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A Competitive Brain Computer Interface: Multi-person Car Racing System

Junhua Li, Ye Liu, Zhen Lu, and Liqing Zhang

Abstract—**Brain computer interface (BCI) technique is successfully utilized to bridge the interruption between brain and peripheral nerves and muscles, and to establish a new pathway making brain directly output information (or command). Up to now, a majority of BCI systems are developed to restore communication ability or movement functionality for people with severe disabilities, especially for paralyzed patients. To our best knowledge, other researchers haven't developed a multi-person BCI with competitive mode. Therefore, in this paper, we introduced a multi-person car racing system, which allows more than one person to play game at the same time and they can compete with each other for the aim of first reaching destination. The reason of development of car racing system has two aspects. At one hand, we introduced BCI to entertainment industry and provided a prototype for entertainment. At the other hand, we proposed a competitive mode for BCI. According to practical evaluation, the results demonstrated that our proposed system achieved a good performance.**

I. INTRODUCTION

By the past decades of years, brain computer interface technique has been advanced significantly. More and more researchers coming from different disciplines engaged in BCI research and contributed their efforts. Up to now, a lot of BCI systems have been developed for a variety of application purposes. For example, researchers at Graz university of technology have developed an EEG-based neuro-prosthesis by which a patient was able to grasp a simple object, and then release it after moving it from one place to another place [1], and a system integrated with functional electrical stimulation (FES) by which a tetraplegic patient could grasp a cylinder with the paralyzed hand through the control of beta oscillation signal [2]. Their laboratory also built a BCI system walking in virtual environments, such as virtual national library [3] and virtual scene [4]. The former allows user to explore in a virtual national library, and the latter lets user ramble in a typical virtual outdoor environment with tree and hedge. In addition, McFarland D. J. and his colleagues have established a cursor system, which is controlled by mu (8-12 Hz) rhythm using electrodes placed on the scalp [5]. It finished to move a cursor from the center to one of potential targets located at the top and bottom edges, respectively. In 2010, they complicated the cursor system and extended two-dimensional control to three-dimensional control [6]. Each dimension (i.e. vertical, horizontal, depth) movement is controlled by independent signal. User needs to modulate brain activities simultaneously for three-dimensional control. Moreover, they designed a typing system based on P300 signal, which appears when an occasional stimulus occurs in a series of stimuli (named oddball paradigm). This system is incorporated into the famous BCI 2000, which includes signal-processing methods, operating protocols and so forth [7]. Additionally, the BBCI group achieved motor imagery based typing system, called "Hex-o-Spell" [8]. All symbols (26 English letters plus punctuation marks) are divided into a set of small groups. User selects a symbol expected to output through hierarchical selection till an impartible unit. The BCMI laboratory designed an assistive wheelchair system, which is directly steered by thoughts [9]. Shangkai Gao and her research team developed dialing system using steady state visual evoked potential (SSVEP), with which user can select desired number by focusing on that number on the flickering panel.

All systems mentioned above are developed as a tool, which could help paralyzed or severely disabled people restore the abilities of communication with external world or augment their remained motor function to better control of their limbs. We should pay attention to entertainment requirement of those people except enhancing their independence of living. Besides, those systems are used for one user and lack of motivation from opponent. In order to compensate the absence of such BCI system, we developed a multi-person car racing system, by which more than one person may play the game at the same time and they may compete with each other to first reach the destination. Our system is not only for patients, but also for healthy people. It provided a recreational BCI prototype, which has a positive effect on entertainment industry. And our developed system shows a new BCI paradigm with competitive mode, which allows users to make a competition.

II. SYSTEM FRAMEWORK

A. Instruments Connection

In multi-person car racing system, a g.USBamp amplifier (Guger Technologies, Austria), two EEG caps with some electrodes, a desktop computer with 22-inch screen compose the hardware configuration. Fig. 1 illustrated connection relationship between them. There are totally four groups of input ports in an amplifier. We grouped two groups of input ports together to form a big group for one player. As shown in Fig. 1, ground ports and reference ports in a big group are, respectively, connected as one ground and one reference. Ground electrode is set on the medial frontal cortex, and reference electrodes are placed on bilateral earlobes. EEG signals are recorded from sensorimotor cortex. Real-time

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J. Li, Y. Liu, Z. Lu and L. Zhang are with MOE-Microsoft Key Laboratory for Intelligent Computing and Intelligent Systems, Department of Computer Science and Engineering, Shanghai Jiao Tong University, Shanghai, 200240, China (phone: +86-021-34204423; fax: +86-021-34204423; e-mail: juhalee@sjtu.edu.cn, zhang-lq@cs.sjtu.edu.cn)

recorded EEG signal is transmitted to desktop computer by a USB cable. BCI model analyzes the received EEG signal and makes a classification, which is as input signal for application program interface (API). API, here, serves as a mapping that classification output coming from BCI model is translated into a control command used to control corresponding virtual car in the game (Game is modified from MultiRacer originally developed by Franticware to suit our application requirement). Computer displayer shows feedback of car status in real-time.

