Self-organizing Maps for Event-Related Potential Data Analysis

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Abstract: Event-Related Potentials (ERPs) and especially the P300 component have been gaining attention in brain-computer interface design and neurobiological research. The detection of the P300 component in electroencephalographic signal is challenging since its signal-to-noise ratio is very low. Instead of using traditional supervised pattern recognition, this paper discusses using unsupervised neural networks for the P300 classification purposes. To validate the proposed approach, a method for the P300 detection based on matching pursuit and self-organizing maps is proposed and evaluated. The results may be applied to the design of brain-computer interfaces.

1 INTRODUCTION

Exogenous event-related potentials (ERPs) are electrical changes recorded from the brain as it makes the decision or initiates the response. (Picton et al., 1995)

In experiments, event-related potentials are triggered by stimulation while recording electroencephalographic (EEG) signal. There are several ERP components, differing by latency (time delay after the stimulus onset) and polarity. Both parameters are typically reflected by naming conventions (e.g. the N100 is an ERP with a negative amplitude located approximately 100 ms after the stimulus onset). (Luck, 2005)

Event-related potentials with higher latencies tend to occur in association with specific experiment paradigms. For example, oddball paradigm (Luck, 2005) is commonly used for the P300 elicitation. In this technique, low-probability target stimuli are mixed with high-probability non-target stimuli. Both stimuli trigger a reaction which can be measured and detected shortly after the event in the EEG signal and consists of multiple ERP components. However, the target stimuli tend to cause a different reaction, with the P300 waveform (sometimes referred to as the P3 component) being most significant. This waveform (and especially its sub-component P3b (Polich, 2007)) is probably related to the process of decision making - it is elicited when the subjects classifies the last stimulus as the target (for example by silent counting). The P300 is usually the strongest ERP component and it occurs approximately 250 - 450 ms after the target stimulus as a positive peak. This ERP component is frequently used in brain-computer interfaces. (Luck, 2005)

Many different pattern recognition algorithms have been proposed for brain-computer interfaces (BCIs). BCIs allow the paralyzed users to communicate with the outside world without using their muscles, i.e. their intention is read from their EEG signal directly. For example, the P300 speller stimulates the user with a matrix containing letters. Rows and columns randomly flash. When the user acknowledges the letter he/she is indented to write, the row flash is followed by the P300 component that can be detected in the signal.

Unfortunately, ERP components including the P300 component are usually hidden in EEG noise, i.e. signal-to-noise ratio is very low. This problem is commonly addressed by averaging together subsequent trials. Random EEG activity is suppressed and non-random ERP components time-locked to stimuli stand out (Luck, 2005). Fig. 1 shows an example of averaged event-related potentials for target and non-target stimuli.

This paper discusses the problems of state-of-the-art P300 BCI systems and proposes a new approach towards the P300 detection based on self-organizing maps. The benefits of this approach are discussed. Furthermore, the validity of proposals was verified on an experimental off-line BCI system. Matching pursuit was used for feature extraction and self-organizing maps were used for classification.

State of the art of the field is presented in Section 1.1. The new approach is proposed in Section

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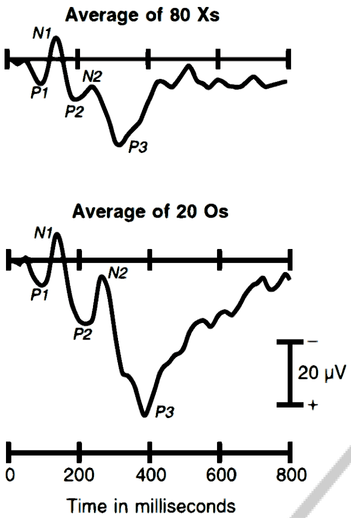

Figure 1: Comparison of averaged EEG responses to non-target stimuli (Xs) and target stimuli (Os). The ensemble averaging is necessary, otherwise the event-related potentials could hardly be distinguished from noisy EEG signal. There is a clear P3b component following the Os stimuli. Negative is plotted upward (Luck, 2005).

1.2. Section 2 presents an experimental off-line BCI system to evaluate the previously formulated hypothesis. To describe the method, theoretical background is introduced in Sections 2.1.1 and 2.1.2. Section 2.2 describes the process of data acquisition. The method for pattern recognition is described in Section 2.3. In Section 2.4, the proposed method is evaluated. The paper is concluded in Section 3.

