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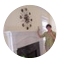

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Towards an Adaptive Brain-Computer Interface – An Error Potential Approach

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Abstract. In this paper a new adaptive Brain Computer Interface (BCI) architecture is proposed that allows to autonomously adapt the BCI parameters in malfunctioning situations. Such situations are detected by discriminating EEG Error Potentials and when necessary the BCI mode is switched back to the training stage in order to improve its performance. First, the modules of the adaptive BCI are presented, then the scenarios for identification of the user reaction to intentionally introduced errors are discussed and finally promising preliminary results are commented. The proposed concept has the potential to increase the reliability of BCI systems.

1 Introduction

Brain-Computer interface (BCI) [11] research seeks to develop an alternative communication channel between humans and machines which implies no muscular intervention in the communication process. The main goal is to give to the users, basic communication and control capabilities allowing them to operate external computerized devices or applications like word processing programs or neuro-prostheses. This kind of devices determine the intent of the user from scalp-recorded electrical brain signals (EEG - Electroencephalogram), or from electrodes surgically implanted on the cortical surface (ECoG- Electrocorticography) or within the brain (neuronal action potentials or local field potentials). These signals are translated into commands that operate a computerized application. Despite of the advances in this research field the BCI systems are still presenting several challenges that can be resumed in: Usability, Accuracy and Speed. Many factors determine the performance of a BCI system [3], among them are the quality of the brain signals, the methods used to extract signal information, the output applications, and the user himself. A BCI device must take in account all of these factors to provide a reliable performance.

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The traditional BCI system has two distinct stages. The training stage where mutual adaptation of the BCI system and the user is performed. During this stage, the BCI parameters are tuned based on specific training scenarios. The second stage corresponds to the normal functioning of the BCI, termed in this paper as the on-line stage, where the BCI parameters are fixed. However the EEG signals are non-stationary, their statistics can suffer significant changes over time, and periodic calibration of the system may improve its reliability.

In order to address these issues, the key characteristic of the BCI is its adaptability. The BCI system must be able to identify malfunctioning events (for example accumulation of errors in interpreting the user intentions) and provide a way to correct them.

The platforms usually used in the BCI experiments, like BCI2000 [9] or OpenVibe [1,8], do not provide a convenient autonomous switch between training and online stages of the BCI modules.

In this work, a new adaptive BCI architecture is proposed that can switch back to the training stage in order to adapt the BCI parameters in malfunctioning situations. Such situations are detected by extracting EEG Error Potentials (EP) [2,4,5,7,10]. EP are signals that exhibit a negative peak between 50–100 ms related with the cognitive reaction of the user when its intention is wrongly interpreted by the BCI system. The architecture, that allows to perform this operation in an autonomous mode is presented in the next section.

2 Adaptive IEETA BCI Architecture

A BCI architecture is usually composed by three main modules: Signal Acquisition, Signal Processing and Feedback modules (see Fig. 1, top structure). Signal Acquisition is responsible to acquire the EEG and/or ECoG signals and store data in an appropriate format. In the Signal Processing blocks the data is preprocessed, relevant features are selected, extracted and classified in order to provide a proper decision. Finally, the Feedback module has to present the results of the decision to the user.

During the training stage the BCI system guides the user by indicating the sequence of targets. For example, in the BCI speller based on P300 paradigm [10] the system indicates the character which the user should identify. In the motor imagery BCI, the targeted moving direction is indicated to the user, for instance, by moving a certain object on the screen. During the online stage (normal BCI functioning) the user can choose the target, the BCI system does not have access to the target information. Due to technical (related with the BCI system itself) or subjective (related with the user) reasons such an open-loop architecture can significantly degrade its performance and there is no way to detect and eventually correct it.

The contribution of this paper is the introduction of a new module, termed Error Evaluation (EE) module (see Fig. 1, the bottom structure), which was tested on the noninvasive EEG-based BCI testbed developed in our research lab (IEETA BCI) [6].

