Classification of Evoked Potentials Associated with Error Observation Using Artificial Neural Networks

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Abstract— **Observation plays an important role in learning processes. Human development takes place through observation. Observational learning studies indicate that the processes through which observation contributes to learning resemble mechanisms contributing to self-action learning. Scalp-recorded Evoked Potentials (EPs) reflect brain electrical activity related to processing of stimuli and preparation of responses. An EP waveform is recorded when an incorrect action is committed by a person called Error-Related Negativity (ERN). ERN is also recorded, with a longer latency and reduced amplitude, when errors are not committed but observed by the person whose EPs are recorded. In the present work the performance of a classifier that discriminates between EPs that are produced by observation of correct or incorrect actions is investigated. Initially, first- order statistical features (mean value, standard deviation, kurtosis, skewness, energy, entropy) from the histogram of each EP recording are calculated. Then, the most significant features are selected using the Sequential Floating Forward Selection (SFFS) algorithm. The Artificial Neural Network (ANN) algorithm combined with the leave-one-out technique is used for the classification task. The overall accuracy for the two classes to be differentiated is above 85%. The successful implementation of systems based on the proposed classifier might enable the improvement of the performance of brain-computer interfaces (BCI) that base their action, among other parameters, on the brain signals that the user emits when he/she detects an undesired response of the BCI.**

Keywords— **Error Observation, Evoked Potentials, Error-Related Negativity, Sequential Floating Forward Selection, Artificial Neural Networks.**

I. 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 results of studies in observational learning suggest that the mechanisms through which observation contributes to learning are similar to the mechanisms that contribute to learning through self-action [1]. It is known that when an incorrect action is committed by a person, or the person is reprimanded for an action, then a negative peak (called Error-Related Negativity (ERN)) is present in that person's electroencephalographic Evoked Potentials (EPs). The maximum of the peak takes place at around 80ms after the start of the wrong response/action. Van Schie et al. [2] found that ERNs are generated not only when errors are committed by the person whose EPs are recorded, but also when errors are observed by the person whose EPs are recorded, albeit with diminished amplitude and longer latency (time occurrence of the EP peak), than those recorded from the scalp of actors who behave incorrectly. Those findings strengthen the hypothesis that the same mechanisms are activated both when committing and when observing errors. Nevertheless, because it has been found that sometimes a negative ERN-like deflection is produced even for correct actions [3], something similar could happen when observation of the action of other persons takes place.

The existence of differences in the EPs of observers, when observing correct and incorrect actions, might foster the development of classification systems capable of detecting performance errors of a human - or an artificial agent – in need of being monitored in a joint-action situation. The primary aim of the present study was the development and implementation of a classification system for discriminating observations of correct and incorrect actions, based on scalp-recorded EPs, using histogram-related features.

II. MATERIAL AND METHODS

A. Subjects and EPs' recording procedure

The EP data used in the present study were collected in previous research [2]. The data were acquired from eight (8) healthy volunteers (observers), who observed correct or

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incorrect responses of subjects (actors) performing a special designed task. In particular, the actors were faced 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. EEG activity of the observers was recorded from 47 electrodes, as well as vertical and horizontal electro-oculograms (Fig. 1) with sampling rate 250 Hz.

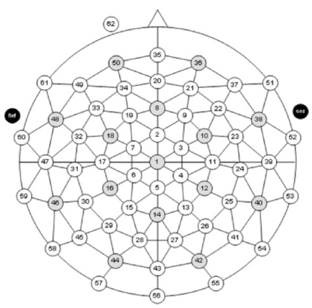

Fig.1 Graphic representation of the electrode placement.

Observations of correct and incorrect responses were averaged over a 800 ms epoch (baseline [-100 , 0] ms before response). Trials to be included in the averaging process had been selected according to an RT-matching procedure between correct and incorrect trials (described in [2]) to mitigate the differential contribution of stimulus-related activity in the EP. 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 16×47 = 752 EP recordings were available for analysis. From the available recordings, 8×47 = 376 recordings corresponded to observation of correct actions and the rest 8×47 = 376 recordings corresponded to observations of incorrect actions.

