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Whether generic model works for rapid ERP-based BCI calibration

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HIGHLIGHTS

- ► We survey whether one generic model works for all subjects.
- ► We show the performance of a generic model using an online training strategy when participants could use the generic model.
- ► Four of the subjects could not use this generic model, which shows that one generic mode is not generic for all subjects.
- ► When generic model could be used by the subjects, the mean training time for generic model would be less than 2 min.

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ABSTRACT

Event-related potential (ERP)-based brain–computer interfacing (BCI) is an effective method of basic communication. However, collecting calibration data, and classifier training, detracts from the amount of time allocated for online communication. Decreasing calibration time can reduce preparation time thereby allowing for additional online use, potentially lower fatigue, and improved performance. Previous studies, using generic online training models which avoid offline calibration, afford more time for online spelling. Such studies have not examined the direct effects of the model on individual performance, and the training sequence exceeded the time reported here.

The first goal of this work is to survey whether one generic model works for all subjects and the second goal is to show the performance of a generic model using an online training strategy when participants could use the generic model. The generic model was derived from 10 participant's data. An additional 11 participants were recruited for the current study. Seven of the participants were able to use the generic model during online training. Moreover, the generic model performed as well as models obtained from participant specific offline data with a mean training time of less than 2 min. However, four of the participants could not use this generic model, which shows that one generic mode is not generic for all subjects. More research on ERPs of subjects with different characteristics should be done, which would be helpful to build generic models for subject groups. This result shows a potential valuable direction for improving the BCI system.

1. Introduction

Brain–computer interfaces (BCIs) translate brain activity into command and control signals. Common BCI techniques and inputs include motor imagery (Pfurtscheller and Neuper, 2001), event-related potentials (Farwell and Donchin, 1988; Allison and Pineda, 2003; Hong et al., 2009; Jin et al., 2012; Kaufmann et al., 2011; Zhang et al., 2012), and steady state evoked potentials (Vidal, 1972).

Farwell and Donchin (1988) introduced the P300-based BCI. Today, improving the system's usability by increasing online accuracy and information transfer rate (ITR) is a high priority for BCI research. Sophisticated calibration methods are paramount for high online accuracy and ITR, and clean EEG, with well-differentiated target and non-target activity, lends to training a robust classifier, necessary for efficient use of the system. One strategy for improving accuracy entails selecting provocative visual images to elicit pronounced target responses. Manipulating visual stimuli (e.g., motion and images of faces) to enhance the amplitude of evoked potentials affords more descriptive data for classification (Hong et al., 2009; Jin et al., 2012; Kaufmann et al., 2011; Zhang et al., 2012).

In almost all cases, ERP-based BCIs require offline calibration to train a classifier model (Farwell and Donchin, 1988; Hong et al., 2009; Jin et al., 2012; Kaufmann et al., 2011; Zhang et al., 2012). Reducing the duration of offline calibration would increase BCI

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usability, decrease overall fatigue, and increase the amount of time available for online communication purposes. Rivet et al. (2011) proposed an adaptive training session to diminish time allocated to offline calibration for ERP-based BCIs. Long et al. (2011) reported that online data could be used to improve an offline calibration model. Vidaurre et al. (2011) developed a novel method for online training of a motor imagery BCI based on unsupervised adaptation of LDA classifiers.

Lu et al. (2009) used an online training strategy and a generic model in order to optimize calibration for each individual. The generic model was used to obtain the identity of an online selection, which would then be used to train the online classifier. If the generic model incorrectly labeled a selection, the data provided to the online classifier would label desired selections as undesired, and undesired selections as desired. The erroneously labeled data would add noise to the classifier, which would result in decreased efficiency of the online system. Moreover, the samples obtained from the online process need to be saved in memory, requiring additional computational resources.The online training strategy presented in this paper was designed to reduce the time needed for calibration and computational resources. Eleven subjects used the generic model to test its online generalizability across participants. In the online training process, participants completed a copy-spelling task which provided correct labels for each selection, since target identity was predetermined. Furthermore, the online model was trained by one sample each time (Kuncheva and Plumpton, 2008; Vidaurre et al., 2011) eliminating the need to save previous samples in memory.

