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Hangman BCI: An unsupervised adaptive self-paced Brain–Computer Interface for playing games

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ABSTRACT

This paper presents a novel user interface suitable for adaptive Brain Computer Interface (BCI) system. A customized self-paced BCI architecture is introduced where the system combines onset detection system along with an adaptive classifier working in parallel. An unsupervised adaptive method based on sequential expectation maximization for Gaussian mixture model is employed with new timing scheme and an additional averaging step to avoid over-fitting. Sigmoid function based post-processing approach is proposed to enhance the classifiers' output. The adaptive system is compared to a non-adaptive one and tested on five subjects who used the BCI to play the hangman game. The results show significant improvement of the True–False difference for all the classes and a reduction in the number of steps required to solve the problem.

1. Introduction

Brain–Computer Interfacing (BCI) is a relatively new approach to communication between man and machine, which translates brain activity into commands for communication and control [1,2]. A BCI user can perform several well studied motor imagery tasks to induce changes in brain activity detectable via non-invasive electroencephalography (EEG) [3–5]. Such a system must be able to distinguish EEG patterns produced by these tasks within a time frame suitable for control.

A major challenge for building realistic non-invasive BCIs is the non-stationarity of EEG data. Non-stationarity is caused by intrinsic and extrinsic causes such as subject fatigue, attention, internal state of mind, electrodes impedance, amplifier noise, and environmental noise. Ref. [6] provides a systematic evidence of statistical difference in data recorded during offline and online sessions. These non-stationarities can cause a reduction in the system performance during online experiments and affect the overall user experience.

Wolpaw [2] viewed BCI as a communication system that involves two adaptive participants, the brain and the BCI system. The user must learn how to control the BCI system and the system must adapt to the non-stationary user's signals. To achieve successful control the user and the system must adapt to each other initially and continuously. A BCI system can be adaptive on different levels from feature extraction to classification and post-processing. In [7] an invariant Common Spatial Pattern (CSP) method was introduced to construct CSP features that are invariant to EEG non-stationarities. An adaptive CSP method is presented in [8] based on weighted update of the signal covariance matrix.

Linear Discriminant Analysis (LDA) is a well known stable classifier and its behaviour is well studied and understood in the BCI community. LDA is favored for adaptive classification because it has very few parameters to tune allowing for more efficient and robust adaptation. Several adaptation methods were developed for LDA including supervised, unsupervised and Kalman filter approaches [6,9,10]. Bayesian methods were also studied for adaptive BCI systems [11]. Bayesian approaches are advantageous as they are sequential by nature and they incorporate prior knowledge to avoid over-fitting. On the other hand they can be computationally very expensive limiting the possible number of channels (features) used online. A least mean square (LMS) method was proposed in [12] to adapt the weights of a two-dimensional control BCI system.

An unsupervised adaptive method for LDA based on a Gaussian mixture model (GMM) was proposed in [13]. The idea is to consider LDA as an initial state for GMM that is updated using a batch expectation-maximization (EM) method. The initialization approach is improved in [14] by averaging the model over some initial adaptation windows. A similar approach is employed here to adapt LDA using adaptive sequential EM with the corresponding GMM [15,16].

To test the adaptive scheme a novel interface, Hangman game, is put to use. The interface operates in discrete control mode with

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a special design allowing easy monitoring of subject performance. In addition, the interface provides feedback and vital information to the adaptation algorithm. In [17] an online labeling scheme was introduced that facilitates a supervised online adaptive system which controls a simulated robot. The labels were unreliable due to ambiguity in the possible routes the robot can take which required offline analysis to evaluate the system performance.

Next section describes the interface and the hangman problem. Section 1.2 states the design motivation, while Section 2 explains in detail the system architecture with the methods used. Section 3 details the experiments carried out to test the system. Section 4 discusses the results and Section 5 presents conclusions.

1.1. Hangman BCI

Hangman BCI is a brain actuated game. It uses a motor-imagery self-paced BCI system to select a letter that solves a simplified hangman problem.

The goal of a hangman problem is to find a missing letter(s) from a dictionary word. The player tries to find the missing letter from a set of randomly generated letters. Should the player selects an incorrect letter, one part of the hangman body is drawn. If the full body is drawn the player loses, otherwise the correct letter is found and the player wins. The player uses two controls to play the game. The first control is called "Move" which moves the cursor from the highlighted letter to the next one (one directional move only according to the user preference). The second is called "Select" and is used to select the highlighted letter as the missing letter.

