Analysis of Brain Signals for the Discrimination of Observations of Correct and Incorrect Actions

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***Abstract*—The aim of this paper is to present a methodology that is capable to discriminate between observations of correct actions and observations of incorrect. Towards this end, Event-Related Potentials (ERPs) were recorded from 47 locations on the scalp of 16 healthy volunteers, who observed correct or incorrect actions of other subjects. The recorded signals were analyzed in the frequency domain and the normalized signal power at various frequency bands was calculated. Feature selection was applied in order to reduce the number of available features. Finally, the obtained feature vectors were clustered using the fuzzy c-means algorithm resulting in clustering accuracy 84.4%.**

***Index Terms*—event-related potentials, EEG rhythms, frequency analysis, clustering, fuzzy c-means**

I. Introduction

Event-Related Potentials (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 [1].

A major area of application of ERPs is for generating models that describe the processes that are activated in the human brain when committing errors or observing other people's errors. Specifically, it has been observed that a negative peak, known as error-related negativity (ERN), occurs in ERPs at around 80ms after the start of an incorrect action (for example by using the left hand to respond to a stimulus requiring the right-hand response) and is maximal at fronto-central scalp sites [1]. ERN is consistently observed when a mismatch occurs between representations of anticipated and actual responses [2]. There are strong indications that ERNs are also present in ERPs of subjects that observe incorrect actions of other subjects. However, the ERNs during observation are characterized by diminished amplitude and longer latency (time occurrence of the peak), than those recorded from the scalp of the subjects who perform the incorrect actions [3].

The reliable detection of correct/incorrect actions can be the basis for the development of brain computer interface (BCI) systems [4]. BCI systems decode brain signals into actions controlling devices that will assist the users of the system. In such systems, an interface usually has to recognize the user's intent. When the user perceives that the interface made an error in recognizing his/her intent, it has been repeatedly shown that an error-related potential, of a similar kind to ERN (known as interaction ErrP) is elicited [5]. This potential reflects the fact that it is produced by the interaction between the computer's actions and the user who recognizes them as incorrect. Interaction ErrP exhibits a different morphology as compared to the ERN elicited in classical forced-choice experiments.

Several methods have been developed for the processing and analysis of ERPs from subjects that perform or observe incorrect actions in order to improve the performance of BCI systems. These methods are based on the use of pattern recognition techniques that involve extraction of features, feature selection and classification or clustering. In a study, classifying ERNs evoked by the subjects' own response, classification performance, as expressed by the area under the Receiver Operating Characteristic (ROC) curve, reached 0.91, using a Gaussian classifier [6]. In another work, more than 85% of errors were detected using Fisher's Discriminant classifier with adapted bias [7]. Ferrez and Millan [5] used a Gaussian classifier for discriminating between correct and incorrect single-trial interaction ErrPs generated during simulated brain–computer interaction. The mean percentage of correctly recognized error trials was at least 79% and the mean percentage of

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correctly recognized correct trials was at least 82.4%. The same classifier was used in [8], where the focus was on the observation ERN of a human user observing the performance of an external agent. Mean classification accuracy was 75.8% and 63.2% for correct and error trials, respectively, when the agent's error rate was 20%, and 64.4% and 59.4% for correct and error trials, respectively, when the agent's error rate was 40%. In the study of Spuler *et al.* [9], for a BCI speller, data from 6 amyotrophic lateral sclerosis (ALS) patients were used together with data from 9 young and 8 elderly healthy controls and 6 motor impaired participants. Classification of ErrP was done using support vector machines (SVM) with radial basis function (RBF) kernel. Off-line ErrP detection in the ALS group resulted in average specificity of 90% and sensitivity of 40%.

The aim of the present study is to present a methodology for discriminating between observations of correct actions and observations of incorrect actions, based on scalp-recorded ERPs. In particular, ERPs that were recorded during the observation of a correct or an incorrect action were analyzed in the frequency domain and several features were extracted. Then, the most prominent features were selected and formed feature vectors that were used in order to perform clustering of the data in the two groups of interest by means of the fuzzy c-means algorithm (FCM).

II. Material and Methods

A. *Subjects and ERPs' Recording Procedure*

The ERP data used in the present study were collected in a previous research [3]. The data were acquired from sixteen (16) healthy volunteers (observers), who observed correct or incorrect actions of subjects (actors) performing a special designed task [3]. In particular, the actors were seated in front of a table facing an experimenter, 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).

