A Head-Up Display-Based P300 Brain - Computer Interface for Destination Selection

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Introduction

- Brain–computer interfaces (BCIs) can translate user brain activity patterns into corresponding commands to communicate with or control the external world without using conventional communication channels.
- The brain signals widely used to develop EEG-based BCIs include:

➢ 1) P300 potentials, which are a positive potential deflection on the ongoing brain activity signal at latency of roughly 300 ms after the random occurrence of a desired target stimulus from nontarget stimuli

➢ 2) steady-state visual evoked potentials (SSVEPs), which are visually evoked by a stimulus modulated at a fixed frequency and occur as an increase in EEG activities at the stimulus frequency; and

➢ 3) the event-related desynchronizations (ERDs) and event-related synchronization (ERS), which are induced by performing mental tasks such as motor imagery, mental arithmetic, or mental rotation.

Introduction

- Since P300-based BCI systems are more suitable to output more commands compared with SSVEP-based and ERD/ERS-based BCI systems and have a relatively high level of accuracy, P300-based BCIs are currently used for destination selections.
- The preliminary experimental results provide an indication of the feasibility of using EEG to drive a vehicle.
- However, they did not describe the specific speed of the controlled simulated car and the specific accuracy.

Introduction

- Their long-term goal is to develop a brain-controlled vehicle by using BCI systems to select a destination and issue a control command.
- In this paper, they proposed a new P300 BCI with visual stimuli presented on a windshield via a head-up display (HUD) and develop a destination selection system for a simulated vehicle using the proposed BCI.
- Furthermore, to improve the usability of this destination selection system, they analyze the effects of the number of rounds of EEG on the performance of the proposed system.
- This paper lays a foundation for developing a brain-controlled vehicle that uses a BCI to select a desired destination from a list of predefined destinations and then uses an autonomous navigation system to reach the desired destination.

Head-up Display

- A HUD is any transparent display that presents data without requiring users to look away from their usual viewpoints.
- HUDs were initially developed for military aviation, they are now used in commercial aircraft, automobiles, and other applications.

Hud-Based P300 BCI for destination selection

A. Visual Stimuli

- The P300 visual stimuli used in this paper are a 3*3 matrix of characters, which are displayed on a real windshield (whose top, bottom, left, and right edges are 102, 138, 59, and 59 cm) of vehicles via a HUD system constructed by ourselves.

- Each character represents a predefined destination.

  “B” -> “Bank”, “H” -> “Hospital.”

