33rd Annual International Conference of the IEEE EMBS
Boston, Massachusetts USA, August 30 - September 3, 2011

Mental Tasks Classification for BCI Using Image Correlation

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Abstract— **This paper describes a classifier based on image correlation of EEG maps to distinguish between three mental tasks in a Brain-Computer Interface (BCI). The data set V of BCI Competition 2003 has been used to test the classifier. To that end, the EEG maps obtained from this data set have been studied to find the ideal parameters of processing time and frequency. The classifier designed is based on a normalized cross-correlation of images which makes possible to obtain a proper similarity index to perform the classification. The success percentage of the classifier has been shown for different combinations of data. The results obtained are very successful, showing that this kind of techniques may be able to classify between three mental tasks with good results in a future online testing.**

I. INTRODUCTION

A Brain Computer Interface (BCI) registers the bioelectrical activity of the brain through electrodes and generates commands to control external devices [1]. This kind of systems are a natural way of improving human communication and mean a particularly relevant advance for people with severe motor disabilities as well as an improvement of human-machine interaction for healthy users [2].

In non-invasive Brain Computer Interfaces several electrodes are placed on the scalp to obtain the electroencephalographic signals (EEG) [3]. This kind of interfaces are divided in evoked and spontaneous. In evoked systems the registered signals reflect the automatic response of the brain to certain external stimuli (evoked potential) [4], [5]. On the other hand, in a BCI based on spontaneous signals, the user performs a voluntary cognitive process or thought in order to generate a command [6], [7]. This is an important advantage as the user controls the system instead of being controlled by the system. This can be done synchronously, where there is a predefined time to perform an action; or asynchronously, where the user can freely generate the command at any moment.

After getting the data, the EEG signals should be processed to extract the most important features and then, these features should be classified to obtain the different mental tasks. There are several methods of classification mainly based on mathematical algorithms such as Linear Discriminant Analysis (LDA), Support Vector Machine (SVM) or Bayesian Classifiers, among others [8], [9]. In this paper, a new approach based on EEG mapping is studied.

This work has been supported by the Ministerio de Ciencia e Innovación of the Spanish Government through project DPI2008-06875-C03-03 and by the Consellería d'Educació de la Generalitat Valenciana through grant BEST/2010/047, grant ACOMP/2011/066 and grant FPA/2011/058

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EEG mapping consists of plotting the electrical activity of the brain in a geometrical matrix. This approach gives a much more accurate and representative view of the mental activity obtained from the electrodes placed on the scalp. This can be done with a voltage/time representation or a frequency based representation. There are works related to brain topography to differentiate several kinds of diagnoses, including some mental diseases whose origin is located in EEG alterations such as epilepsy [10], [11] or schizophrenia [12]. EEG mapping has been also used in electrotherapy [13]. This kind of studies involve processing sessions of several minutes while on BCIs the frequency of each decision is critic. This work shows the results obtained for a short period of processing time. To this end, the data are processed in windows of a few seconds to obtain the EEG maps. These maps are used as models by the classifier to distinguish between the three different mental tasks through an image correlation analysis.

The remainder of this paper is organized as follows. In Section II, the obtention of EEG maps is explained. The classifier based on EEG mapping is described in section III. The results obtained are shown in Section IV. Finally, Section V contains the conclusions.

II. EEG MAPPING PROCESSING

In a BCI, the features of the EEG signals are extracted and classified into the different classes. As it has been mentioned in Section I, the classifiers are usually based on mathematical methods. In previous works, a LDA-based classifier has been used to obtain the different mental tasks [6]. It was capable of distinguish between three different cognitive processes related to motor imagery: imagination

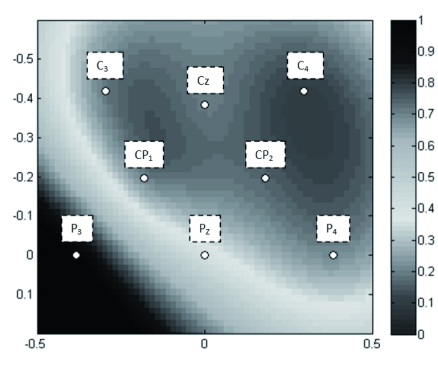

Fig. 1. Example of EEG map. The scale is normalized between 0 and 1 as it can be seen on the scale bar. Each electrode is placed in its particular position and the value generates the map.