B. Classification methodology

The proposed methodology consists of three stages:

- Feature calculation
- Feature selection
- Classification

Each stage is described below.

a) Feature calculation

Let $\mathbf{x} = [x_1, x_2, \ldots, x_{176}]$ be a vector with the samples of an EP recording and $\{p_k\}$ ($k = 0,1,\ldots,M-1$) are estimates of the probability density function of the data vector $\mathbf{x}$ at points $\overline{c}_k$. Then, the following features of the probability density function can be calculated:

1. *Mean value*, which quantifies the central value of a distribution:
$$\mu = \sum_{k=0}^{M-1} p_k \overline{c}_k$$
2. *Standard deviation*, which is a measure of variability around the mean value:
$$\sigma = \sqrt{\sum_{k=0}^{M-1} \left(\overline{c}_k - \mu\right)^2 p_k}$$
3. *Skewness*, a nondimensional quantity which characterizes the degree of asymmetry of a distribution around its mean:
$$skew = \frac{\sum_{k=0}^{M-1} \left(c_k - \mu\right)^3 p_k}{\sigma^3}$$
4. *Kurtosis*, a nondimensional quantity which measures the relative peakedness or flatness of a distribution:
$$kurt = \frac{\sum_{k=0}^{M-1} \left(c_k - \mu\right)^4 p_k}{\sigma^4}$$
5. *Entropy*, which is a measure of uniformity of the histogram:
$$Entr = -\sum_{k=0}^{M-1} p_k \log_2 p_k$$
6. *Energy*: $Ener = \sum_{k=0}^{M-1} p_k^2$

The estimates of the probability density function were calculated by means of the kernel density technique (Parzen window) [3], where the underlying distribution of the data is modeled by the mixture of Gaussian probability density functions. In total, from each participant's EPs, $47 \times 6 = 282$ features were calculated

b) Feature selection

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 was applied prior to classification, with the purpose of discovering a subset of features that optimize the classification process, in terms of accuracy. The sequential floating forward selection (SFFS) technique has been employed as a feature selection process [4]. The SFFS technique is a variant of the standard sequential forward selection, which involves not only the addition of features but also the removal of features. Thus, during the execution of the algorithm the dimensionality of the feature set is floating.

In the present study, the selected evaluation function was the clustering accuracy of the fuzzy c-means (FCM) algorithm [5].

c) Classification

The classification was performed by means of artificial neural network (ANN) algorithm. A neural network is defined as an interconnection pattern between different layers of neurons [3]. Each neuron contacts with the neurons of the previous layer and sends data to the neurons of the following layers. The advantages that made neural networks attractive are their ability to use non-linear classification boundaries obtained during the training of the network, and their ability to learn with the selection of a good training set with all possible features the classification boundaries in its feature space. In the present work, an ANN with one input layer, one hidden layer and one output layer was used. The number of neurons in the hidden layer was determined experimentally, as shown in the next section. The ANN was trained using the scaled conjugate gradient backpropagation algorithm [7]. The training was terminated if the mean square error was below 10^{-6} or the magnitude of the gradient was below 10^{-6} or the number of epochs exceeded 1,000.

The classification accuracy was evaluated using the leave-one-out (LOO) cross-validation procedure [6]. The LOO procedure was adopted in order to evaluate the performance of the ANN classifier in a reliable manner, taking into account the limited number of cases available in the classes, and in the same time avoid overtraining and achieving an acceptable generalization in the classification. According to this procedure, the ANN 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 ANN 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. Using the LOO cross-validation procedure, the resulting ANN classifiers present slight differences between each other, by inference of the slight variation of the training and testing feature vectors sets used in each one.

Since the weights of an ANN are initialized randomly, for the sake of generality, each step of the LOO cross-validation procedure was repeated 51 times (with different initial weights each time) and the test pattern was assigned to the class that was outputted by the ANN at least 26 times. The classification accuracy was computed by the aggregate sums of correctly classified or misclassified observations of correct and incorrect actions.