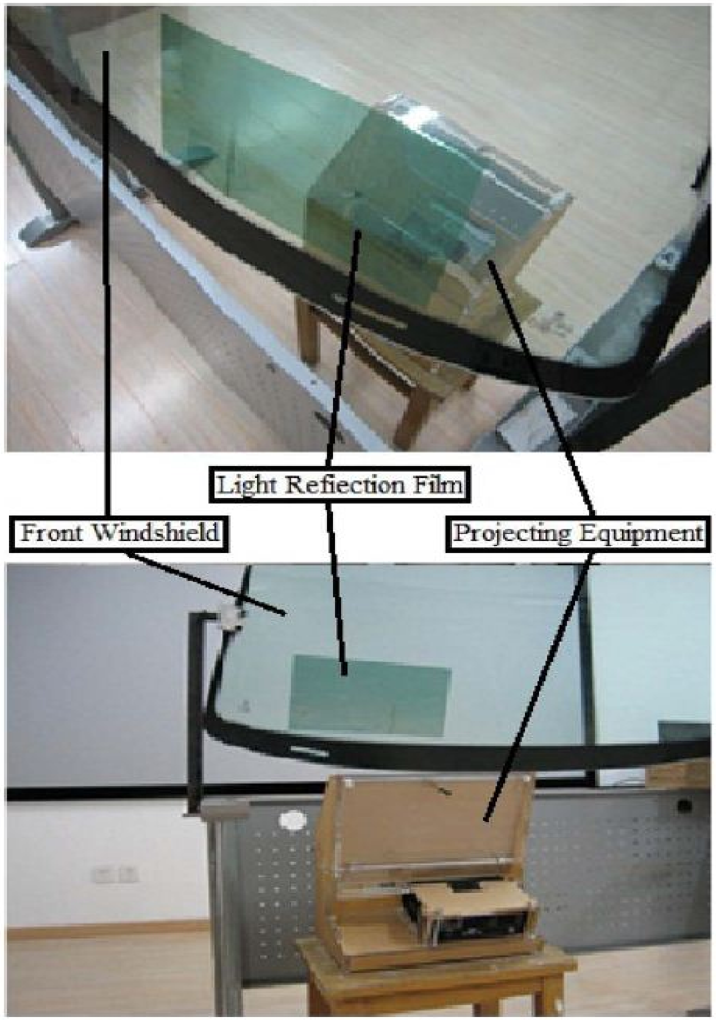


Fig. 1. HUD system.

Hud-Based P300 BCI for destination selection

A. Visual Stimuli

- The HUD system consists of a projecting device and some light reflection films (17.5 cm * 13 cm in size) pasted on the bottom-left area of the windshield.
- All of the nine characters flash on the windshield in sequence and in random order in each round.
- Each flash lasts 125 ms with an interstimulus interval of 15 ms, and thus, each round takes 1260 ms ((125 + 15) * 9).
- When the user wants to reach a destination, he focuses attention on the character associated with the destination, and the BCI interprets the EEG to infer the character to which the user is attending.

Hud-Based P300 BCI for destination selection

B. Data Collection

- They used a 16-channel amplifier to acquire the EEG signals at eight standard locations (i.e., Fz, Cz, Pz, Oz, P3, P4, P7, and P8), as shown in Fig. 2.
- The reference potential was the average of the potentials of the left and right earlobes.
- The EEG signals were amplified and digitalized with a sampling rate of 1000 Hz and a power-line notch filter to remove the line noise.

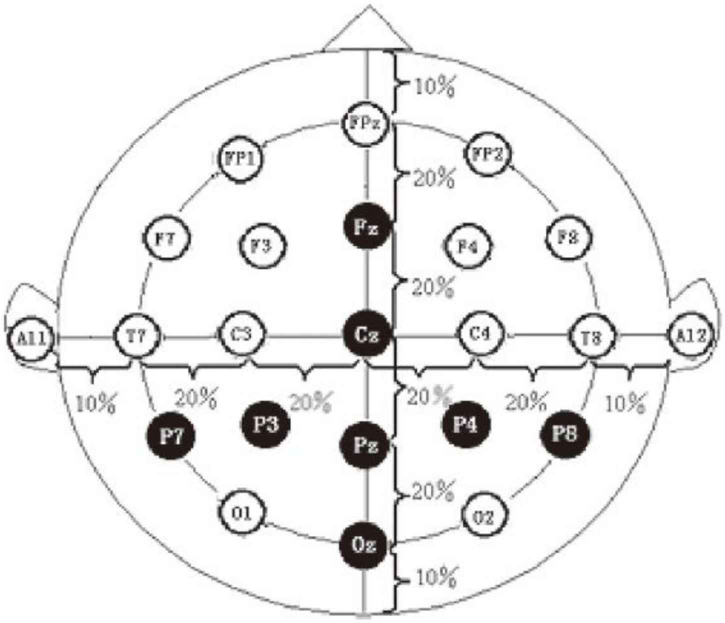


Fig. 2. Placements of eight channels used to collect EEG data are marked in black.

Hud-Based P300 BCI for destination selection

C. Signal Processing and Classification

- The collected EEG data are first decimated by a factor of 2 and filtered with a bandpass filter between 0.53 and 15 Hz.
- To improve the signal-to-noise ratio, *M* rounds of EEG data are summed. (M is number)
- To reduce the feature dimensionality in order to lower the redundancy of the features, the principal component analysis (PCA) is used, which transforms the feature space into an orthogonal space consisting of uncorrelated variables called principal components, and selects components with the highest eigenvalues as new features.

Hud-Based P300 BCI for destination selection

C. Signal Processing and Classification

- The input to the classifier of P300 is a vector of *N* dimensions, as follows:

$$x = [x(1), x(2), \ldots, x(N)]$$

- where *x*(*N*) is the *N*th new feature of each sample selected from the original features by using PCA.

