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A mental switch-based asynchronous brain-computer interface for 2D cursor control

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Abstract— **In the present study, we developed a mental switch-based asynchronous brain-computer interface for 2D cursor control. Two mental switches were designed: one was to switch from non-intentional to intentional control state, and the other one for conducting the reverse process. 2D control and mental switches are all based on three-class motor imagery. With four subjects participating in the study, the experimental results demonstrated the efficiency of the proposed asynchronous 2D control strategy.**

I. Introduction

Brain-computer interface (BCI), as an assistive technology, can help patients suffering from cortical or spinal injuries. BCI enables them to communicate with the external environment through translating their brain activity to commands [1], without using the normal pathways of peripheral nerves and muscles.

Based on the signal acquisition method, BCIs fall into two main categories: invasive BCIs and non-invasive BCIs. In invasive BCIs, micro-electrodes are planted into the user's cortex to record signals with high signal-to-noise ratio (SNR), which then accurately translated into commands. However, it can increase the risk of brain infection [2]. In non-invasive BCIs, electroencephalogram (EEG)-based BCIs are widely used as they are easily recorded from the surface of scalp [3]. Depending on the operation protocol, BCIs can be used in synchronous and asynchronous modes. In the synchronous mode, the subject controls the BCI following a visual cue provided by the system [4]. However, the synchronous BCI is not convenient for communicating with other devices or external environment, since it strictly follows the cue. On the contrary, the asynchronous (self-paced) mode is a natural course of interaction that generates commands following the user's intent [5, 6].

The significance of asynchronous BCI system is that the user can make self-paced decisions to switch between non-intentional control (NC) and intentional control (IC) states. Since in asynchronous mode, the system can continuously detect the state of the intention. One main challenge of the asynchronous BCIs is the high false positive rate during the NC state, which is always frustrating for the user. To reduce the false positive rate, mental task based switch, which needs to be stable and easy to control, was applied to transform the system from NC to IC. As reported by Mason et al., a low-frequency asynchronous signal detector switch based on the 1-4 Hz feature set can differentiate the attentive idle from real movement-related EEG. However, it was only verified through real movement, and not by motor imagery (MI) [7]. Subsequently, the low-frequency asynchronous brain switch was improved and shown to be applicable to motor imagery and attempted movement. It was reported that spinal-injured subjects could operate it as well as able-bodied ones [8, 9]. Muller et al. developed an event related synchronization (ERS) detection based brain switch, which monitored the ERS of the foot motor imagery (MI) in Cz electrode. The true positive rate and the positive predictive value were 79% and 84% respectively [10]. Hasan et al. used an onset detection method to classify the recorded EEG into real movement and idle state; however, the average of true-false difference was only 88% for the onset detection of the real movement [11]. Qian et al. developed a brain switch by detecting the event related desynchronization (ERD) of MI of finger repetitive pinching, which took a long time to activate the switch [12]. Kato et al. also introduced a BCI switch based on the contingent negative variation related potentials between warning and imperative stimuli to startup or shutdown BCIs. This visual stimulus may increase the users' workload and consequently lead to eye fatigue [13]. Majority of the previously mentioned studies validated the feasibility and effectiveness of the proposed switch strategies without applying them to real applications. In Robert et al. study, a switch based asynchronous BCI, which detects band power of EEG to shift between IC and NC states, was introduced [14]. In that system, the subject carries out limited operations to navigate in the virtual environment.

In order to implement an asynchronous BCI system, asynchronous protocol and application need to be considered simultaneously. Multi-dimensional control as in brain-actuated wheelchair or cursor control has drawn considerable attention in the field of BCI research. However, in real applications, self-paced 2D control has gained more interest. Millan et al. presented an asynchronous brain-actuated mobile robot system by combining three-class MI with an intelligent robot, which achieves 74% performance of manual control. [15]. Zhao et al. introduced a threshold-based asynchronous BCI system to classify current states as NC providing the classification accuracy to be lower than 90% [16]. This condition, however, was difficult to meet in most of the subjects. Scherer et al. trained two specialized classifiers: classifier 1 to distinguish between IC and NC states, and classifier 2 to identify MI tasks [17]. Chae et al. employed the intentional activity classifier and the move direction

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classifier to identify a feature belonged to NC or a specific mental task [18].