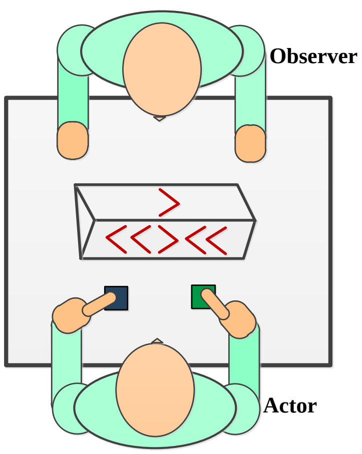

Figure 1. Experimental setup

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 250Hz. Electrodes were mounted in an elastic cap (Easy cap, Montage 10) configured for equal arrangement of the electrodes over the scalp (Fig. 2) [3]. The electrode common was placed on the sternum. Ocular artifacts were corrected using the method described in [10].

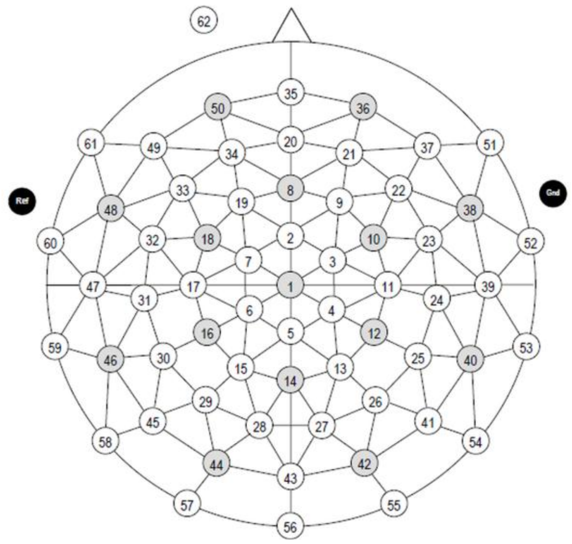

Figure 2. Electrode placement according to easy cap, montage 10

The experimental session involved 8 runs of 100 trials of the task and the observations of correct and incorrect responses were averaged over a 800ms epoch (baseline [-100, 0] ms before response) (Fig. 3). This procedure is necessary in order to discriminate the ERP signal from noise (brain activity that is not relevant to the task).

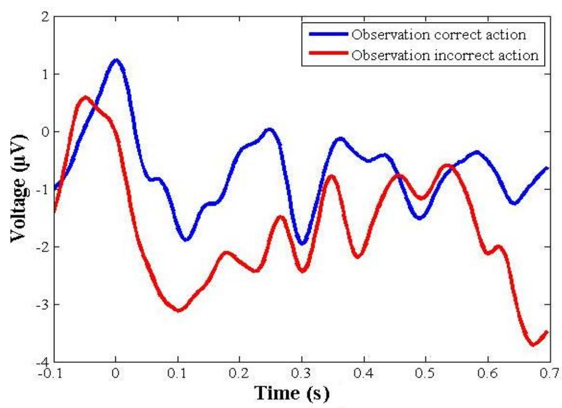

Figure 3. Representative ERP signals for observation of correct and incorrect actions

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

B. Methodology

The proposed methodology consists of two stages:

- Feature extraction
- Feature selection and clustering

Each stage is described below.

1) Feature extraction

As was aforementioned, 47 ERP signals were recorded from each observer with 176 samples per signal. In order to be able to perform clustering efficiently and accurately, a number of features (descriptors) were extracted. Specifically, each signal was analyzed in the frequency domain by means of the Fast Fourier Transform (FFT). Six frequency bands that correspond to various rhythms of brain activity signal were considered [11]:

B1. Lower alpha rhythm: extends between 8-12Hz.
B2. Higher alpha rhythm: extends between 10-14Hz.
B3. Lower beta rhythm: extends between 16-20Hz.
B4. Mid beta rhythm: extends between 18-22Hz.
B5. Higher beta rhythm: extends between 20-24Hz.
B6. Gamma rhythm: extends between 30-100Hz.

Alpha rhythm appears when closing eyes and with relaxation, and attenuates when opening eyes or mental exertion. Beta rhythm is associated to motor behavior and is generally less prominent during active movements. Finally, gamma rhythm represents binding of different populations of neurons together into a network for the purpose of carrying out a certain cognitive or motor function.

For each frequency band, the signal power was calculated by summing the corresponding squared values of the amplitude of the Fourier transformed signal. The values were normalized with respect to the total signal power in the range 0.5-100Hz. Thus, if $X(k)$ denotes the Fourier transform on an ERP signal $x(n)$ with N samples ($k,\ n = 0,\ 1,\ 2,\ \ldots,\ N-1$), then for each one of the aforementioned frequency bands B_i ($i = 1,\ 2,\ \ldots,\ 6$) the normalized power, NP_i, was estimated by means of the following formula:

$$NP_i = \frac{\sum_{f_k \in B_i} \left|X(k)\right|^2}{\sum_{f_k \in B} \left|X(k)\right|^2} \qquad (1)$$

where $f_k = k\frac{f_s}{N}$, $f_s = 250\text{Hz}$ is the sampling frequency and B is the 0.5-100Hz band.