- Linear discriminant analysis (LDA) was first used to develop the classifier, which can be represented in the following form

$$y = w^T x$$

- where *w* is the projection direction determined by maximizing the following cost function.

$$J_F(w) = \frac{w^T S_b w}{w^T S_w w}$$

- where S_b is the between-class scatter matrix, and S_w is the within-class scatter matrix.

Experiment

A. Experimental Platform

- A simulated vehicle has been designed and constructed. It includes three main parts, as shown in Fig. 3.
- 1) the HUD-based P300 BCI system for destination selection.
- 2) the 3-D driving scene and simulated vehicle based on the virtual reality technology.
- 3) the communication system between the computer supporting the 3-D driving scene and virtual vehicle.

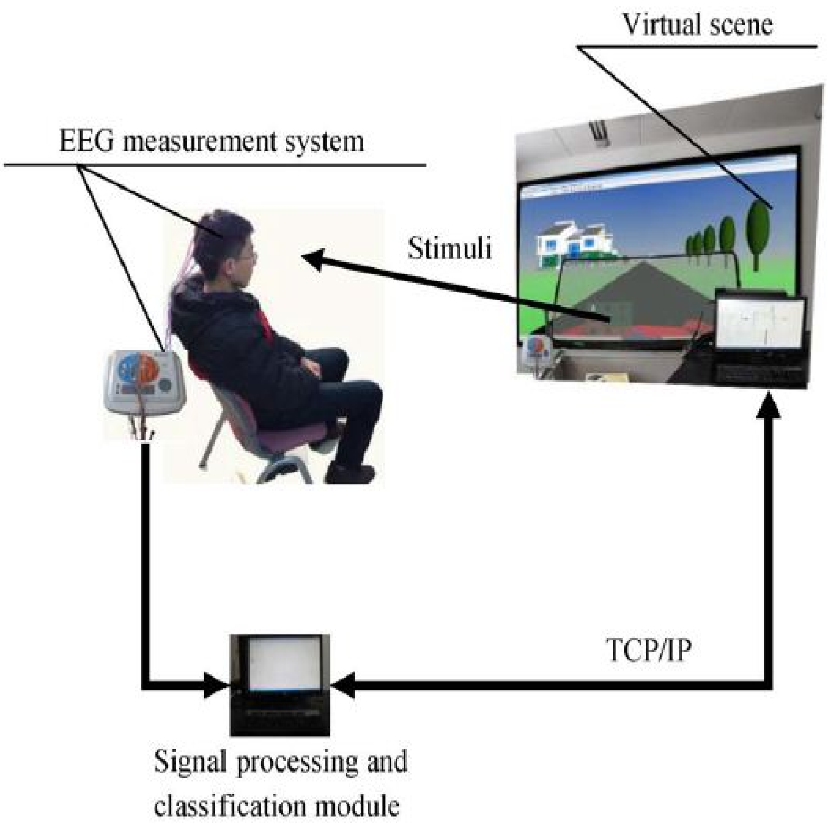


Fig. 3. Block diagram of the brain-controlled virtual vehicle.

Experiment

B. Experimental Procedures

- The experimental procedure includes two phases.
- The first is for training the HUD-based P300 BCI model for destination selection, and the second one is for evaluating and testing the destination selection system.
- In the phase of training the destination selection model, each participant completed four sessions of the P300 experiment in order to collect the data and train the model offline.
- In the second phase, they investigated the effects of the number of EEG rounds on the performance of the proposed system and demonstrated the simulated vehicles based on the destination selection system using a static and a dynamic experiment.

Result

- They used the 108 training samples collected in the experimental procedure to determine the parameters of the model of each subject, and 50 features selected by PCA are used for each model.
- In practice, first, it is desirable for the destination selection system to have high accuracy and short selection time.
- They investigated the destination selection accuracy as a function of the number of rounds when this system is used online.
- Second, given the required accuracy and selection time, it is desirable to reduce the time needed to build the corresponding model.
- They analyzed the selection accuracy as a function of the number of rounds used in building the model of each subject given the required selection time.

