

## Identification of Error-Related Observations from Event Related Potentials Using Pattern Recognition Techniques

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### Abstract

This article presents a comparison of pattern recognition techniques that have been used for the identification of correct or incorrect actions by means of Event Related Potentials (ERPs). ERP data from 47 electrodes were acquired from sixteen volunteers (observers), who observed correct or incorrect responses of subjects (actors) performing a special designed task. First and second order statistical features, features from the frequency domain as well as the  $\Sigma$ - $\Phi$ - $\Omega$  features were extracted from the ERP signals. Three different feature selection methods were applied, namely the Sequential Floating Forward Selection (SFFS), the Wilcoxon rank testing and the Genetic Algorithms. Two supervised algorithms, Artificial Neural Networks (ANN) and Support Vector Machines (SVM), and one unsupervised algorithm, Fuzzy C-Means (FCM), were used for the classification task. Five combinations of feature selection and classification algorithm were compared with respect to their classification accuracy by means of the leave one out method. Results indicate that classification accuracy between 84.4% and 100% can be achieved.

### Introduction

A significant part of the learning process in human development takes place through observation. The behavior of an observer might be influenced by the positive or negative consequences of a behavioral model. An observer will emulate the behavior of a model, if this includes characteristics which the observer deems attracting or desirable, such as talent, intelligence, power etc. Furthermore, the way through which the model is treated will influence the observer. If the model is rewarded, it is more probable that the observer will emulate the rewarded behavior, while the opposite is expected to happen when an observed behavior is reprimanded.

The brain activity when a subject performs an action or observes the actions of other people can be analyzed by means of Event Related Potentials (ERPs). ERPs are a special category of electroencephalographic (EEG) signals, which are recorded from various locations on a subject's scalp when the subject is presented with external stimuli or events. ERPs provide non-invasive measurements of the electrical activity of the brain and describe the specific cognitive processes that are responsible for processing the stimuli or the events. The reliable detection of correct/incorrect actions is the basis for the implementation of brain computer interface (BCI) systems that decode brain electrical activity into actions controlling devices that will assist the users of the system.

This paper provides comparative results from the application of five pattern recognition techniques on the task of discriminating between observations of correct and incorrect actions using ERPs.

### Materials and Methods

The ERP data used in the present study were collected in previous research (van Schie et al., 2004). The data were acquired from sixteen (16) healthy volunteers (observers), who observed correct or incorrect responses of subjects (actors) performing a special designed task. In particular, the actors were seated in front of a table facing an observer, having in front of them, on the table, two joystick devices positioned to the left and right of a LED stimulus device. The actors were asked to respond to the direction of a center arrowhead surrounded by distracting flankers pointing either in the same direction as the center arrow, or in opposite direction (Fig. 1).

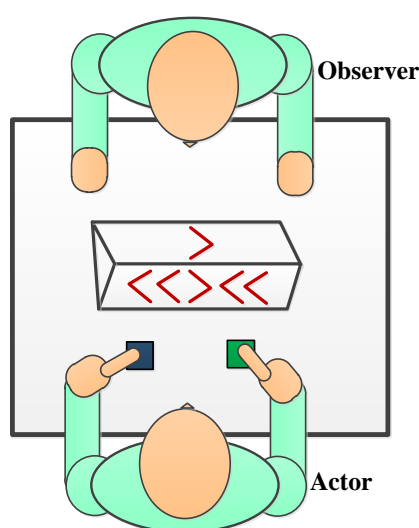


Figure 1. Experimental setup

The brain electrical activity of the observers was recorded from 47 Ag/AgCl electrodes as well as vertical and horizontal electro-oculograms and was sampled with sampling rate 250 Hz. Electrodes were mounted in an elastic cap (Easy cap, Montage 10) configured for equal arrangement of the electrodes over the scalp (van Schie et al., 2004). The experimental session involved 8 runs of 100 trials of the task and the observations of correct or incorrect responses were averaged over a 800ms epoch (baseline [-100 , 0] ms before response). This procedure is necessary in order to discriminate the ERP signal from noise (brain activity that is not relevant to the task).

A time window, starting at -6 msec and ending at 700 msec (corresponding to 176 samples) after the response, was selected for analysis. A total of  $32 \times 47 = 1504$  ERP recordings were available for analysis. From the available recordings,  $16 \times 47 = 752$  recordings corresponded to observation of correct actions and the rest  $16 \times 47 = 752$  recordings corresponded to observations of incorrect actions.

The analysis of ERP signals using pattern recognition methods involves 3 steps:

1. Feature calculation: in this task, a number of quantitative features that provide a compact description of the available raw data is extracted. The features are organized in feature vectors, also known as patterns.
2. Feature selection: this task aims to select a subset of features from the original set of the available features in order to achieve the best classification performance.

3. Classification: in this task, the available patterns, using the selected features, are classified in the classes of interest.

Several features were extracted from each electrode, including:

- First order statistical features (Asvestas et al., 2013a)
- Second order statistical features (Asvestas et al., 2015a)
- Frequency domain features (Asvestas et al., 2015c)
- $\Sigma$ - $\Phi$ - $\Omega$  EEG features (Wackermann, 1999)

There are several feature selection techniques that can be applied (Theodoridis and Koutroumbas, 2009). Three of the most well-known techniques are:

- Feature ranking by means of a statistical criterion (Wilcoxon test)
- Sequential Floating Forward Selection (SFFS)
- Feature selection by means of Genetic Algorithm (GA)

The final classification was performed using the following algorithms (Theodoridis and Koutroumbas, 2009):

- Artificial Neural Networks (ANN)
- Support Vector Machine (SVM)
- Fuzzy C-Means (FCM)

## Results and Discussion

The classification performance for the SVM and the FCM was evaluated using the leave-one-out (LOO) cross-validation procedure (Schenker and Agarwal, 1996). According to this procedure, the classifier was trained using feature vectors from observations of both types of actions (correct and incorrect), except from one observation (no matter whether it corresponded to a correct or incorrect actions), that was used for testing, afterwards. The generalization ability of the specific SVM classifier was then tested using the feature vector that was singled out. The above training-testing procedure was repeated, each time retaining a different feature vector for testing, until each feature vector was used once for testing. The classification performance was computed by the aggregate sums of correctly classified or misclassified observations of correct and incorrect actions.

The performance of the FCM algorithm was evaluated using the clustering accuracy (Asvestas et al., 2015c).

The combinations of features, feature selection and classification under comparison are shown in the following table.

Features	Feature selection method	Classification Algorithm	Performance	Reference
1 <sup>st</sup> order statistical	Wilcoxon ranking	SVM	100%	(Asvestas et al., 2013a)
$\Sigma$ - $\Phi$ - $\Omega$	GA	FCM	93.8%	(Asvestas et al., 2015b)
1 <sup>st</sup> order statistical	SFFS	ANN	87.5%	(Asvestas et al., 2013b)
Frequency domain	SFFS	FCM	84.4%	(Asvestas et al., 2015c)
2 <sup>nd</sup> order statistical	Wilcoxon ranking	SVM	84.4%	(Asvestas et al., 2015a)

Table 1. Comparative results of the five methods

As can be seen, all methods provide satisfactory results, above 84.4%. The best performance, 100%, is achieved using first order statistical features, with Wilcoxon ranking and SVM algorithm.

## Concluding Remarks

The machine-learning methods produced comparable results concerning accuracy, enabling their use for implementing the required classification systems. The selection of the method to use should therefore be based on considerations of the time needed for performing the classification, since this parameter will be crucial for on-line implementations of the system.

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