1.1 State of the Art

The P300 speller has been studied extensively and is one of the well established BCI systems. However, a recent review of the field (Mak et al., 2011) concludes that more work still needs to be done to optimize the speed and accuracy before the P300 speller is practical to use with disabled patients. This becomes even more relevant when considering that paralyzed patients can display widely varying P300 responses between subjects. A reliable BCI system must be able to adapt to the unique ERP responses of each subject and to handle the variations between trials within a subject. When using traditional supervised pattern recognition techniques, it is common to train the BCI system for each new subject, allowing it to only learn the characteristics of his/her ERP responses. Therefore, some approaches might have difficulty if they use a priori information to make assumptions about the temporal and spatial characteristics of the standard P300 response, especially when applied to abnormal ERPs from paralyzed patients. (Cashero, 2012)

Therefore, the universal BCI system should not only rely on a priori information about expected event-related response, but should also be able to adapt and to provide reasonable accuracy for different subjects.

1.2 Using Unsupervised Neural Networks

In the paper, using unsupervised neural networks (UNNs), e.g. self-organizing maps, will be explored. When traditional supervised learning methods are used, all attention is concentrated on separating the classes using class labels, and any other information is ignored by the classifier. Instead of using class labels from a supervisor, unsupervised neural networks learn representation of different kinds of data types that occur in the data sets. Since no assumptions of the class structure of the data are made, the networks may discover new clusters that have not been apparent before. Therefore, the method may also contribute to understand the related feature vectors. Self-organizing maps were successfully applied to recognition of topographic patterns of EEG spectra in (Joutsiniemi et al., 1995). Six classes in total were used, for continuous alpha activity, flat EEG, theta activity, eye movements, muscle activity and bad electrodes contact. The authors concluded that SOMs were able to recognize similar topographic patterns in different EEGs, also in EEGs not used for the training of the map. According to (Lotte et al., 2007), Learning Vector Quantization is the closest approach that has been investigated regarding P300 BCIs. In (Liang and Bougrain, 2008), supervised LVQ1 has successfully been applied to the P300 data. This further supports the hypothesis that similar models may be beneficial for P300 BCIs.

Unsupervised ANN, e.g. self-organizing maps can be trained on the data from a simple odd-ball experiment. At least two clusters and possibly also a "noise" cluster should appear after training. One cluster is expected to be associated with target features, another one with nontarget features and in addition, the rest will probably be undecidable. An expert can associate the clusters with classification classes, or training features with known classes can be propagated through the network to create the associations. For each subject, the clusters will be distributed differently over the map. The percentage of training features that will be associated with the undecidable cluster may indicate to which extent the subject is suitable for P300 BCIs. The trained neural network could be applied to a more complex BCI paradigm, e.g. the P300 speller. If the classification class of a single trial pattern cannot be decided, the trial can be averaged with the next corresponding trial to gradually increase signal to noise ratio.

2 EXPERIMENTAL OFF-LINE BCI SYSTEM

To evaluate the benefits of using UNNs for the P300 detection, an experimental off-line BCI system was designed and evaluated on P300 datasets. Pattern recognition was based on matching pursuit and self-organizing maps.

2.1 Theoretical Background

2.1.1 Signal Decomposition using Matching Pursuit

Matching pursuit is an algorithm used for continuous EEG signal processing (Durka and Blinowska, 1995). However, its use for event-related potential data processing has been discussed only in a few publications (Tomas Rondik and Mautner, 2011).

It decomposes any signal into a linear expansion of waveforms. These waveforms are selected from a redundant dictionary of functions. At each iteration, a waveform is chosen in order to best match the significant structures of the signal. Typically, this part is approximated by a Gabor atom, which has the highest scalar product with the original signal, and then it is subtracted from the signal (Mallat and Zhang, 1993). This process is repeated until the whole signal is approximated by Gabor atoms with an acceptable error. Suppose we have a function g as follows:

$$g(t) = e^{-\pi t^2} \tag{1}$$

The Gabor atom has the following definition:

$$g_{s,u,v,w}(t) = g(\frac{t-u}{s})\cos(vt+w) \tag{2}$$

where s means scale, u latency, v frequency and w phase. These four parameters define each individual atom.