Result

A. Destination Selection Accuracy

- Fig. 4 shows the accuracy of the HUD-based BCI system used to select a destination as a function of the number of rounds of EEG used online by the model of the selection system.
- In this figure, the *x*-axis represents the number of rounds whereas the *y*-axis represents the accuracy gained if the BCI system selects a destination using only as many rounds as the *x*-axis.

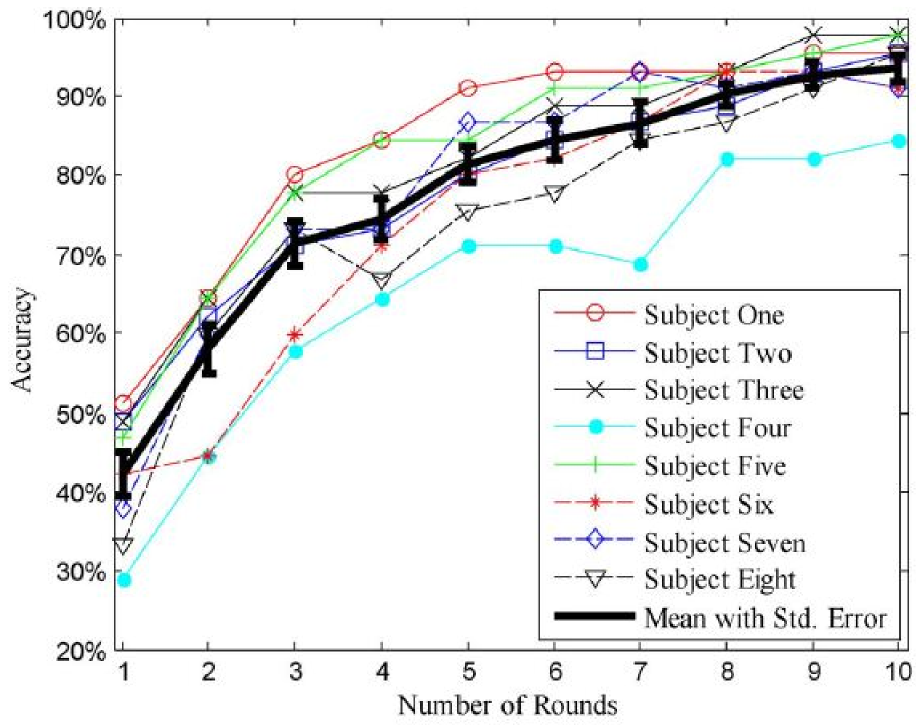


Fig. 4. Accuracy of the models as a function of the number of rounds of EEG data in testing.

Result

B. Reducing the Time Needed to Build a Model

- Given the desired accuracy and selection time to explore whether they can reduce the time needed to build the models, they analyzed the accuracy as a function of the number of rounds used in building the model of each subject.
- Fig. 5 shows the accuracy of the models as a function of the number of rounds used to build models by using ten rounds of EEG data to test each model.