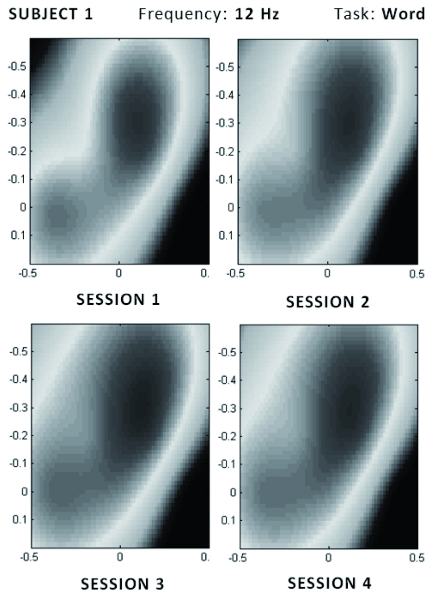

Fig. 2. Stability of the image: EEG Maps for the same task, frequency and user.

of low circular movements of the left and right arm and a rest state consisting of counting backwards.

As an alternative, a different approach is going to be studied based on EEG mapping. The visual plotting of the brain activity has been proved to be a very representative view in clinical diagnosis, so it may be also accurate in techniques related to BCIs. To prove that, the data provided in BCI Competition [14] are going to be used to obtain the EEG maps and an image correlation classifier is going to be applied. The registers made are based on motor imagery and provide results of success and accuracy in the classification that can be compared with our classifier.

A. Data Used

The data set V of "mental imagery, multi-class" provided by IDIAP Research Institute for BCI Competition 2003 has been used to do the EEG mapping [14]. This data set contains data from 3 normal subjects during 4 non-feedback sessions (3 for training and 1 for test). The subjects made these experiments in 4 sessions on the same day, each one lasting 4 minutes and with 5-10 minutes breaks between them. For each session, the subjects performed three different tasks:

1) Imagination of repetitive self-paced left hand movements ("left" mental task).
2) Imagination of repetitive self-paced right hand movements ("right" mental task).
3) Generation of words beginning with the same random letter ("word" mental task).

The data are provided in two ways: raw EEG signals with a sampling rate of 512 Hz, and precomputed features. To obtain these features the raw EEG potentials were first spatially filtered with a surface Laplacian and then, every 62.5 ms (16 times per second), the power spectral density (PSD) in the band 8-30 Hz was estimated over the last second of data with a frequency resolution of 2 Hz.

The electrodes used to register the EEG signals are the 8 centro-parietal of the 10/20 International System: C3, Cz, C4, CP1, CP2, P3, Pz and P4. The final EEG sample is a 96-dimensional vector (8 channels with 12 frequency components).

B. Image Obtention Protocol

The precomputed features (PSD) of the 8 electrodes has been plotted using Matlab. To that end, a geometrical grid of 99x99 pixels interpolating from the value of the electrodes using the real position of each electrode has been obtained (Figure 1). The axis show the position of the electrodes and the bar is scaled between 0 and 1 to improve the difference between each electrode. Each EEG map shows a particular frequency. This means that a total of 432 images (3 users x 4 sessions x 3 tasks x 12 frequencies) can be obtained as models to visually study the brain activity.

After defining the EEG map representation, the time interval of study should be chosen. In BCIs the processing time is critic as they are systems that work in real-time. To obtain a proper model, the EEG map processed must be stable and similar for each user, task and frequency. A qualitative analysis of this time interval has been made and a minimum amount of time of 5 seconds has been chosen as a preliminary interval of processing. With this time interval it is shown that the different mental tasks are stable and similar for each user and frequency during all sessions and trials. As an example, the EEG map of Subject 1 for Word Task with a frequency of 12 Hz is shown for different sessions (Figure 2). The shape of the image is clearly similar between each session.

III. CLASSIFIER

After defining the method to obtain the EEG maps, the images obtained should be used to perform the classification of the different mental tasks. This process will follow several steps:

A. Study of the significant frequencies

As it was mentioned in Section II, 12 different frequencies have been obtained after preprocessing the raw EEG signals. To classify the different mental tasks it is essential to have an appreciable difference between the maps obtained for each tasks. To that end, a qualitative analysis of the data of each subject has been made.

