEG during drug induced epileptic seizures. The model orders were arbitrarily selected to be 11 or 13. Spectra and coherences were calculated from the AR coefficients and plotted versus time. From the phase delays, they concluded that 8.8 Hz activity is generated in one corner of the electrode grid and gradually spreads to other areas during the onset of a seizure.

Multivariate models can be efficiently implemented on electroencephalogram (EEG) or event related potentials (ERPs) data, as those data contain simultaneous waveforms elicited from different lead during an acquisition procedure. In this context it should be noted that event related potentials (ERPs) constitute a useful tool, providing valuable information with regard to the brain-behavior relations [6][7]. Particularly the P600 component of ERPs (elicited between 500 and 800 msec after warning stimulus) is accepted as reflecting the completion of any synchronized...
operation immediately following target detection [8][9]. When using the Multivariate Autoregressive model, in ERPs classification problems, for the construction of the feature vector, a number of parameters is required to be defined regarding the number and the kind of leads, the time interval of the waveforms and the order of the model used. The exhaustive search for the best selection of these parameters, that achieve the best classification rate, seems practically very difficult. Additionally, a further disadvantage of the Multivariate Autoregressive model is the relation of the model coefficients with the input signals used; thus any differentiation of the ERP leads requires recalculation of the multivariate autoregression coefficients.

For these reasons, a new method for the extraction of multivariate autoregressive coefficients from ERP signals is proposed on this paper. This method combines the Multivariate Autoregressive model with a global optimisation method, the Simulated Annealing technique, in order to detect optimum combinations of leads (number and kind), time interval and model order, regarding the classification rate achieved using a neural network classifier.

II. SUBJECTS AND ERP RECORDING PROCEDURE

Twenty-three (23) patients suffering from OCD, fourteen (14) first episode schizophrenics (FES), twenty-four (24) depressives and eighteen (18) drug users were matched for age, sex and educational level to thirty (30) healthy controls. All patients met DSM-IV criteria [10] for schizophrenic disorder, paranoid type. The diagnosis was verified independently by two psychiatrists. Age at onset was defined as the earliest age at which medical advice was sought for psychiatric reasons or at which subjective distress or impairment of functioning [11]. The controls were recruited from hospital staff and local volunteer groups. They were free of psychiatric and physical illness. All participants had no history of any neurological or hearing problems. All participants were right-handed as assessed by the Edinburg Inventory [12]. Written informed consent was obtained from both patients and controls.

Patients and controls were evaluated by a computerised version of the digit span Wechsler test [13][14]. Although the digit span of the Wechsler test is considered a test of short-term memory, more recent reports emphasise its relevance to working memory (WM). The subjects sat on an anatomical chair inside an electromagnetically shielded room. An outline of the procedure is presented in Figure 1.

Subjects were presented with a single sound of high (3000 Hz) or low (500 Hz) frequency, and were asked to memorise the numbers that followed. The warning stimulus lasted 100 msec, followed by a one-second interval and then the numbers. At the end of the number sequence, the signal tone was repeated and patients were asked to recall the numbers as quickly as possible, in the order in which they were presented (low frequency tone) or the opposite order (high frequency tone). Before ERPs were recorded, subjects completed a number of trials until they understood the different tones and the requirements of the test. There was then a rest period of five minutes before the recording.

ERPs were recorded during the one-second interval between the warning stimulus and the first number. Electrophysiological signals were recorded using Ag/AgCl electrodes. Electrode resistance was kept constantly below 5 kOhms. EEG activity was recorded from 15 scalp electrodes based on the international 10–20 system of electroencephalography [15], referred to both earlobes. An electrode on the forehead served as ground. The bandwidth of the amplifiers was set at 0.1 Hz to 35 Hz. The subjects closed their eyes while stimuli were given, to minimise eye movements and blinks. Eye movements were recorded using electro-oculograms (EOG) and recordings with EOG activity higher than 75 µV were rejected.

Warning stimuli and numbers were delivered using earphones at 65 dB. The evoked biopotential (analogue) signal was digitised at a sampling rate of 500 Hz. Each session involved 26 repetitions of the trial. One or two recordings per investigation were rejected, when eye movements were associated with EOG greater than 75 µV. The minimum number of artefact-free trials used to calculate an ERP was 24.

The parameters calculated were ERPs for each subject as well as for each of the leads Fp1, Fp2, F3, F4, Fz, C3, C4, Cz, (C3-T5)/2, (C4-T6)/2, P3, P4, Pz, O1, O2, resulting from the twenty six (26) test repetitions. These signals were then averaged as a pre-processing de-noising step of the procedure. The positions (C3-T5)/2 and (C4-T6)/2 were used as electrode leads, because these correspond to brain areas for verbal memory and language [16].