After a given amount of iterations, the signal is decomposed into a set of Gabor atoms.

Although matching pursuit is traditionally based on Gabor atoms, it is also possible to apply the same principal to any other normalized base. For example, in this paper, we focus on Gaussian base, i.e. Gabor base with both v and w parameters set to 0. This base also resembles the shape of event-related potentials (Luck, 2005). Furthermore, it is less complex and thus matching with Gaussian base has lower computational complexity.

2.1.2 Self-organizing Maps

Self-Organizing Maps (SOMs) are neural networks in the unsupervised-learning category.

SOM converts complex, nonlinear statistical relationship between high-dimensional data items into simple geometric relationship on a low-dimensional display. To allow this, a topological structure among the cluster units is assumed. There are m cluster units, arranged typically in a two-dimensional array and the input signals are n-tuples. (Kohonen, 1989)

The weight vector of a cluster unit, commonly referred to as a codebook vector, serves as an input pattern associated with that cluster. During the self-organization process, the cluster unit whose weight vector matches the input pattern most closely (typically, by means of the square of the minimum Euclidean distance) is chosen as the winner. The winning unit and typically also its neighboring units (in terms of topology of the cluster units) update their weights. The weight vectors of the neighboring units do not have to be close to the input pattern. The architecture and algorithm that follow for the net can be used to cluster a set of p continuous-valued vectors $x = (x_1, x_2, .., x_n)$ into m clusters. (Fausett, 1994)

2.2 Data Acquisition

2.2.1 Stimulation Device

The experiments that were used to produce the data for this paper were based on three-stimulus-paradigm. The subjects were visually stimulated with three high power Light-Emitting Diodes (LEDs) differing by their color: red, green and yellow. Fig. 2 shows the stimulation LED module. The core of the stimulator is an 8bit micro-controller that generates required stimuli. It also generates additional synchronization signals for an EEG recorder. The stimulator is described in more detail in (Dudacek et al., Sept).

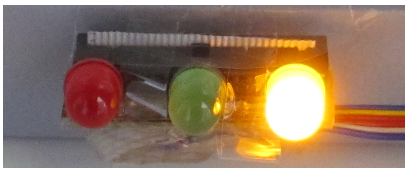

Figure 2: Stimulation device with flashing diodes.

2.2.2 Experimental Setup

Six healhy individuals (4 males and 2 females, university students, aged 22-29) participated in our experiment. The following setting of the stimulation device was used: each diode flashed once a second and each flash took 500 ms. The probabilities of the red, green and yellow diodes flashing were 75%, 20% and 5%, respectively. The subjects were sitting 1 m from the stimulation device for 20 minutes. They were asked to sit comfortably, not to move and to limit their eye blinking. They were instructed to pay attention to the scenario and not to perform another task-relevant cognitive or behavioral activity.

2.3 Pattern Recognition

Pattern recognition algorithm was designed as a process consisting of feature extraction and subsequent clustering of the features. The features were extracted to correspond to the ERP components. Clustering and subsequent analysis were used to separate various P300 component candidates on the map and to tag the corresponding SOM codebook vectors. This allowed the SOM to act as a P300 classifier on a testing dataset.

2.3.1 Preprocessing and Feature Extraction

The input signal was split into epochs using stimuli markers. For the P300 classification purposes, only the data associated with target and non-target stimuli (green and red diodes flashing) were extracted. Given the sampling frequency of 1 kHz and the fact that each epoch started 100 ms before the stimulus onset and ended 1 s afterwards, 1100 samples were needed for the epoch description. The samples corresponding to the first 100 ms were used only for baseline correction (adjusting these values to average zero). The remaining samples were crucial for the procedure itself. Each sample is a real number, corresponding to its recorded voltage value in μV. From each stimulus, the epochs corresponding to the channel Cz were saved. From each measured subject, 10% of the target and nontarget epochs were randomly chosen and merged into a training data-set. The remaining epochs were used for evaluation. The preprocessing of the epochs continued in the following steps:

1. The extracted epochs were randomly shuffled.
2. The epochs damaged by eye-blinking artifacts were automatically removed according to the amplitude criterium (Luck, 2005) with the decision threshold being set to 45 μV.

