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Control 2-dimensional movement using a three-class motor imagery based Brain-Computer Interface

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Abstract— **2-dimensional movement control is an interesting issue in Brain-Computer Interface. In this paper, we present a motor imagery based 2-D cursor control paradigm. To move the cursor to a random position, two-class motor imagery is simultaneously combined to output 2-D command ,which directly points to target position. A center-out experiment (8 targets) is set to verify the proposed paradigm. The results of the online experiment (three subjects participated) validate the proposed strategy very well.**

I. INTRODUCTION

Brain-Computer Interface (BCI) system provides a new, no muscular communication and control channel between the brain and the external world [1]. In BCI system, the subject's intent is translated into instruction without using brain nervous peripherals or muscles. BCI has received considerable attention in the past years.

Multi-dimensional control is a very important issue in BCI research. To achieve multi-dimensional control, invasive BCI is always applied, such as controlling cursor or prosthesis. Though the advantage of invasive method is obtaining high SNR brain signals, it will meet technical difficulties and clinical risks. On the contrary, electroencephalography (EEG)-based non-invasive BCIs are commonly used because EEG signals are easier to be recorded than invasive methods. In BCI research, cursor control is generally applied to verify multi-dimensional control paradigm. [2], [3], [4], [5], [6]. These BCI systems can be divided into two groups according to the EEG modality. In the first group, the BCIs are based on single EEG modality (such as P300, SSVEP or ERD/ERS). To control one dimensional cursor movement, mu rhythm regulation based BCI was used to control two direction respectively[7]. Wolpaw et. al [3] presented a 2-D cursor control paradigm, in which subject could regulate mu and beta rhythms to provide independent two control signals. However, even if subjects had controlled cursor movement very fast and smoothly in this system, they were required for an intensive training. Steady-state visual evoked potential (SSVEP) was also used as discrete control paradigm for 2-D BCI [4], [6]. Subjects were only asked to look at specific visual stimulus to move the cursor and the minimal training was required in this BCI system. The result showed that control was rapid and reliable. But the SSVEP based BCI only outputted discrete command, it would move cursor in a zigzag route and can not reach any position in 2-D plane. P300 based 2-D control system has the same drawback[5].

In the second group, hybrid BCI was used for 2-D cursor control. Motor imagery and P300 are combined to control 2-D cursor movement[8]. Motor imagery was used to control the horizontal movement and the vertical movements was controlled by P300. This advanced approach can move the cursor to arbitrary position rapidly. Although hybrid BCI offered flexible control method, it would bring additional workload because subjects were requested to work on two-modality BCI simultaneously.

In this work, we developed a 2-D cursor control system based on three-class motor imagery (left hand ,right hand, feet). In the proposed BCI system, a 2-D command, which point to target position, is directly outputted instead of providing two independent control signals for vertical or horizontal movement control respectively. The essential of this system is combining two-class motor imagery to generate command vector.

II. SYSTEM STRATEGY

In this work, we presented a three-class motor imagery based BCI for 2-D cursor control.Common Spatial Pattern (CSP) [9] was applied to extract features and a linear Support Vector Machine (SVM) [10] classifier was used to discriminate the three-class EEG patterns (left hand, right hand and feet motor imagery). The output probability $P1, P2, P3$, predicting probabilities of classifier, are mapped to three vectors. As shown in Fig. 1(a), $P1$ is the probability of left hand imagery , $P2$ and $P3$ are the probabilities of right hand and foot imagery. Three vectors point to left upper , right upper, and downward respectively. The angle between two vectors is $120°$ and the value of vector is equal to the related output probability. Fig. 1(b) showed how to move cursor. The green circle is the current position of cursor and the red circle is the target. To move cursor to hit target, three vectors should compose a new vector V which means subject should do three-class motor imagery in proportion simultaneously. In this case, P3 (Feet motor imagery) will provide negative contribution. If subject can make $P3$ as small as possible, it will be helpful to accelerate the movement of cursor. On the other hand, it is difficult to do three-class motor imagery at the same time. Therefore, we instructed subject only focusing on left and right hand imagery and ignoring feet, which will output a smaller value of $P3$ than $P1$ or $P2$. Thus, we can consider that the vector V is composed only of $P1$ and $P2$,