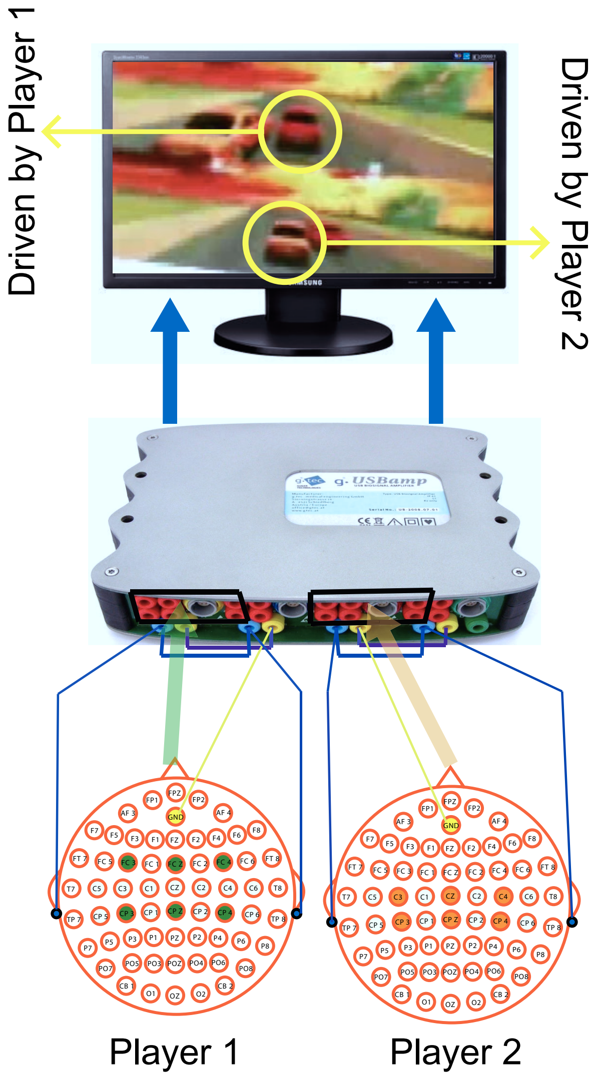

Figure 1. Hardware connection relationship. Electrodes on the sensorimotor cortex are used for recording EEG signals, grounded at electrode on the medial frontal cortex and referenced at electrodes on the bilateral earlobes. Two small groups are grouped together to form a big group of input ports for a player. Classification of EEG signal is translated into control command for driving virtual car and computer displayer shows feedback of car status in real-time.

B. *Control Manner*

Different motor imageries are adopted to elicit different expression in brain activities. It caused spectral power difference, especially in subband of alpha. Left, right arm motor imageries and feet motor imagery are chosen to control car making left turning, right turning, and going forward, respectively. For the turning commands, a forward force component is added to keep car move forward. We required participants to imagine arm movements due to that the performance of arm imagination is good for the most of people according to our previous experience [10]. Additionally, motor imagery has an advantage of self-paced modulation. This point is important for development of recreational BCI, and is necessary for good user experience.

C. *Parameter Settings of Online Testing*

All parameters used for practical online testing are listed in the table 1. The length of EEG segment used for feature extraction is 1000 ms (sliding window width). The window slid forward every 125 ms. Classifier outputted a classified result after each sliding. After one second, all probabilistic outputs within this one-second are averaged to generate final probabilistic values for each class of motor imagery. The class with highest probabilistic value is considered as control command. Whether this command is outputted depends on its probabilistic value (outputting if the value exceeds predefined threshold).

TABLE I. PARAMETER SETTINGS FOR PRACTICAL ONLINE TESTING. L, R, AND F STAND FOR LEFT, RIGHT, AND FEET MOTOR IMAGERIES, RESPECTIVELY.