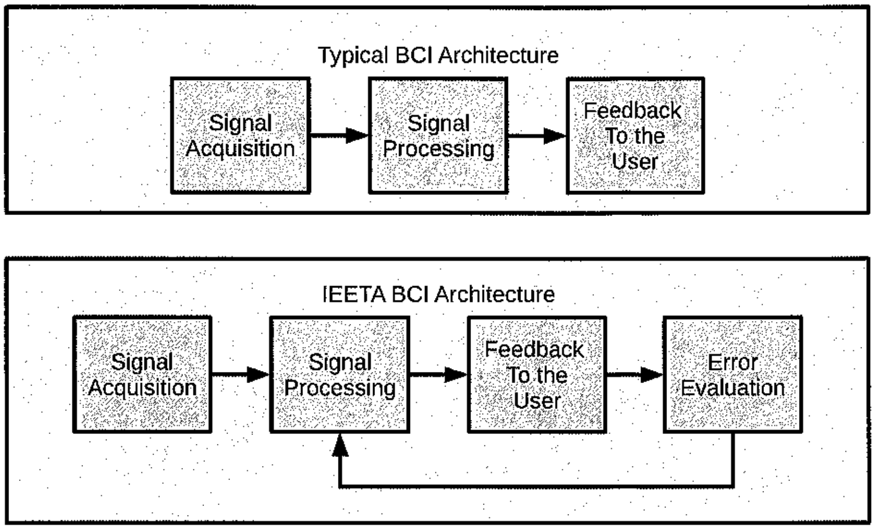


Fig. 1. Typical and IEETA BCI Architectures. The Error Evaluation block detects system errors and start a new training stage.

The EE block processes the user reaction to the Feedback that has been presented to him. When the EE block identifies malfunctioning in the system it commands to the Signal Processing block to start a new training. The main goal of this closed loop architecture is to provide the BCI with a criteria to automatically switch between train and online modes. The user is notified that the BCI accuracy is degrading and a new training stage will be initiated. Once in training mode, the BCI parameters are re-tuned following the training protocol and when the EE block evaluates the classification accuracy is over a certain threshold the system switches again to the online mode. This simple adaptive procedure allows the system to deal with non-stationarity of the EEG signals and other perturbations that can worsen the BCI performance.

A key issue regarding this adaptive closed-loop BCI is how to identify the malfunctions and what is the criterion to switch from one mode to the other. We propose two approaches: (i) Error Potentials (EP); (ii) Error Detection by the application itself.

In the first approach (EP), the Error Evaluation module identifies the BCI bad performance by analyzing the brain activity. If EPs are identified (negative peaks between 50–100 ms over a short time sequence of EEG recordings) the BCI will start train session to re-adapt its parameters. In the second approach the application itself must identify the error by analyzing its performance (or expected performance). For instance in a BCI speller application, the switching criterion can be if the spelled word(s) exists in a specified dictionary. The non-existence of the written word is counted as an error. It is also possible to identify errors by statistical analysis, for example, in a two choice application (right or left), the expected probability of choosing each one of the possibilities is studied. A significant difference between the expected statistics and the observations is counted as an error.

3 Experiment Setup and Details

To study the Error Potentials and to identify the reaction of the user to errors in the system performance we developed a modular BCI to acquire and process the EEG signals and provide a feedback to the user. The application Main Window and the acquisition driver configuration are depicted on Fig. 2. The EEG signals were registered by the Trackit Acquisition device, a portable equipment that acquires up to 8 EEG channels at a sampling rate of 256 Hz per channel. The experiment consisted in presenting to the user a task of moving a ball to a given target (right or left). In the first phase only errors produced by the BCI system were studied. For this, the moving direction was defined by the BCI system itself and not by the translated user intention using his/her brain waves. In order to assess the user reaction to BCI errors we intentionally introduced random errors in the direction of the ball moves. Each session was composed by 11 runs with increasing number of intentionally introduced errors (from 0 % to 50 %). The sessions were divided in two modes:

- Observation Mode: the user only observes the BCI system behavior.
- Play Mode: the user chooses the ball moving direction by pressing right or left keys on the computer keyboard.

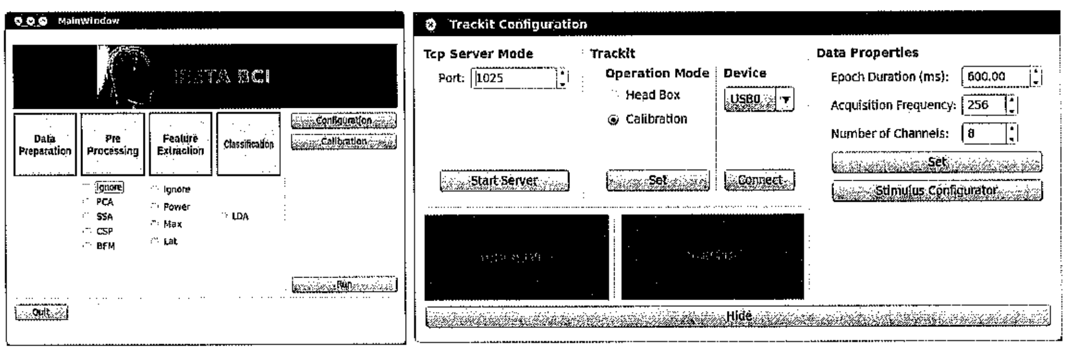
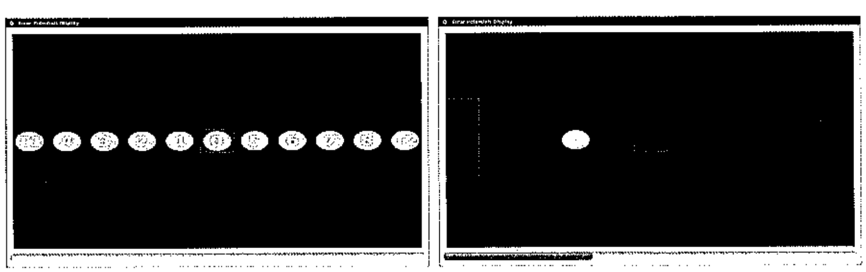