III. Results

As was mentioned before, 282 features were calculated from each participant's EPs. The probability density function for each EP recording was estimated at $M = 100$ equally spaced points $\overline{c}_k$ (k = 1, 2,…, M). The feature selection algorithm was applied using the 16 available feature vectors. In Table I, the features and the corresponding electrodes that were finally selected are shown. It is also shown the mean value and the standard deviation in parenthesis of each feature for the two classes, namely observation of correct actions (Class 1) and observation of incorrect actions (Class 2).

Table 1 Extracted features and corresponding electrodes

Feature	Electrode	Class 1	Class 2
Skewness	23	0.425 (0.74)	-1.117 (0.82)
Kurtosis	47	0.303 (1.17)	-0.483 (0.70)
Mean value	6	0.456 (1.11)	-0.465 (1.38)
Standard deviation	44	-0.329 (0.62)	0.938 (1.38)
Entropy	42	-0.257 (1.13)	0.421 (0.62)

The placement of the selected electrodes is shown in Fig. 2.

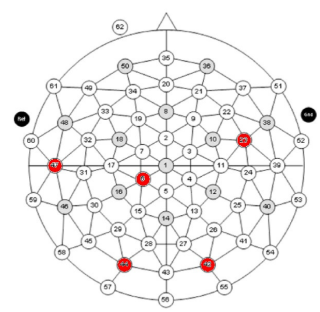

Fig.2 Graphic representation of the electrode placement.

Considering the results that are listed in Table 1, the following observations can be drawn:

- The skewness of electrode 23 in Class 1 (Class 2) is positive (negative), which in turn means that the corresponding histograms of EPs have a larger asymmetric tail towards positive (negative) values.
- The kurtosis of electrode 47 in Class 1 (Class 2) is positive (negative), which in turn means that the corresponding histograms of EPs are in general leptokurtic (platykurtic).
- The mean value of the EPs for electrode 6 in Class 1 is larger than the mean value of the EPs for electrode 6 in Class 2.

- The standard deviation of electrode 44 is larger in Class 2 than in Class 1
- The entropy of electrode 42 is in average larger in Class 2 than in Class 1, which means that the corresponding histograms of Class 1 are more uniform than these of Class 2.

The classification results (classification accuracy for class 1, class 2 and total classification accuracy) with respect to the number of neurons in the hidden layer are listed in Table 2.

Table 2 Classification accuracy with respect to the number of neurons in the hidden layer

Number of neurons in hidden layer	Classification accuracy (%)		
	Class 1	Class 2	Total
5	87.5	87.5	87.5
10	87.5	87.5	87.5
15	87.5	87.5	87.5
20	87.5	87.5	87.5

As is evident from Table 2, the number of neurons in the hidden layer does not affect the performance of ANN.

Finally, Fig. 3 shows how many times each test pattern was classified in Class 1 or Class 2 during the 51 repetitions of the LOO cross-validation procedure for an ANN with five hidden neurons.

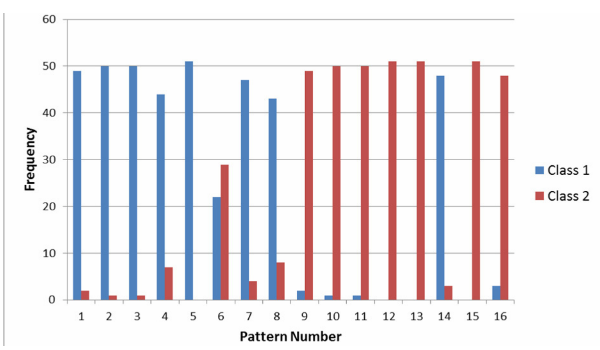

Fig.3 Bar graph of the output of the ANN during the LOO cross-validation. Patterns 1-8 (9-16) correspond to observations of correct (incorrect) action.

IV. CONCLUSIONS

In this paper, a methodology capable of discriminating between a subject's brain potentials that observe correct and incorrect actions was presented. The methodology consisted of two steps: the feature selection, which was based on SFFS, and the classification which was based on the ANN algorithm using a leave one out procedure. The proposed methodology reduced significantly the initial large number of features, providing satisfactory results.

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