According to this procedure, for each observer a feature vector with $6 \times 47 = 282$ features (components) was formed.

2) Feature selection and clustering

Due to the high number of calculated features, it is necessary to eliminate features that are linearly correlated or carry no diagnostic information. Therefore, a process of feature selection is applied prior to classification, with the purpose of discovering the most prominent features. The sequential floating forward search (SFFS) technique has been employed as a feature selection process [12]. This technique is a variant of the well-known sequential forward search (SFS) [13]. The SFFS is a bottom up search procedure that selects new features by means of the basic SFS procedure starting from the current feature set. The inclusion of new features is followed by successive removals of the worst features in the newly updated as long as the generated subsets are the best among their respective size. Practically, SFFS can be considered as an optimization technique, which tries to maximize, with respect to the features, a multivariate objective function. Specifically, let $\mathbf{D}$ be a matrix with Q rows and P columns. Each row corresponds to a feature vector that is formed by concatenating all the feature values from the 47 recordings of an observer. Each column corresponds to a feature. In our case, Q=32 and P=282. Let $\mathbf{x} = (x_1,\ x_2,\ \ldots,\ x_P)$ be a vector of binary values, where $x_i = 1$ (respectively $x_i = 0$) indicates that the feature i is selected (not selected) ($i = 1,\ 2,\ \ldots,\ P$). Furthermore, let $J(\mathbf{x};\mathbf{D}): B^P \to R$ be an objective function with parameter the matrix $\mathbf{D}$ and $B = \{0,\ 1\}$. Then, the SFFS technique tries to find a (local) maximum of the function $J(\mathbf{x};\mathbf{D})$. If there are two vectors $\mathbf{x}_1$ and $\mathbf{x}_2$ that provide the same value for the local maximum, then the one with minimum number of 1s will be selected.

The flowchart of the SFFS is given in Fig. 4 [13], where p is the size of the currently selected subset and $P_{\max}$ is the desired number of features. SBS denotes the sequential backward selection method, which excludes conditionally the worst feature.

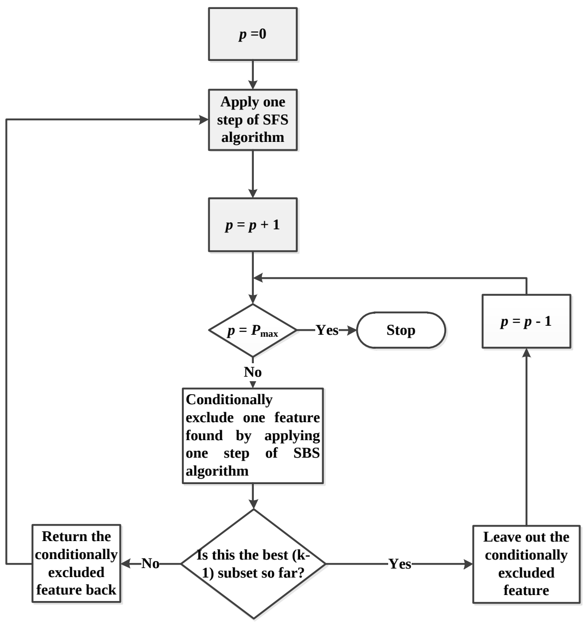

Figure 4. SFFS flow chart.

In the present study, the selected objective function was the clustering accuracy (see (6) below) of the fuzzy c-means (FCM) algorithm [14]. The FCM algorithm is an unsupervised clustering algorithm, which allows one feature vector to belong to two or more clusters according to the value of a membership function, which represents the fuzzy behavior of this algorithm. A feature vector $\mathbf{d}_i$ is assigned to the cluster m using the following rule:

$$m = \arg\max_j \{u_{ij}\} \tag{2}$$

where u_{ij} is the degree of membership of $\mathbf{d}_i$ in cluster j.

The degree of membership u_{ij} is estimated iteratively by means of the following formulas:

$$\mathbf{c}_j^{(l)} = \frac{\sum_{i=1}^{N} \left(u_{ij}^{(l-1)}\right)^m \mathbf{d}_i}{\sum_{i=1}^{N} \left(u_{ij}^{(l-1)}\right)^m} \tag{3}$$

$$u_{ij}^{(l)} = \frac{1}{\sum_{p=1}^{C} \left(\frac{\left\| \mathbf{d}_i - \mathbf{c}_j^{(l)} \right\|}{\left\| \mathbf{d}_i - \mathbf{c}_p^{(l)} \right\|} \right)^2} \tag{4}$$

where l is the iteration variable, $\mathbf{c}_j$ denotes the centroid of each cluster and C is the number of clusters ($C = 2$ in our case).