Parameter	Configuration
Sampling Rate	256 Hz
Filtering Band	8-30Hz
Recording Electrodes	Player 1: FC3, FCz, FC4, CP3, CPz, CP4
	Player 2: C3, Cz, C4, CP3, CPz, CP4
Threshold for Noise Detection	100 μV
Feature Extraction	CSP+Band Power
Classifier	Linear SVM
Sliding Forward Step	125 ms
Sliding Window Width	1000 ms
Command outputted Rate	1000 ms
Period Used for Voting	1000 ms
Voting Strategy	Averaged
Thresholds for outputting Command	Player 1: L=0.9 R=0.9 F=0.85
	Player 2: L=0.85 R=0.9 F=0.8

III. NEURAL MECHANISM

Different motor imageries cause changes of oscillation spreading across the whole scalp. For instance, left motor imagery leads to a desynchronized phenomenon on sensorimotor cortex of contralateral hemisphere. Fig. 2 shows spectral power of three typical channels located on sensorimotor cortex. Spectral power drawn in Fig. 2 is obtained by averaging powers between 8 Hz and 12 Hz (alpha band), which is considered as the most important band relevant to motor imagery. From the Fig. 2, we can see that spectral power of left motor imagery is higher than that of right motor imagery at the channel CP3 across time. Spectral power is adverse at the channel CP4.

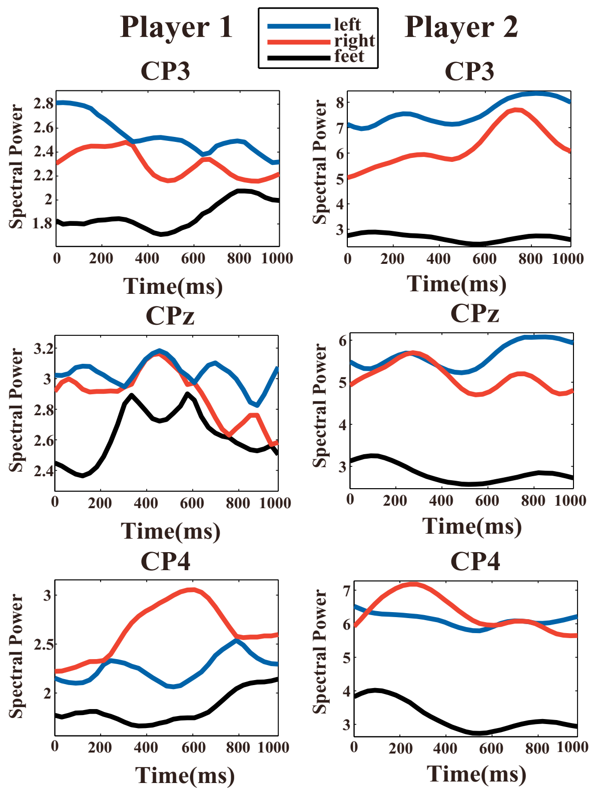

Figure 2. Spectral power at electrodes CP3, CPz, and CP4. Blue, red, black lines, respectively, represent left, right, and feet motor imageries.

IV. METHOD

Mixed EEG signals simultaneously recorded from two players were first separated according to channel labels. The first six channels were for player 1 and channels from the ninth to the fourteenth were for player 2. And then, this EEG segment was preprocessed. In our system, preprocessing procedure is very simple, only including bandpass filtering (8-30 Hz) and noise detection. Noise, such as EMG, EOG, is detected by checking if averaged amplitude of signal exceeds threshold. The reason why preprocessing is so simple is to ensure good instantaneity of system. In the step of feature extraction, we employed common spatial pattern (CSP) [11] to extract the most discriminative spatio-temporal features, and combined features of spectral power of subband to form final features [12]. Final features are fed to support vector machine (SVM) [13] for classification.

CSP is proposed for processing problem of two classes. In the case of three classes, we utilized a manner of one versus the rest. Namely, other two classes are treated as the same class when one class is chosen. In this way, we employed three CSP extractors to transform three-class problem to three two-class problems. The sum of spatial covariance of two populations of EEG is written as followings:

$$C_{Sum} = \frac{1}{n_X}\sum_{i=1}^{n_X}\frac{E_{X_i} * E_{X_i}^{'}}{trace(E_{X_i} * E_{X_i}^{'})} + \frac{1}{n_{Rest}}\sum_{j=1}^{n_{Rest}}\frac{E_{Rest_j} * E_{Rest_j}^{'}}{trace(E_{Rest_j} * E_{Rest_j}^{'})}. \quad (1)$$

Where E_X and E_{Rest} represent segments of chosen class and all other segments of the rest classes except chosen class, respectively. n_X and n_{Rest} are respectively the number of segments of chosen class and the number of segments of the rest classes. After whitening transformation, C_{Sum} can be rewritten as

$$\begin{aligned} C_{Sum\_whitened} &= F\ I\ F^{'} \\ &= F\,(\lambda_X + \lambda_{Rest})\,F^{'}. \end{aligned} \quad (2)$$

From Eq. (2), we can see that one class has a large eigenvalue in λ_X while the rest classes have a small eigenvalue in λ_{Rest} due to the sum of their eigenvalues is always equal to one. Therefore, $2m$ eigenvectors coming from the m largest and m smallest eigenvalues span a projection space which will be maximal for EEG population of one class and minimal for EEG population of the rest classes at the same time. According to this principle, three extractors, respectively assigned to each class of motor imagery, were generated. And then, we respectively combined features derived from three CSP extractors with band power features to form three sets of new features, which were respectively used for training corresponding SVM classifier. During real-time classification, an EEG segment (one second width, updated every 125 ms) was extracted to obtain features by three CSP extractors. Subsequently, SVM classifier was used to recognize features coming from corresponding CSP extractor. Three SVM classifiers output probabilities for each class of motor imagery. In order to let the sum of probabilities of all classes be as one, we normalized outputted probabilities and got the final classification label for which there was the highest probability.