III. CLASSIFICATION SYSTEM

The proposed DSS consists of two basic modules: the feature extraction and the classification modules, as presented in Figure 2.

Figure 1: Outline of the experimental procedure.

Figure 2: Block Diagram of the proposed DSS for the classification of the ERPs into two classes: patients and healthy controls.
The input to the first module is the signals of different leads of a specific ERP data set, for all subjects. The appropriate features are extracted and processed by the extraction module, and then fed to the classification module. The output of the DSS is one of two classes: patients or normal subjects.

A) Feature Extraction Module

The feature extraction module comprises the implementation of the Multivariate Autoregressive model (MVAR model) in conjunction with the Simulated Annealing technique (SA technique), for the selection of optimum features.

The implementation of the Multivariate Autoregressive model to ERP signals, keeps up with the idea that ERPs are described by a linear filter fed with noise. According to this model, each value of the signal can be estimated using some previous values of it, as follows [17]:

\[ x(k) = -A(1)x(k-1) - A(2)x(k-2) + \cdots - A(p)x(k-p) + e(k) \]

where \( x(k) \) is a \( d \)-dimensional vector of data at time \( k \) and \( e(k) \) is a \( d \)-dimensional vector of random input. The \( A(i), i = 1, \ldots, p \) are the \( d \times d \) matrices of the autoregression coefficients to be estimated from \( x(k), k = 1, \ldots, N \) and \( p \) is the model order. These coefficients construct the feature vector of each subject.

In this paper the Multivariate Autoregressive model is implemented in conjunction with the Simulated Annealing technique, according to the following procedure. Firstly, an optimum combination of leads (number and kind) is found using the MVAR model in conjunction with the SA technique [18][19]. The optimum selection is based on the classification rate obtained by the Fuzzy C-Means Algorithm [20]. The optimum combination of leads obtained by the previous step, is further examined by a fine-tuning process in order to be finalized. This methodology is presented in pseudo-code as follows:

**Step 1:** Define the model order \( p \).

**Step 2:** Search for the optimum combination of leads using the SA technique

**Step 2.1:** Define the kind and number of leads

Set initial temperature (T).

Random selection of initial combination of leads

For \( i = 1 \) to a number of temperatures do

Begin

For \( j = 1 \) to maximum number of combinations per temperature

Begin

**Step 2.2:** Selection of next combination of leads based on the current combination of leads and the current temperature

**Step 2.3:** Calculation of MVAR Coefficients

**Step 2.4:** Calculation of classification rate, using the Fuzzy C-Means algorithm

**Step 2.5:** Acceptance of the current combination based on the Boltzmann distribution

End

Reduction of temperature

End

According to the aforementioned Multivariate Autoregressive model, a feature vector is constructed for the finalized optimum combination of leads, with dimensionality \( p \times d \times d \), where \( p \) is the model order and \( d \) is the number of leads used.

B) Classification Module

The second module of the proposed DSS is a classifier, implemented with neural networks (NNs) [21]. In this system, the classifier consists of a single NN with three layers (see Figure 3).

![Figure 3: Architecture of the Classifier.](image)

The input layer consists of a number of neurons equal to the number of the selected features. The hidden layer has a variable number of neurons. The output layer consists of one neuron, encoding the two classes of the subjects: patient and normal (0=patient and 1=normal). The back-propagation algorithm with adaptive learning rate and momentum has been used in order to train the NN [22]. The initial weights of the neurons have been randomly selected in the range \([-1.0, +1.0]\). The log-sigmoid and tan-sigmoid activation functions have been used for the hidden and the output layer, respectively. The appropriate number of hidden neurons has been estimated according to the formula of \( \sqrt{m \times n} \), where \( m \) is the number of neurons of the input layer and \( n \) the number of neurons of the output layer. The values of the learning rate and the momentum have been estimated using a process of trial-and-error until no further improvement in classification could be obtained.

In order to avoid overtraining and achieve an accepted generalization in the classification, three data sets have been selected: training set, validation set and testing set. The NN is trained using the training set and the training phase stops when the performance in the validation set is maximized. The generalization ability is tested using the testing set, which contains samples that have not been used previously.
IV. RESULTS

Implementation Parameters

A) Feature Extraction Module Parameters

In the feature extraction module, during the implementation process on real ERP data, the following leads Fp1, F3, (C3-T5)/2, C3, Fp2, F4, (C4-T6)/2, C4, Pz, Cz, Fz of ERPs were combined, with the number of leads in a combination varying from 2 up to 8. The chosen time period of signals was the 500-800 msec time interval, because this time period corresponds to the P600 ERP component, which represents the completion of any synchronized brain operations concerning a decision taken after the presentation of a warning stimulus. Additionally, the order of the model used was tested for different values varying from 3 up to 15.

