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A Practical Arabic P300-Speller

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***Abstract*— Human Computer interaction is one of the basic requirements of people in our time, humanity has been interacting with computers in every possible way, this work focuses on communication capabilities using brain signals. Such technology offers a great potential especially for people suffering from limited communication capabilities and require assistive devices. This type of communication schemes is usually referred to as brain computer interface (BCI), which is a system that establishes a direct link with the human brain without any muscular movement by translating neurons electrical activity into useful commands. However, such system usually suffers from low information transfer rate as well as low accuracies. This represents a challenge when used to deliver information of large set of characters as in natural language. This paper aims at designing a spelling application based on brain computer interface using Arabic Letters. The BCI adopted in this work uses event-related potential (ERP) by stimulating the neurons into generating detectable signals. When the subject pays attention to a stimulus presented in real-time signal is recoded, processed and classified into commands performed by the spelling application. The system has been tested under various parameters and conditions, the proposed method has indeed proved to be operational and adequate.**

***Keywords*— HCI, BCI, P300, Arabic Speller.**

I. INTRODUCTION

Researchers have been working on the development of new communication methods since the creation of the very first generation of computers with main focus on control and information entry schemes, beginning with punched cards till mouse and keyboard all are considered HCI devices. In the last few decades enormous research efforts have been employed to design a more user-friendly and ergonomic interfaces. As a consequence, some successful products, such as hand gestures and voice recognition softwares, have been launched to the masses.

In the recent years an entirely different scientific interest started to emerge which focuses on alternative methods of interactions more suitable for people suffering from the loss of muscle control [1].

The development of modern computers alongside neuroscience with an increased knowledge of human brain all these factors combined made controlling devices and computers directly by using brain's activity a more feasible task. Brain computer interface (BCI) is defined as a real-time communication system which enables the human brain activity to control computers directly [2].

From this aspect, a BCI system should help severely disabled people to restore some of the communication channels [3]. Ultimately the goal would be to provide an alternative interface for interaction to the general population [4].

There are two major considerations when designing a BCI system: obtaining a brain signal that the user can reliably control without any muscular movements and developing a software that handles detecting as well as analysing these specific brain signals.

Regardless of the fact that the current BCIs systems only allowed limited communication, but it had shown very good potential for the basic control of various computer interfaces such as a mouse cursor, a spelling program, a wheelchair, a robotic arm, or some other devices, this can greatly improve the quality of life for a locked-in user.

The brain signals used for the BCI system in this paper can be obtained using non-invasive methods using the International 10-20 system from a set of electrodes placed directly on the scalp these electrodes detect the electrical activity occurring in the specific area of the brain that they are placed upon. Since the electric signal needs to pass the skull to be recorded, it is inherently prone to be very noisy, which results in many challenges for signal analysis and pattern recognition.

There are numerous and various approaches for BCI systems, each with different advantages and disadvantages, in this work the user is required to focus his attention on a specific stimulus that evokes an event-related potential (ERP) in the EEG signals. The BCI system detects this ERP in order to determine the user intended action which is more suitable for selecting large sets of targets such as letters [5].

It is well known that BCI systems usually offers relatively low transfer rates with a significant variance of accuracy between subjects and across signals acquisition sessions. For this reason many applications design should take into consideration minimizing the number of required inputs needed to perform the desired command in order to increase its immunity to errors.

Our work will focus on the P300 Speller, which is an interface that applies a visual stimulation to generate, obtain and classify brain signals in order to determine the stimulation target. Powerful Predictive algorithms will be embedded into the P300 Speller for the purpose of improving its performance.

II. MATERIALS AND METHODS

A. Subjects

Two healthy subjects participated in the BCI experiments performed for this paper. Only healthy individuals have been considered since the BCI system is still a prototype and assessing its performance before testing it on subjects with disabilities is vital.

The two participants are aged at 26, one male and female, none of them had any prior encounters with BCI systems before the beginning of this thesis. Subjects are referred to with the first letter of their names, being M and N.

B. Instrumentation

In order to acquire, digitize and amplify the EEG signals Emotiv EPOC+ has been used, as demonstrated in fig. 1. The device has 14 channels with a separate reference (mastoids). The unit is connected to a laptop through wireless adapter operating at 2.4 GHz. The laptop was running on internal battery power throughout the experiments.