2. Methods

2.1. Participants

Eleven healthy participants (10 male and 1 female, aged 24–35, mean 29) participated in the study. Subjects nationalities and ages are presented in Table 1. All subjects were familiar with the Western characters used in the display. Subjects 1, 4, 5, 11 have experience on P300 BCI. Subjects 2, 3, 6, 7, 8, 9, 10 are naïve for BCI.The target stimuli constituted alphabetic characters which changed to a famous face (familiar to all participants). Kaufmann et al. (2011) reported that presenting images of famous faces could evoke the N400 response, improving the classification accuracy of ERP-based BCIs.Calibration modelsFive calibration models were tested to determine the optimal training method:

1. *Typical calibration*: For each participant a model was derived from three runs, each containing five characters; online training was not utilized. This condition was the gold standard used to compare performance of the other conditions. Offline calibration time was 720 s.
2. *Single run*: This model included one run containing five characters per participant; online training was not utilized. This condition tests whether a single run is sufficient to operate the system. Offline calibration time was 240 s.
3. *Generic model*: A model derived from ten participant's data (not enrolled in the current study) was used during online training. This model was used in place of models derived from each participant's data. Calibration time was 0 s (no online training and offline calibration time).
4. *Online training single run*: This condition derived a model from one offline run of data collected from each participant and tests whether one run and the online training strategy can reduce the number of offline runs. Average calibration time was offline calibration time + average online training time: 240 s + 125.1 s = 365.1 s.
5. *Online generic model*: The generic model was used in conjunction with the online training strategy. This model tests whether multiple participants' data can work as well as unique data when the online training strategy is also used. Average online training time was 108.3 s.

2.3. Stimuli and procedure

Participants sat approximately 105 cm in front of a monitor 30 cm tall (visual angle: 16.3 degrees) and 48 cm wide (visual angle: 25.7 degrees). During data acquisition, researchers instructed participants to relax and avoid unnecessary movement. The display portrays a 6×6 matrix comprised of gray English letters and symbols against a black background (see Fig. 1). During a stimulus event, target characters are replaced momentarily with face images, described as flashing.

Instead of grouping the flashed characters into rows and columns, we developed an alternative flash pattern approach (described in Jin et al., 2012).

2.4. Experiment set up and offline and online protocols

EEG signals were recorded with a g.USBamp and a g.EEGcap (Guger Technologies, Graz, Austria) with a sensitivity of 100 μV, band pass filtered between 0.1 Hz and 30 Hz, and sampled at 256 Hz. We recorded from EEG electrode positions F3, Fz, F4, Cz, Pz, Oz, P3, P4, P7, P8, O1, and O2 from the extended International 10–20 system. EEG was referenced at the right mastoid and grounded at the front electrode (FPz). Based on the report of Curran and Hancock (2007) electrode locations F3 and F4 were monitored to examine the N400.

A sub-trial is defined as one flash of one of a twelve flash pattern. A trial is complete when all 12 flashes have been presented. A trial block consists of 16 complete trials for offline testing, and target characters are uniform across trials. An offline run consists of five trial blocks. In each paradigm, participants complete three offline runs. Participants are given a 5 min break between each paradigm in the offline experiment. During online testing, the number of trials per trial block is variable, because the system adjusts the number of trials to optimize performance (see Section 2.8).

The study tested five classification conditions. The two offline methods were performed during session 1 (i.e., *typical calibration and single run*). During session 2 the participants completed the following three conditions: *generic model*, *online training single run*, and *online generic model*.

For conditions 1, 2 and 4, offline date recorded in this study was used to train the classifier. For conditions 3 and 5, generic model was used without using the offline date recorded in this study. In conditions 1, 2 and 3, participants spelt 20 characters in each session in online experiment. Online training was not used in conditions 1, 2 and 3. In conditions 4 and 5, online training was used. Participants spelt five characters (A, B, C, D, and E; see Fig. 1) to train the classifier online. In the online training stage, the adaptive strategy (see Section 2.6) was used after five trials had been presented to provide a more stable data sample for classifier training. After subjects finished spelling five characters, if the spelling accuracy was higher than or equal to 80%, the online training stage would end. Then, participants spelt another 20 characters using a single trial of flashes. If the spelling accuracy was lower than 80%, participants would be asked to repeat the task, until their error rate decreased to 20%, or until online training exceeded 10 min. If online training exceeded 10 min, the task would be stopped and no online result would be obtained. Eighty percent spelling accuracy was selected to ensure that participants could feasibly use this speller system. If the online training duration was longer than 10 min, the experiment was stopped. In this case, it was assumed that the participant