To design a practical asynchronous 2D control system, we introduced a two-switch based asynchronous BCI. We applied one switch to transform from NC to IC, and the reverse state transformation is using different one. The switches and 2D cursor control are based on a three-class motor imagery BCI.

II. Method

A. Signal processing

In this work, three-class motor imagery (left hand, right hand, and feet) is applied to implement an asynchronous BCI for 2D cursor control. Different MI tasks have distinct spatial patterns. Common Spatial Pattern (CSP) is used to extract the EEG spatial features by maximizing the difference between tasks [19, 20]. To obtain control commands, a linear Support Vector Machine (SVM) classifier is applied to discriminate the three-class MI patterns. However, to design switches and 2D control paradigm, the predicted probabilities of SVM classifier are used as an alternative to the discrete classification results.

B. System strategy

1) ONSwitch: An ONSwitch, which based on a threshold of predict probability and time course (Fig. 1), was used to transform the system from NC state to IC state. The system initially remains in the NC state. To switch it on, the user conducts one of the three motor imagery tasks to make the corresponding probability exceed a threshold in the course of Δ t. The threshold value is inversely related to length of the time course. The ONSwitch is switched on faster if the user achieves a higher predict probability in a time course.

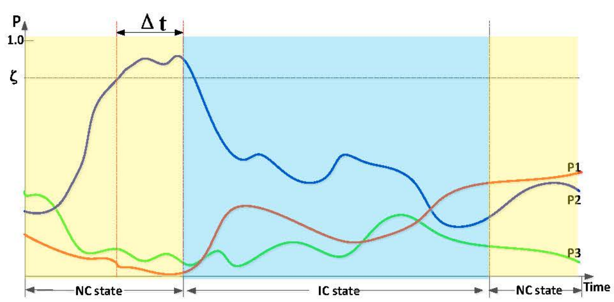

Figure 1. Illustration of ONSwitch strategy.

2) 2-D movement control strategy: We mapped the output probabilities (P_1, P_2, and P_3 are the probabilities of left hand, right hand, and feet respectively) of SVM classifier to three vectors with the angle interval of 120° (as shown in Fig. 2(a)). The norms of vectors are chosen based on the values of related output probability. To move the cursor to the upper right, the subject combines two related motor imagery tasks (left and right hand motor imagery) to generate initial velocity vector $\overrightarrow{V_0}$ with ignoring unrelated motor task (feet motor imagery), which indicates the smaller probability of it. When the cursor begins to move, its acceleration and direction can be controlled by the user. In order to turn right, the subject focuses on the right hand MI and ignores the others. The combinations of probabilities will be a new vector $\overrightarrow{V_{10}}$. To avoid changing velocity too fast, we use an attenuation factor α within the range of [0.1 1]. The current velocity vector $\overrightarrow{V_1}$ is synthesized by $\alpha * \overrightarrow{V_{10}}$ and original velocity vector $\overrightarrow{V_0}$ (As shown in Fig 2.b).

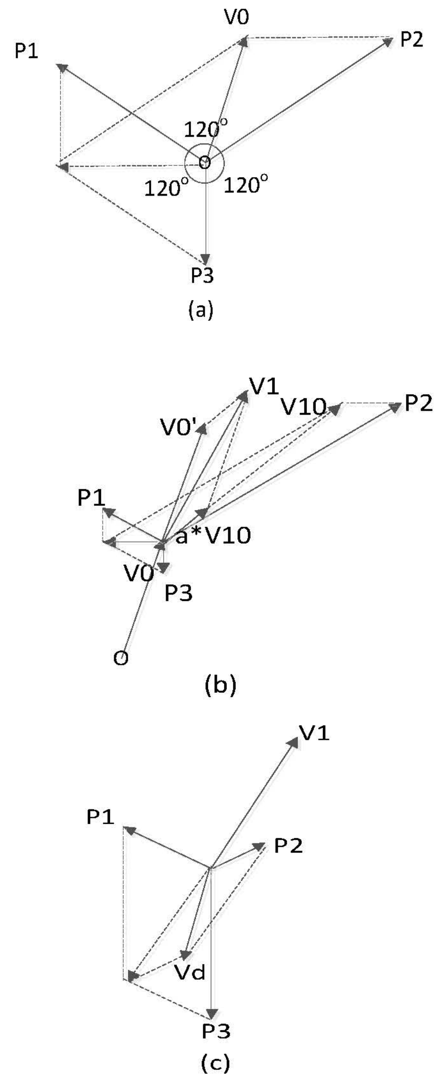

Figure 2. (a) Mapping of predicted probabilities to velocity vectors. (b) The process of synthetizing velocity vectors. (c) Illustration of