The Emotiv EPOC+ applies a high-pass filtering at 0.1 Hz to all EEG channels, so that DC and low frequency components are removed and a digital low-pass filter is applied before the signal is down-sampled to the desired frequency. A sampling frequency of 128 Hz has been used for all the experiments, hence the subsequent valuable band as per the specifications is 0.1-30 Hz. Signal acquisition, filtering and processing is handled by a modified version of BCI2000.

Fig. 1 Emotiv EPOC + Headset.

C. Calibration Sessions

Calibration sessions have been performed with the two subjects on two distinct dates. On day one two different acquisition sessions have been performed, while on day two as subjects became more familiar with the system three acquisition sessions were performed with a 30 minutes break in between each session for both dates. Each session was made out of 5 runs separated by a 3 minute break. Each run was in turn made out of spelling 13 letters in 10 sequences each having 12 stimuli on 6x6 Arabic letters Matrix. Hence a total of 15600 stimulus on day one and 23400 stimuli on day two was considered, being 39000 the total number of stimuli presented for each subject. During a run the subject was asked to count the number of intensifications for each letter to be spelled and to remain relaxed while focusing on the visual stimulus being displayed on the screen.

Each intensification was displayed for 62.5ms and when this time was over there was no intensifications on the screen for 62.5ms before the next stimulus appeared. Between the two sequences there was a break of 3.5s in which the screen was showing the next letter to be spelled and the subject may stretch or blink. Stimuli were randomized in order to avoid adaption, yet each stimulus was displayed precisely 2 times per sequence. Subjects were asked to minimize any physical movement if possible including blinking and eye movement during the stimuli presentation time.

Fig. 2 Arabic P300 Keyboard.

D. Signal Processing

The signal is first digitized using a ADC of 128 Hz Sampling Rate, then the signal is passed to frequency filters in order to remove non-desired frequency components, noise and artifacts. According to various researches it has been suggested that the P300 components can be mainly found in the δ and θ with some components found in the α band [6], [7]. Therefore, a low pass filter at 30Hz through a 2nd order Butterworth infinite impulse response (IIR) filter, High Pass filter at 0.1 Hz through 1st order IIR filter to eliminate any DC offset and a 50 Hz Notch filter through 3rd order Chebyshev bandstop filter which is performed to eliminate power-line noise. The Emotive EPOC headset is used for this study references to common mode sense (CMS) active electrode and driven right leg (DRL) passive electrode (also called known as CMS/DRL referencing).

E. Feature extraction

For each channel, all data samples between 0 to 800 ms posterior to the beginning of an intensification has been extracted. Assuming that the evoked potentials appear about 300 ms after the stimulus, that window is large enough to capture required time features and then these windows are averaged over 10 trails before being fed to the classifier. As the typical P300 response has a width of 150-200 ms. The peak potential of a P300 is typically $2 - 5\mu V$, which is less than the brain's background activity. Thus, the single P300's SNR is low, and is typically enhanced by averaging over multiple responses which improve SNR by a factor of N where N corresponds to number of trials.

F. Classification

The Linear Classifier takes waveform data from multiple locations and time points to linearly combine them into a single number. The Linear Classifier computes a projection of a high-dimensional signal feature space onto a low-dimensional classification space. Thus, each dimension of classification space is a linear combination of signal features. Input data has 2 indices (N channels x M elements), and output data has a single index, thus the linear classifier acts as an N x M x C matrix where C, determining the output after summation over channels and elements [8]:

$$\text{output}_k = \sum_{i=1}^{N} \sum_{j=1}^{M} \text{input}_{ij}\,\text{Classifier}_{ij}$$

The Linear Classifier's input is a sequence of averaged EEG time courses obtained in response to a number of stimuli k, and its output is a single number considered to represent a log-likelihood ratio for each of these responses to be an ERP.