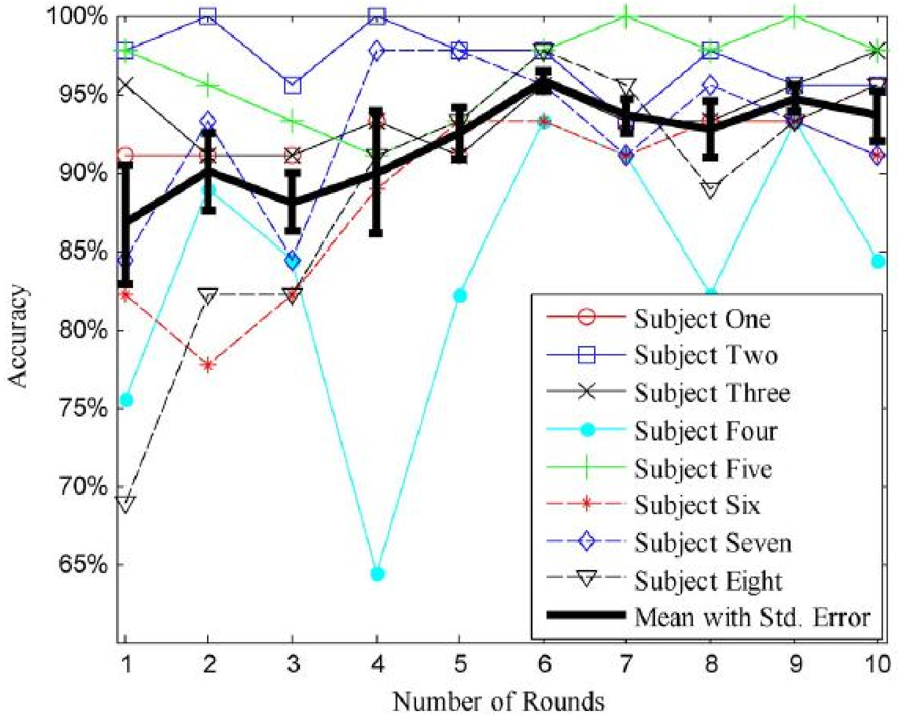


Fig. 5. Model accuracy as a function of the number of rounds of EEG data used in training the models.

Discussion and Conclusion

- First, although the accuracy is 93.6%, this accuracy may not be high enough for some applications.
- Second, the number of predefined destinations of the current system is small.
- Third, the users lose their control of the vehicle after the BCI-based destination selection system sends a destination to the autonomous vehicle.
- Fourth, they conducted the experiment in a laboratory, where the environmental factors were constant. However, in practice, vehicles are used outdoors.
- Their future work focuses on addressing the issues listed above and developing brain-controlled vehicles by combining the HUD-based BCI with other BCIs for issuing motion commands.
- The current and future research in this area will help further improve the mobility, independence, and quality of life for people with disabilities, as well as the general public.

Thank you!

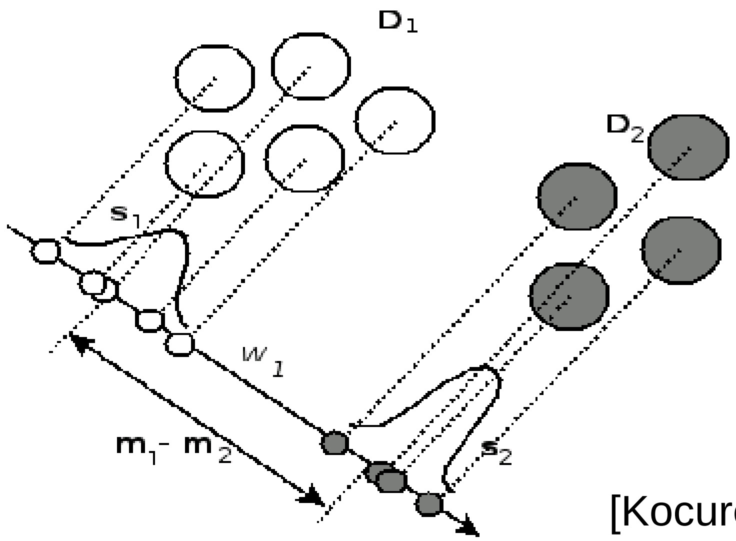
Linear discriminant analysis (LDA)

- The LDA (also known as Fisher's LDA) approach aims to find the optimal direction, $\mathbf{w_1}$, to project data upon and maximize the Fisher ratio:

$$J(\mathbf{w}_1) = \frac{\mathbf{w}_1^T \mathbf{S_B} \mathbf{w}_1}{\mathbf{w}_1^T \mathbf{S_w} \mathbf{w}_1} \qquad \text{where, } \mathbf{S_B} = (\mathbf{m}_1 - \mathbf{m}_2)(\mathbf{m}_1 - \mathbf{m}_2)^T$$

$$\mathbf{S_w} = \sum_i (\mathbf{x} - \mathbf{m}_i)(\mathbf{x} - \mathbf{m}_i)^T$$

- The maximization of mean distances and minimization of class scatters.



[Kocurek 2007]

Principal Component Analysis

- Eigen Vectors show the direction of axes of a fitted ellipsoid.
- Eigen Values show the significance of the corresponding axis.
- The larger the Eigen value, the more separation between mapped data.
- For high dimensional data, only few of Eigen values are significant.