B) Classification Module Parameters

In this paper, a total of 109 subjects, comprising 23 OCD patients, 14 FES patients, 24 depressives, 18 drug users and 30 healthy controls (see section Subjects), have been studied. Data have been randomly distributed in three sets: 60% used for the Training set, 20% used for the Validation set and 20% used for the Testing set (see Table 1).

Table 1: Patients and control subjects. Quantitative distribution of data in Training, Validation and Testing set at the classification module.

<table>
<thead>
<tr>
<th>Class</th>
<th>All Subjects</th>
<th>Training Set</th>
<th>Validation Set</th>
<th>Testing Set</th>
</tr>
</thead>
<tbody>
<tr>
<td>FES</td>
<td>14</td>
<td>8</td>
<td>3</td>
<td>3</td>
</tr>
<tr>
<td>Drug Users</td>
<td>18</td>
<td>10</td>
<td>4</td>
<td>4</td>
</tr>
<tr>
<td>OCD</td>
<td>23</td>
<td>13</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Depressives</td>
<td>24</td>
<td>14</td>
<td>5</td>
<td>5</td>
</tr>
<tr>
<td>Controls</td>
<td>30</td>
<td>18</td>
<td>6</td>
<td>6</td>
</tr>
</tbody>
</table>

Clinical Results

The best classification rate achieved has been up to 100%. Analytically, the classification rate between FES patients and controls, for Fp1, Fp2, F4 and C4 leads and a model order of 4, was 100%. Similarly, the classification rate between drug users and controls, for Fp1, F3, Fp2 and (C4-T6)/2 leads and a model order of 4, was 100%. The best classification rate of OCD patients against control subjects was 91%, obtained for leads F3, (C3-T5)/2, Fp2 and F4 and a model order of 4. The best classification rate of depressives against control subjects was again 91%, obtained for leads F3, Fp2 and F4 and a model order of 4 (see Table 2).

V. DISCUSSION

From the 15 leads (Fp1, Fp2, F3, F4, Fz, C3, C4, Cz, (C3-T5)/2, (C4-T6)/2, P3, P4, Pz, O1, O2) 11 of them (Fp1, Fp2, F3, F4, C3, C4, Cz, (C3-T5)/2, (C4-T6)/2, Pz, Fz) were firstly selected because they concern the anatomical locus of neural activity underlying the generation of P600 component. Intracranial recordings suggest that P600 is associated with activity in wide ranged brain structures including frontal, temporal and superior parietal regions which are believed to contribute significantly to some aspect of information processing during recognition memory [9][23][24].

During the implementation of the proposed methodology, the maximum number of leads combined for the extraction of multivariate autoregression coefficients was set to be up to 8. Our research was focused on the signal’s time period between 500 and 800 msec after the presentation of the warning stimulus. This time period corresponds to the P600 ERP component, as mentioned above, which is accepted as reflecting the completion of any synchronized operations, concerning a decision taken after the presentation of a warning stimulus and the target detection [8][9][23]. Specifically, its amplitude is considered as an index of the onset and duration of processes [9].

Finally, the system was examined in terms of order, in the interval between 3 and 15. This decision was based on the implementation of Order Selection Criteria, as the Schwarz Bayesian Criterion and the Final Prediction Error Criterion, which yielded that the best representation accuracy is achieved with model order varying from to 3 to 8 for all lead combinations. Additionally, existing scientific publications [3] and experimental trials resulted that the optimum classification rate is achieved using a similar value of model order.

The optimum selection of model order, in terms of the classification rate, was also investigated. According to this study, the performance of the proposed methodology (MVAR model in conjunction with the SA technique) was tested for different orders in the interval between 3 and 10, as presented in
According to this figure, the order of 4 is the optimum order in terms of the classification rate (91%) of depressives against normal subjects, combined with the other tested orders of the model using the combination of F3, Fp2 and F4 leads. The same results, i.e. order of 4, were also found by testing the combined leads for all categories presented in Table 2.

Furthermore, to test the performance of the proposed feature extraction methodology (MVAR model in conjunction with the SA technique) in terms of number and kind of leads combined according to the SA algorithm, a further study has also been implemented. In Figure 5, the number and kind of leads have been tested in terms of the classification rate of depressives against normal subjects, for the proposed feature extraction method.

According to the Table 2, the method concluded on optimum combination of F3, Fp2 and F4 leads, for order of 4 and provided a classification rate of 91%. If one of these leads is subtracted, for example F4, the performance of the classifier is reduced to 72%. Similar results (63% classification rate) can also be obtained, if a new lead, for example Fz, is added to the combination. Thus, the combination of the F3, Fp2 and F4 leads, as found by the proposed feature extraction method, is the optimum in terms of classification rate. Similar results were also obtained by testing different combinations of leads, in terms of the number and kind of leads, for all subjects categories presented in Table 2.

Further research is currently carried out in order to increase the number of classes used in the classification module.

REFERENCES