The most significant change between tasks appears in frequencies between 8-14 Hz for all subjects. In particular, 12 Hz is the most significant frequency for Subject 1, 10 Hz for Subject 2 and, finally, 14 Hz for Subject 3. As it is shown in Figure 3, different shapes on the image can be clearly seen for left, right and word mental tasks in the EEG mapping for these frequencies.

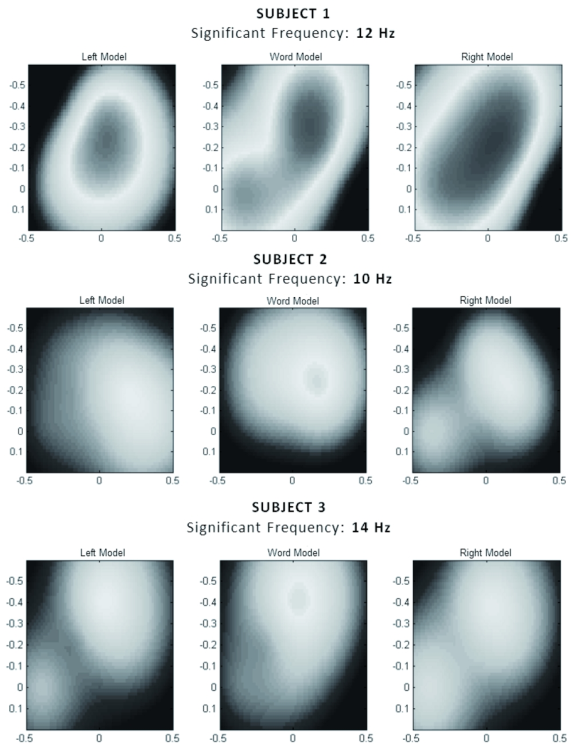

Fig. 3. Example of EEG maps obtained for each subject with the most significant frequencies used.

B. Models Obtention

From the 4 sessions registered offline for each subject, a combination of them can be selected to obtain the EEG maps models for each mental task (left, right and word). A processing window of 5 seconds is selected as well as the significant frequency previously studied. The data of each mental task are processed separately obtaining a collection of 5 second images that are averaged to get a unique EEG map for each task that will be used as the model to compare in the classifier.

C. Classification

After obtaining the three models (left, right and word), a different set of data is used to test the classification. To that end, the data are processed in trials of 5 seconds obtaining the EEG map. This image is compared using a *normalized cross-correlation* [15] with the three models obtained before as it is explained in Figure 4.

TABLE I
OFFLINE SUCCESS (%).

	Subject 1	Subject 2	Subject 3
123-4	81.0	73.8	57.1
124-3	72.1	85.7	45.2
134-2	78.6	66.7	65.9
234-1	59.5	64.3	41.5
Average	72.8	72.6	52.4

The correlation between two signals (cross correlation) is a

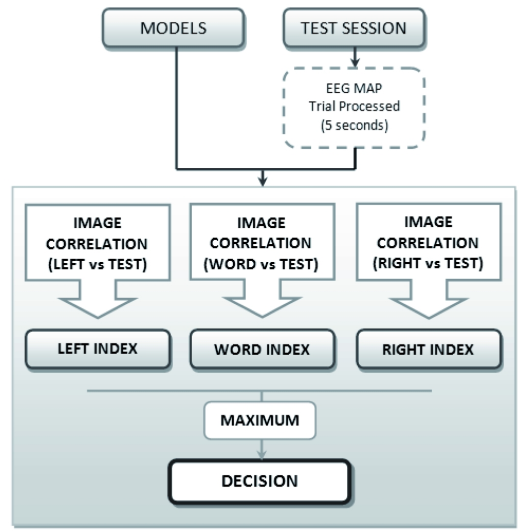

Fig. 4. Classification Algorithm.

standard approach to feature detection and also a component of more sophisticated techniques [15], [16]. However, there are several disadvantages using this technique for template matching or in this case, in image comparison:

- If the image varies with position, matching can fail.
- The range is dependent on the size of the feature. In this case the size of the shape.
- The algorithm is not invariant to changes in image amplitude, which are common in the EEG maps obtained as the the amplitude of the signal is variable.