Fig. 2. IEETA BCI Application: Main Window and Acquisition Driver Configuration Window.



(a) All possible positions (b) Moving ball example

Fig. 3. Error Potential Scenario (Color figure online)

In the first mode we want to assess the user passive reaction to errors of the BCI system. In the second mode we want to assess the user active reaction to errors that he/she is personally involved. On Fig. 3a is shown the feedback screen with all possible positions of the ball. At the beginning of each run a target screen is presented to the user that indicates the target moving direction of the ball is indicated by the green color (Fig. 3b). In Play mode the ball movements and the time left to decide the desired direction are also indicated.

4 Results

Preliminary results of the experiments with one 26 years old subject are summarized here. The EEG signals from channels Cz, C4, C3, Fz, Pz, O2, O1 (according to the international 10–20 system) were acquired and processed offline. Two sessions were recorded, one in Observation Mode (1) and one in Play Mode (2). Session 1 contains 125 trials in total with 39 trials containing error stimulus. Session 2 contains 98 trials, 26 of those with error stimulus. The raw data was filtered with a low pass filter up to 25 Hz. Figure 4 depicts the Cz channel in Play Mode scenario after being filtered. The Error Potential (EP) is usually identified as a negative peak between 50–100 ms. Since the EP is characterized by a significant variance in the latency a wider interval (between 0–100 ms) is considered. The averaged signals were then visually inspected and the peak values between 0–100 ms were selected corresponding to the error condition in every channel. To verify the accuracy of the classification 20 % of the data was used to test the classification using a k-fold validation. The validation test was repeated 50 times (randomly choosing the test data) and the final averaged results are summarized in Table 1.

This is an on-going research, however the preliminary results reported here are encouraging that the proposed adaptive BCI structure can contribute to detect EPs and further improve the accuracy of the non-invasive EEG-based BCI technologies. However, experiments with more subjects are required before making final conclusions.

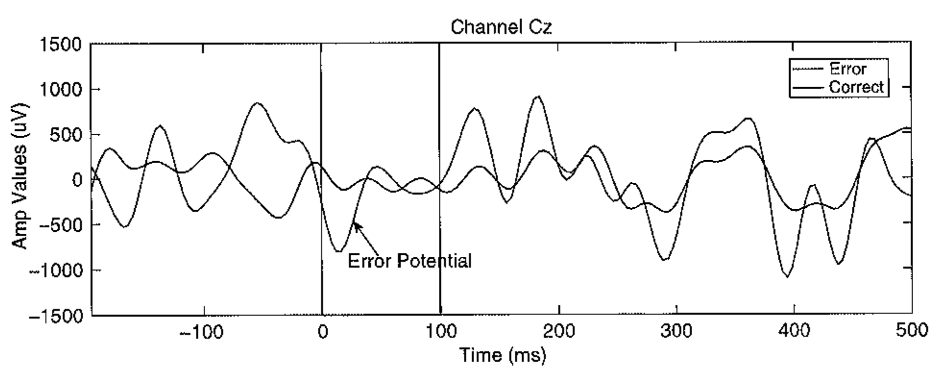


Fig. 4. Cz channel in Play Mode scenario

Table 1. K-Fold Test Accuracy

Experiment	Mean	Std
Observation mode	73.95 %	5.10 %
Play mode	69.60 %	9.68 %

5 Conclusion

In this paper an adaptive Brain-Computer Interface is proposed termed IEETA BCI, that allows to autonomously switch between two modes - training or normal functioning (on-line mode). The training mode is chosen when persisting Error Potentials are detected into the ongoing EEG signals of the BCI user or by errors detected into the proper BCI application.

The main novelty of the proposed architecture, compared with existing BCIs, is the additional Error Evaluation module. This module transforms the BCI into a closed loop structure able to compensate degradation of the BCI performance due to various reasons as for example the non-stationarity of the EEG signals. In the experiments performed, the EPs related with motor imagery tasks were successfully identified. The EPs were related with the perception of the user on his proper mistakes when moving direction different from the suggested appears on the screen. The proposed simple way of adaptation has the potential to increase the reliability of BCI systems however studies with more users are still required.

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