A confusion matrix can be obtained by counting the number of feature vectors that are assigned to each cluster. For example, for two clusters as in our case, the confusion matrix is as follows:

$$CM = \begin{bmatrix} cm_{11} & cm_{12} \\ cm_{21} & cm_{22} \end{bmatrix} \tag{5}$$

where cm_{kl} ($k,\ l = 1,\ 2$) denotes the number of data vectors from class k (observation of correct vs. observation of incorrect action) that are assigned to cluster l. Consequently, the clustering accuracy, *CA*, can be quantified as follows:

$$CA = \frac{\max\{cm_{11} + cm_{22}, cm_{21} + cm_{12}\}}{Q} \tag{6}$$

Thus, the SFFS technique combined with the FCM algorithm provide the feature subset that achieves the best clustering performance for the available feature vectors.

III. Results

The feature selection process provided five features, which are shown in Table I. The locations of the corresponding electrodes are shown in Fig. 5 in red circle.

TABLE I. Selected Features and Corresponding Electrodes.

Numbering	Feature	Electrode number
1	Lower beta rhythm	25
2	Lower beta rhythm	27
3	Mid beta rhythm	27
4	Mid beta rhythm	43
5	Mid beta rhythm	37

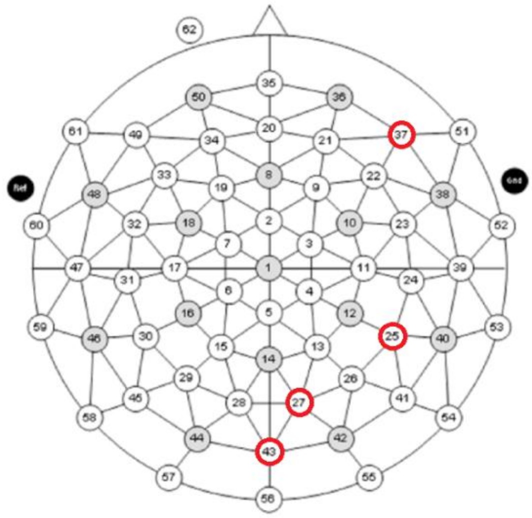

Figure 5. Selected electrodes in red circle.

Table II presents the clustering results using the selected features. As can be seen, 12 out of 16 (i.e. 75%) feature vectors from ERPs that correspond to observations of correct actions were assigned to cluster 1 and 15 out of 16 (i.e. 93.75%) feature vectors from ERPs that correspond to observations of correct actions were assigned to cluster 2. The total clustering accuracy was 84.4% (27/32).

TABLE II. Clustering Results.

Feature vectors	Cluster 1	Cluster 2
Observation of correct action	12	4
Observation of incorrect action	1	15

The average values of the degree of membership in the two clusters of the feature vectors from the two types of observations were calculated and are listed in Table III. Table III also lists the ratio of the average degree of membership in the majority cluster with respect to the one in the minority cluster. The majority (minority) cluster is the cluster that contains the majority (minority) of the feature vectors for each type of observation. As can be seen, the ratio is larger for the case of observation of incorrect actions than that for the case of observation of correct actions, which means that the corresponding feature vectors are grouped more “tightly”.

TABLE III. Average Value of Degree of Membership per Cluster and the Corresponding Ratio.

	Cluster 1	Cluster 2	Ratio
Observation of correct action	0.5725	0.4275	1.3392
Observation of incorrect action	0.2376	0.7624	3.2088

The centroids of the two clusters are shown in Table IV. The centroid of a cluster can be considered as a representative feature vector. For each selected feature, the components of the centroid for cluster 1 (observation of correct action) have higher value than the ones for cluster 2 (observation of incorrect action). In other words, the normalized power for the selected frequency band and electrodes is consistently higher when observing correct actions that when observing incorrect actions.

TABLE IV. CENTROIDS OF THE TWO CLUSTERS.

Numbering	Cluster 1	Cluster 2
1	0.0044	0.0026
2	0.0041	0.0024
3	0.0030	0.0015
4	0.0024	0.0019
5	0.0050	0.0024

IV. CONCLUSION

In this paper, a methodology capable of discriminating observations of correct and incorrect actions using brain potentials was presented. The methodology consisted of two steps: the feature selection, which was based on the SFFS method, and the clustering which performed by means of the FCM algorithm. Since the FCM algorithm is an unsupervised clustering algorithm, it does not require the splitting of the available feature vectors in training and testing sets, as happens with other classification algorithms (for example, k-Nearest Neighbor, Neural Networks, etc.). This is an advantage in our case, since the available data are limited. Furthermore, FCM is easy to implement and is characterized by very good performance. If a larger set of data were available, then the k-Nearest Neighbor or the Support Vector Machines (SVM) [15] algorithm could be used.

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