Fig. 1 shows a screen shot of the game during a test scenario. The player here made five mistakes but was able to select the letter correctly saving the hangman. The interface provides feedback to the user in two ways: first the confidence in the classification output for each of the classes is presented in separate windows with a line representing the threshold used to give the user a better feeling of how the system is responding to their actions. The second feedback is the drawing of the hangman.

1.2. Design motivation

The main motivation behind the special design of this interface is to develop a testbed for self-paced motor-imagery BCIs in general and adaptive BCIs in particular.

Unlike the continuous movement used in the state-of-the-art self-paced systems [18,19], the interface uses a discrete movement, i.e. the movement of the cursor over the letters. Discrete movement facilitates better analysis of the system behavior (using True–False difference for example), it is also easy to maintain and more user friendly. The robot control simulator [20] uses continuous control to move the robot in order to reach its target. The Berlin-BCI speller [21] uses a discrete user interface but has no defined goal to the subject, which makes it hard to evaluate the user performance online.

Hangman interface is suitable for testing both supervised and unsupervised adaptation methods. The task is easy enough to predict the behavior of the subject. This prediction can be used to label EEG data (with some degree of uncertainty). In supervised adaptation mode the interface provides real-time labels to the adaptive algorithm. In unsupervised adaptation mode the interface monitors the performance of the user (e.g. using the average number of movements required to find the correct letter) and provides viable information to the adaptation algorithm. These include timing information (i.e. when to start/stop adaptation) and the performance of the adapted system.

2. Methods

2.1. System architecture

The system is a motor-imagery self-paced BCI system that uses $\mu(8-12$ Hz) and $\beta(13-16$ Hz) rhythms for control. For the sake of comparison the system comes in two versions: static and adaptive. Fig. 2 outlines the adaptive version of the system. The user interface feeds back adaptation timing information to the adaptive movement classifier. The timing information is based on the evaluation of the user performance. The static system is identical to the adaptive one except that it has no feedback and its classifier is not updated.

Two sub-systems work in parallel: the onset detection sub-system and the movement classification sub-system. The continuous classification outputs of both sub-systems are fed into the interface which performs the tasks accordingly. Algorithm 1 explains how to combine the two parallel systems, where *ONSET* refers to the status of the onset detection system. *ONSET-DWELL* checks if the dwell window (i.e. the minimum number of points

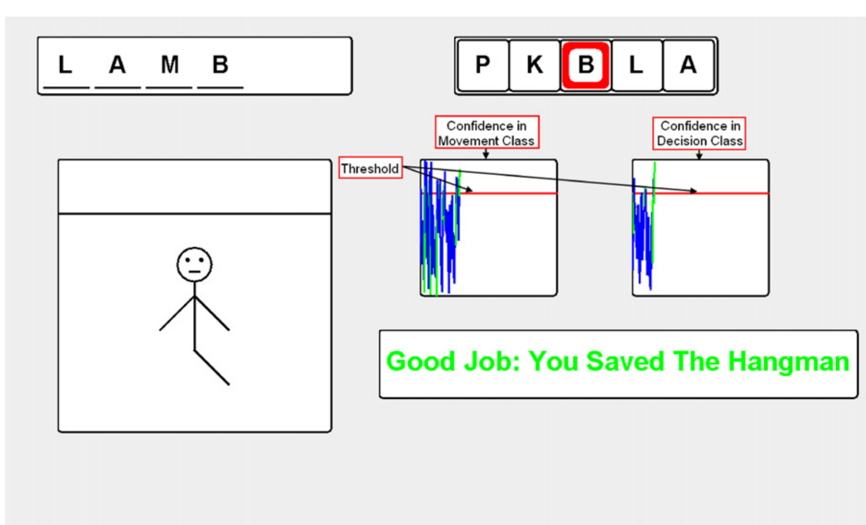

Fig. 1. Screen shot of the Hangman BCI during a test scenario. The subject made five incorrect choices but was then able to find the correct letter. The arrows and label boxes are for demonstration purposes only and do not appear on the interface.