III. Results

A. *Signal Analysis*

The signal behaviour is expected from the neurophysiological studies about ERP. Indeed, ERP tasks were found to be a positive peak in the recorded EEG at around 300-600ms from a stimulus (Fig. 3A & 3B). For subject N the P300 responses associated with stimuli are strong, while the same phenomenon has not been observed for Subject M. Even though similar discrimination patterns have been found for the subjects, the EEG signal and its corresponding r2 values change significantly from subject to subject. The highest r2 values have been found in the time 0-800ms for both subjects, therefore these values have been considered as temporal limits for computing features. It is worth noting that for subject M the P300 responses were detected at frontal scalp channels (Fig. 5B), this behaviour could be due to the limitations employed by the hardware, as Emotiv EPOC+ have more channels residing at the front scalp and thus have better chances of detecting signals at those channels.

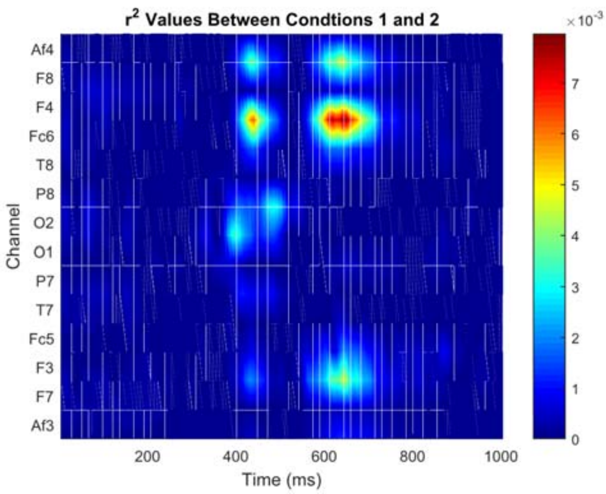

Fig. 3A Subject N r^2 Response for channels over time.

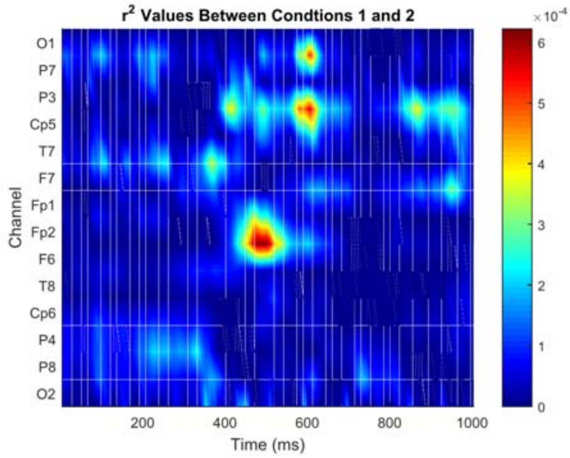

Fig. 3B Subject M r^2 Response for channels over time.

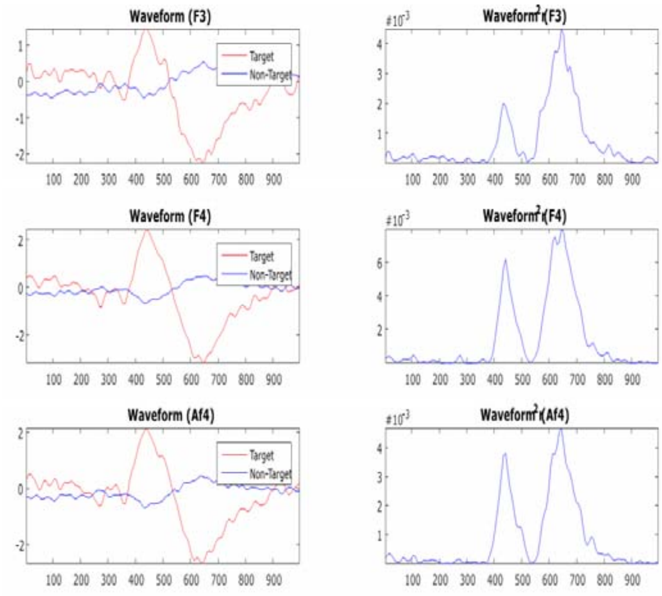

Fig. 4A P300 Signal Response for subject N.