3) OFFSwitch: As a car approaching the destination, the driver needs to gradually slow down the car and finally stop it. In the same way, when the cursor is close to target, the subject should slow it down and eventually stop it. Combination of multi-tasks motor imagery is applied to synthesize a deceleration vector $\overrightarrow{V_d}$ to slow down the cursor (shown in Fig. 2(c)). When the speed of the cursor is lower than one pre-setup threshold (γ), the system is switched to NC state.

III. Experimental Setup

A. Subject

Four healthy subjects (all males) aged from 19 to 25 (average 21.5 ± 2.65) participated in this study. Two of these subjects had previous experience of MI and the other two subjects were naïve. All of the subjects were in good health, and they submitted their consent to be involved in the study. They received a payment for their participation.

B. EEG recording

Subjects sit in a comfortable chair at a distance of 80 centimeters from the computer screen. EEG signals were acquired by a 16-channel g.USBamp amplifier, and the recording electrodes were placed according to the international 10-20 system. 13 channels (FC3, FCZ, FC4, C5, C3, C1, CZ, C2, C4, C6, CP3, CPZ, and CP4) were used to record the EEG data, the ground and the reference electrodes were respectively placed on the FZ channel position and right earlobe. EEG signals were sampled at 256 Hz, and band-pass filtered between 5 and 30 Hz.

C. Online Experimental Paradigm

1) Three-class motor imagery training: All subjects attended a normal three-class MI BCI training program. Based on their experience, the number of training sessions was different for each of them. The training sessions would not stop until the classification accuracy of each motor imagery task was above a threshold (85%). Afterwards, the subject could proceed to the next experiment. After the normal motor imagery training, the subject would attend two additional runs during which the classifier model was trained to be applied in cursor control experiment.

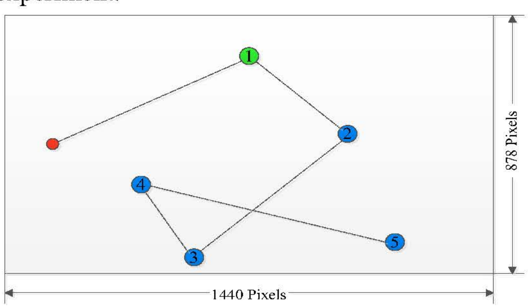

Figure 3. The sketch map of the experimental paradigm. Color of the target balls changes from blue to green in order of 1 to 5.

2) Asynchronous 2-D Cursor Control Online Experiment: To test the asynchronous protocol, a 5-target experimental paradigm was designed as shown in Fig. 3. The red ball indicates the initial position of the cursor, the other five circles are target positions. The ratio of the size of the cursor, the size of the target, and the size of the experimental workspace is 0.00064:0.0025:1. As previously mentioned, the ONSwitch is identified by the threshold of predicted probability and its time course Δt. Considering the unstable performance of the subject, three types of conditions were specified for the ONSwtich. They, on the order of complexity, include; (1) threshold 0.8 with 1.5s; (2) threshold 0.85 with 1.0s; and (3) threshold 0.9 with 0.5s. The constants α was set to be 0.2. In the OFFSwitch, the threshold γ was set to be 0.8 pixels. Initially, the position of the cursor is fixed. The first target changes from blue to green before the cursor begins to move. The subject opens the ONSwitch to move the cursor. While the cursor approaches the target, the subject tries to slow it down and gradually stops it by using the OFFSwitch. If the cursor is stopped, the trial ends and the current target's color changes from back to blue. If the subject cannot finish a trial in 60s, the trial is shut down, and the next target is changed to green. After hitting all the five targets, one run ends.

IV. RESULTS

Subject 1 and subject 4 completed 15 runs. Subject 2 and subject 3 only finished 13 and 12 runs respectively (As shown in TABLE I). The average hit rate is 94.1% within 100.8s. Subject 3 achieved the best performance with 100% hit rate and the average run time of 72.7s, while subject 2 achieved acceptable performance with 83% hit rate. All the missing targets indicate failure of stopping cursor.