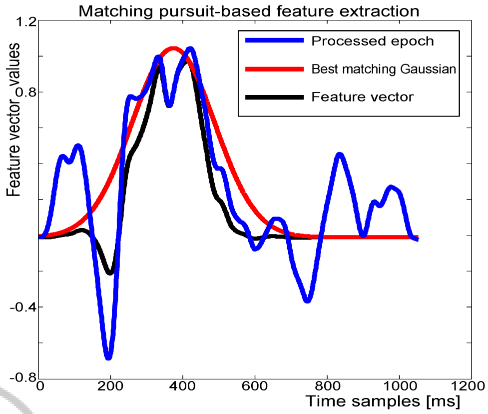

Figure 3: The figure depicts how each single feature vector is extracted from the preprocessed epoch (blue). Matching pursuit selects the best matching Gaussian atom. The atom that was selected in the first iteration is depicted in red. To get the feature vector (plotted in black), element-by-element multiplication of the epoch with the selected Gaussian atom was calculated.

3. Each epoch was band-pass-filtered with the cut-off frequencies of 0.2 and 10 Hz to improve signal-to-noise ratio.
4. The signal was downsampled by factor of 4.

As the next step, matching pursuit with Gaussian base was applied to the pre-processed signal. Five iterations were calculated. However, to extract possible components, matching pursuit atoms were not considered ERP components directly. Instead, the ERP component candidates c were estimating using Equation 3.

$$c(t) = abs(a(t))s(t) \tag{3}$$

In Equation 3, a is the current atom decomposed by matching pursuit, s is the preprocessed epoch, and t corresponds to time samples. An example is shown in Fig. 3.

Finally, the scales of the features were normalized.

2.3.2 Clustering

For the implementation of self-organizing maps, SOM Toolbox (Vesanto et al., 2000) was used. Self-organizing map was trained with the training feature vectors obtained using the procedure described above. The size of the map was automatically adjusted to 18 x 20. Both rough training phase and fine-tuning of the network were calculated to optimize clustering. Fig. 4 shows the codebook vectors of the SOM network. Note that there appears to be a cluster of vectors corresponding to the P300 component.

To separate the P300 component candidates, cross-correlation between the codebook vectors of the

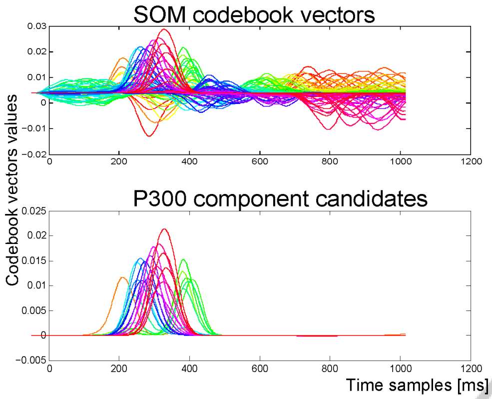

Figure 4: All weight vectors from SOM cluster units are plotted in the upper plot. Note that many of them have latency and polarity that correspond to the P300 component. Unlike the other codebook vectors, these vectors correspond to non-random activity time-locked to stimuli. The bottom plot only depicts the codebook vectors that were tagged as the P300 candidates.

Table 1: Accuracy of classification using the trained SOM network.

Subject ID	Accuracy (Standard deviation) (%)
86	71.4 (3.6)
93	71.0 (3.6)
94	75.1 (3.4)
98	70.6 (3.6)
99	71.6 (3.6)
100	73.2 (3.5)

SOM and the P300 component (approximated by the appropriately scaled Gaussian function) was calculated, but only in the corresponding time intervals where the P300 component can be located (i.e. 250 - 450 ms after the stimulus (Luck, 2005)). Maximum correlation coefficient was compared with a threshold. The threshold represents the decision border between two classification classes (the P300 component detected/not detected). The threshold was empirically set to 0.03. Any cluster unit that was associated with a higher maximum correlation coefficient, was tagged as the P300 candidate cluster unit. The histogram in Fig. 6 illustrates the threshold decision problem.

2.4 Evaluation of the Off-line BCI System

To evaluate the proposed classification algorithm, the following procedure was designed.