V. PERFORMANCE EVALUATION

A. Participants

There are two students (both male) recruited from Shanghai Jiao Tong University attending evaluation of car racing system. As they claimed, they haven't had any neurological or psychiatric disease, and are right handed. Their ages are both 22. They gave their informed consent for attending system evaluation after understanding each step they should engage in the evaluation.

B. Evaluation Surroundings

Evaluation of car racing system was conducted in a 32-square meters room. Subjects were seated in chairs with a posture making themselves comfortable. A 22-inch computer displayer was placed in front of them.

C. Evaluation Procedure

Whole evaluation was divided into two phases: cue-based accuracy evaluation and practical evaluation. Both of phases are conducted in the manner of online. There was a phase of driving practice between accuracy evaluation and practical evaluation, which took five minutes for each participant. Before accuracy evaluation, there was a training phase, during which participants learnt to modulate their brain activities to finish as high accuracy as possible. This training phase spent half an hour. Subsequently, an accuracy evaluation was followed to quantify performance. The protocol used in accuracy evaluation is the same as training

TABLE II. THE RESULTS OF ACCURACY EVALUATION.

Participants	Session Sequence	Sliding Time Window Accuracy	Trial Accuracy
Player 1	1	74.72	80
	2	87.78	100
Player 2	1	88.33	100
	2	78.48	94
Mean		82.33	93.5

phase. At the beginning of each trial, a cue indicated what motor imagery should be imagined in this trial is presented at the center of screen. During the period of imagination, continuous increasing-bar feedback is given to guide participant to modulate better [14]. The interval between trials is two seconds, and fifteen trials compose a session. A trial is four seconds long and divided into 25 sliding time windows through a window with width of 1000 ms slides forward every 125 ms. At accuracy evaluation phase, two sessions for each participant were finished. The results of accuracy evaluation are listed in table 2. Player 1 finished accuracies of 74.72% and 87.78% for sliding time windows and 80% and 100% for trials in the first and second sessions, respectively. Player 2 finished slightly better accuracies than that of player 1. On average, the accuracy of sliding time windows is 82.33% while the accuracy of trials is 93.5%.

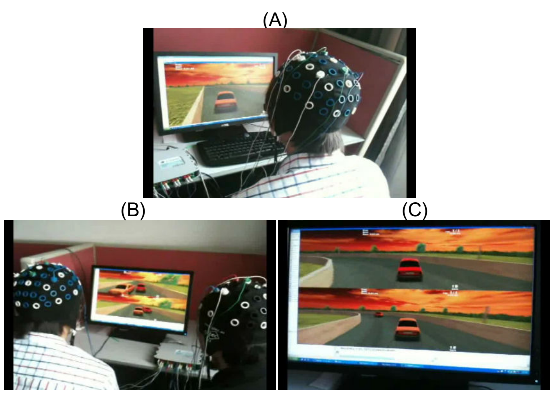

Figure 3. (A): A scene of driving practice for single person (B) Two players respectively controlled crresponding cars by three different motor imageries, and competed with each other. (C) A picture closely shows game environment.

A phase of driving practice was followed after accuracy phase. Fig. 3 (A) shows a scene, in which a player practiced in single person mode for enhancing skill of EEG-based driving. Fig. 3 (B) and (C) show that two players simultaneously paly the game and respectively control corresponding virtual car at the same time by motor imagery. This practical evaluation demonstrated that our multi-person car racing system realized that more than one person simultaneously control corresponding cars by EEG signals, and achieved a good performance. The complete video of practical evaluation can be found at http://bcmi.sjtu.edu.cn/eegbicar.html.

VI. CONCLUSION

This paper introduced a multi-person car racing system, which allows more than one person simultaneously to play the same game by EEG signals, and players may compete with each other. The target users of the proposed system are not only patients, but also healthy people. This is an attempt of extending BCI technique to the field of application of healthy people. In addition, a new paradigm, namely competitive BCI, is contained in the system. This paradigm might be transferred to other BCI applications which require a motivation. For example, competitive paradigm used for BCI model training would highly motivate participants to engage in training better. Training effect might be improved by integrating this competitive paradigm.

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