To solve these problems, a *normalized cross-correlation* is going to be used to obtain the similarity of the different EEG maps as shown in 1, where $\bar{m}$ is the mean of the EEG map of the model and $\bar{f}_{u,v}$ is the mean of f(x,y), i.e. the EEG map of the trial which is going to be classified.

The resulting matrix $\gamma(u, v)$ contains the correlation coefficients, which can range in value from -1 to 1. To obtain a unique correlation coefficient, the highest value of the matrix is selected as the images change in shape and position. This is made to work with a more reliable correlation parameter.

When a particular session of data is tested (Figure 4), each trial of 5 seconds is compared with the models using the *normalized cross-correlation* algorithm. After this comparison, an index of correlation for each task is obtained. The maximum value of the index is selected obtaining the corresponding class.

IV. RESULTS

The image correlation classifier has been tested with all three subjects of the data set V of "mental imagery, multi-class" from BCI Competition 2003. To that end, 3 sessions (75% of the data) have been used to obtain the models and the remaining session (25% of the data) has been used to test the classifier. The success percentage is obtained as the average success of all three classes (Table I). As it can be seen, there is an important improvement in the success

$$\gamma(u,v) = \frac{\sum_{x,y}[f(x,y) - \bar{f}_{u,v}][m(x-u,y-v) - \bar{m}]}{\{\sum_{x,y}[f(x,y) - \bar{f}_{u,v}]^2 \sum_{x,y}[m(x-u,y-v) - \bar{m}]^2\}^{0.5}} \tag{1}$$

TABLE II

SUBJECT 1 - ONLINE SUCCESS FOR DIFFERENT TASKS (%).

	Subject 1			Subject 2			Subject 3		
	Left	Word	Right	Left	Word	Right	Left	Word	Right
123-4	71.4	81.3	91.7	63.6	76.5	78.6	30.8	73.3	64.3
124-3	61.5	82.4	69.2	100	94.4	66.7	13.3	53.8	71.4
134-2	75.0	86.7	73.3	61.5	68.7	69.2	64.3	65.9	46.2
234-1	83.3	35.3	69.2	54.5	76.5	57.1	16.7	50.0	53.3
Average	72.8	71.4	75.9	69.9	79.0	67.9	31.3	60.8	58.8

percentage with respects to the first preliminary image comparison method studied in [17]. The first combination (123-4) shows the results obtained for the test session provided by the data set. Subject 1 achieves the higher accuracy. Subject 2 also obtains a quite remarkable success rate over 70%. Although subject 3 obtains the lowest results, it is also over 50%. This results are congruent with the ones obtained in the BCI Competition [14] and show that this is a valid new method in mental task classification. The other combinations show as well good percentages except from the last one (234-1). This could be due to a lack of experience in the first session of training, as users usually improve their results in later sessions.

In Table II, the results obtained for the three mental tasks (left, right and word) are shown. For subjects 1 and 2, the success rate is quite similar in all three tasks (around 70%). This makes possible an stable classification in future online applications with BCIs. However, subject 3 has an important success decrease when detecting the left task. As it is the worst user of BCI competition [14], it seems that this high error in a particular task is not caused by the classifier itself.

V. CONCLUSION

A new classifier based on image correlation to classify mental tasks in BCIs has been proposed in this paper. The algorithm is based on a normalized cross-correlation between EEG maps. The results obtained when testing data set V from BCI Competition show that the success percentage in the classification of three mental tasks related to motor imagery is similar to previous mathematical classifiers. This mean that the classifier is ready for future online testings. It is also expected that the results will improve with a suitable visual feedback. The findings of this study suggest that the use of EEG mapping will make possible the classification of more than three different mental tasks, as the differences between images are quite important when creating the models.

As future works, a real-time online testing will be performed with new users adding visual feedback. Several improvements in the image correlation classifier will be studied, like the introduction of an uncertainty threshold or the reduction of the processing interval. The use of other mental tasks non related to motor imagery will be introduced to see if the classifier is able to maintain the accuracy shown with only three mental tasks.

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