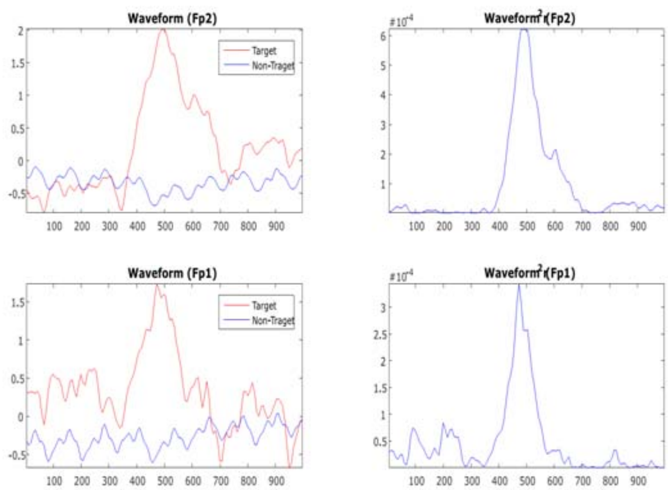

Fig. 4B P300 Signal Response for subject M.

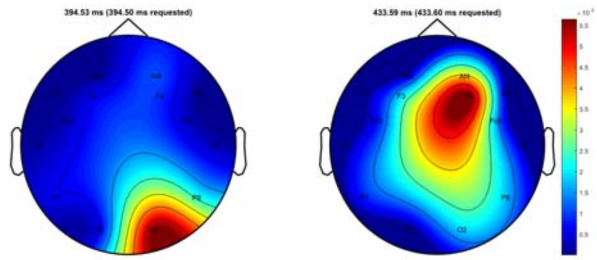

Fig. 5A Subject N Signal Topography

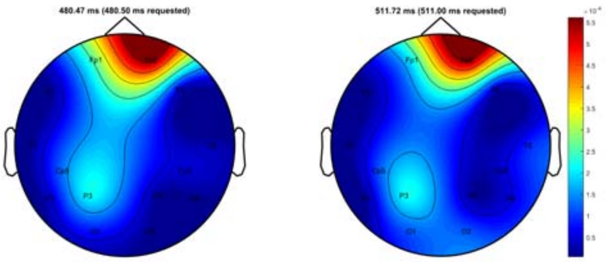

Fig. 5B Subject M Signal Topography

B. *Classification*

While executing offline classification, all data acquired in one date are used for testing and all remaining data are used for training. The reason behind this approach is to avoid training the classifier using data acquired in the same date as the testing date as data recorded in the same settings tend to be correlated and might result in overfitting biases.

In correlation to the signal analysis, subject N is the one for which the best classification performances have been reached. For subject N an overall accuracy of 0.9341 have been achieved. Dealing with subject M, instead, classification performances are much lower compared to those of subject N. An overall classification accuracy equal to 0.652 has been obtained. These results reveal that BCI control based on ERP is characterized by a strong intersubject variability. This is one of the most critical issues in this area of BCI research. Table I shows the results obtained across the five sessions and provides the specific accuracies obtained for each of these sessions.

TABLE I
CLASSIFICATION RESULTS

Session No.	Accuracy Subject N	Accuracy Subject M
1	100	67
2	100	83
3	83	42
4	92	76
5	92	58
Overall	**93.4**	**65.2**

IV. DISCUSSION AND CONCLUSION

In this paper, we have presented an Arabic speller using BCI based on ERP, several experiments were conducted in order to collect data from test subjects to study the effect of brain activity associated with event-related potential. After collecting enough data, offline analyses were performed to identify useful features and generate classifier weights.

In its final version, the BCI system was able to perform data acquisition, signal processing, feature extraction and classification. The classification performance was evaluated for 2 subjects. The obtained results were different for these two subjects.

With subject N a high classification accuracies were obtained. This subject was able to use the application to spell simple phrases and the overall communication rate was about 3 characters per minute. Subject N obtained results verify the latest works related to BCI spelling applications found in literature [9,10,11].

For subject M, lower accuracies have been obtained during classification and the usage of the BCI speller proved to be more challenging. Supporting that the event-related potentials vary significantly from subject to subject and it is highly influenced by the psycho-physical conditions of the users. However several studies recommended that performing an increased number of training sessions is the key to improve the performance of BCI systems that based on ERP.

V. ACKNOWLEDGMENT

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