TABLE I. CURSOR CONTROL PARADIGM PERFORMANCE.

Subject	NO		Hit Rate (%)	Average Move Time Of Finished Run (s)
	Run	Target		
S1	15	75	96.0	85.2
S2	13	65	83.1	134.3
S3	12	60	100.0	72.7
S4	15	75	97.3	110.0
Mean		68.75	94.1	100.8
SD		7.5	7.5	27.3

To evaluate the efficiency of the ONSwitch, we calculated the percentage of each type of the ONSwitch being used by each subject. As shown in Fig. 4, all the subjects mostly used type 3 to activate the ONSwitch, which means they can switch from NC to IC in 0.5s. Type 1 and type 2 of the ONSwitch were rarely used.

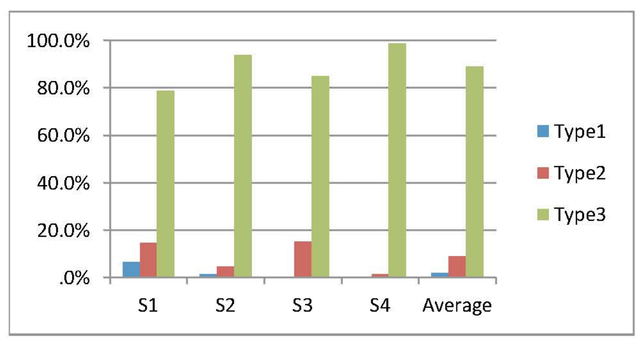

Figure 4. The statistics for ONSwitch styles

The performance of the OFFSwitch is shown in Fig. 5. The average time of activating the OFFSwitch is 7.5s. Subject 2 always needed longer time to stop the cursor. Subject 3, on the other hand, used an average of 3s to stop the cursor.

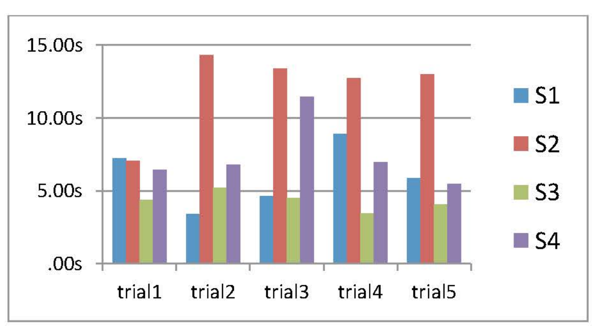

Figure 5. The average time to activate the OFFSwitch.

Specificity and sensitivity are commonly used to evaluate the performance of asynchronous systems. In proposed methods, false positive indicates random ONSwitch happen in the NC state, and false negative represents false stop. False positive is equal to 0, which makes the specificity for the four subjects be 100%. This means the ONSwitch will not be activated randomly. The subjects achieved the average sensitivity of 95.7%, while subject 1 and subject 3 gained the highest value of 97.1%.

TABLE II. COMPARATIVE RESULTS OF SENSITIVITY AND SPECIFICITY

Subject	Sensitivity (%)	Specificity (%)
S1	97.1±2.6	100
S2	92.9±2.9	100
S3	97.1±3.3	100
S4	95.8±3.0	100
Mean	95.7±3.3	100

V. DISCUSSION

In this work, two mental switches are designed based on motor imagery. The ONSwitch is easily controlled by the subjects (Fig. 4). While it is highly reliable, it can adapt to different performance of the subjects. The ONSwitch is designed based on the probability threshold and a time course, which on the case of applying only the probability threshold, the ONSwitch will be randomly activated. For the OFFSwitch, it needs a large amount of time to stop the cursor, normally the subjects can stop it over 94%. The subjects reported the absence of an obvious indication for current direction of the cursor, which makes it difficult to generate the deceleration vector in its opposite direction. In the future work, visual feedback of current direction of the cursor will be provided to help the subject to stop the cursor.

VI. CONCLUSION

In this work, we develop a mental switch based asynchronous BCI system, which enables the user to attentively switch on and off the cursor and to move it to arbitrary positions. The subject can achieve self-paced 2D cursor control through applying only three classes of motor imagery. The experimental results demonstrate the effectiveness of the proposed strategies.

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