Feature vectors from the testing data-set were extracted using the procedure described above (excluding matching pursuit decomposition). Then, the feature vectors were applied to the trained SOM. For each single feature vector, it was verified, if the SOM

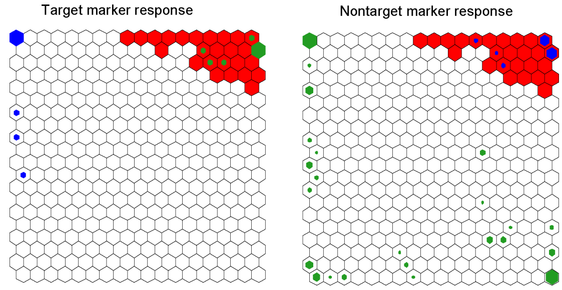

Figure 5: This figure illustrates how the trained SOM responds to the testing data-set. To see the difference, only target epochs (i.e. containing the P300), or only non-target epochs (i.e. containing smaller P300 components) were applied to the SOM network. On the left, it is clearly observable, that more than half of the features are correctly detected as targets. However, some feature vectors were misclassified. In the non-target area, the features are more equally spread. In absolute values, slightly more feature vectors were classified as containing the P300 than in the target group. However, since there are much more non-targets than targets, in relative values, the percentage of misclassification for non-target is lower. If the output matches the expected output, it is depicted in green, otherwise it is depicted in blue.

correctly decided whether the feature vector belongs to the P300 cluster, or not. The decision was based on comparing the tag of the feature with the tag of the winning cluster unit. Tab. 1 contains the results. For all subjects, the accuracy is over 70% for single trials. Fig. 5 illustrates how the SOM responded to the testing data.

3 CONCLUSIONS AND FUTURE WORK

The suggested method has proven to be suitable for the P300 component detection in single EEG channels. In the future, improving the method using spatial filtering may be further explored and tested. In addition, a seed corresponding to the expected target response may be inserted into the network with the expectation that the target patterns will be associated with the neurons positioned nearby. This would allow the researcher to control the process of clustering.

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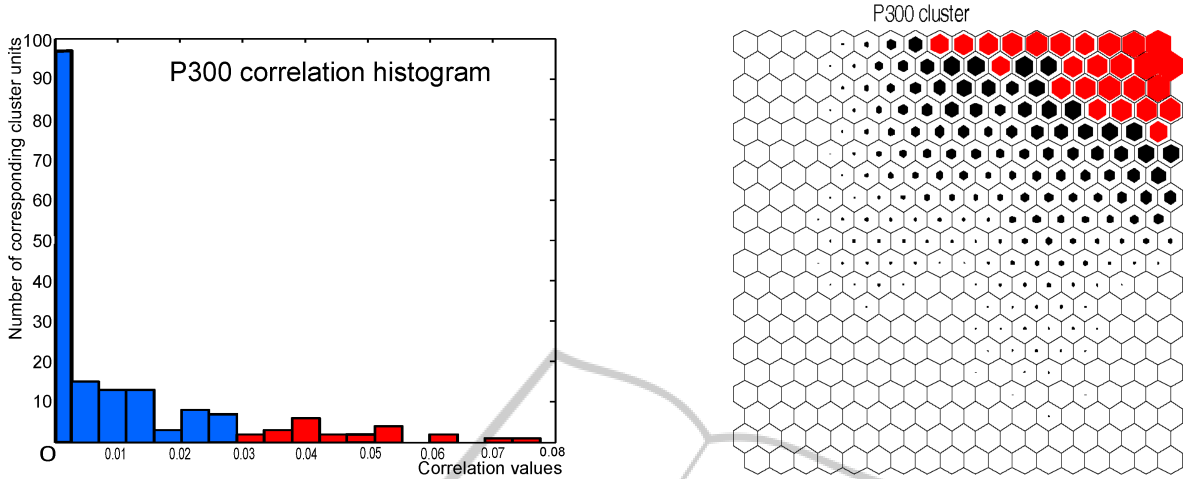

(a) Cross-correlation histogram (b) The P300 cluster in the SOM

Figure 6: The histogram illustrates how the normalized Gaussian function scaled to resemble the P300 component correlates with the SOM codebook vectors. The threshold was set to 0.03 and any cluster units that were associated with higher correlations were tagged as the P300 component candidates (in red). Fig. 6(b) shows the distribution of the P300 candidates on the map. The cluster units in red belong to the P300 component cluster.

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