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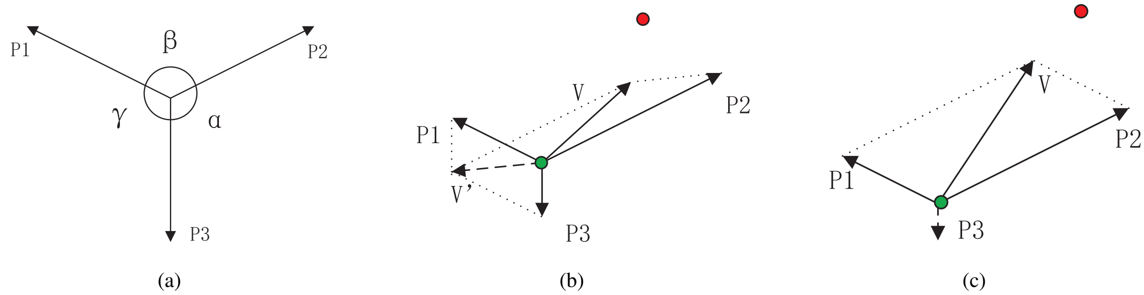

Fig. 1. Illustration of 2D-control paradigm.(a)Output probabilities were mapped into three vectors with 120° between two vectors;(b)Moving vector combined by three probability vectors;(c) Moving vector combined by two probability vectors

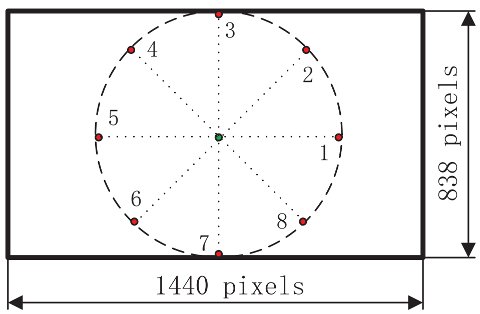

Fig. 2. Simulation environment and the illustration of center-out paradigm.

as shown in Fig. 1(c). In this way, subject only need to do two-class motor imagery to move cursor. There is a special case that subjects do one MI (feet) to move cursor straight down.

For simplicity, we projected three output probabilities P to vertical and horizonal axis. Now the horizontal and vertical displacement of cursor can be calculated as follow:

$$dx = (P2 - P1) \times cos30^\circ \times L, \quad (1)$$

where dx is the step horizontal displacement of cursor. If dx is bigger than zero, cursor will move to right. Vise versa, it will move to left. L is the step length and is set as 8 pixels.

$$dy = [(P1 + P2) \times sin30^\circ - \mathrm{P3}] \times L \quad (2)$$

where dy is the step vertical displacement of cursor. The cursor will move up (or down) if dy is positive (or negative) value. When all the output probabilities satisfy the following condition, dx and dy are close to zero.

$$|P(i) - 1/3| \leq \varepsilon, i = \{1, 2, 3\}; \quad (3)$$

where ε is a smaller positive value.

III. Experiment

A. Experiment environment

As shown in Fig. 2, a rectangle of 1440 x 838 pixels was used as experiment environment. The diameters of the cursor (green circle) and the target (red circle) were both with 16 pixels diameter.

B. Subject

Three subjects (average age of 23) took part in the experiments. All were healthy, right handed and central nervous system normal. For convenience, they were named as S1 , S2, S3. S1 had rich MI BCI experience, while S2 and S3 had taken several sessions in the MI BCI training.

C. EEG Signal recording and preprocessing

The EEG signals are recorded using a 16-channel g.USBamp system, with electrodes placed according to the international 10-20 system. Eleven channels in motor cortex area were chosen(FC3 FCZ FC4 C3 C1 CZ C2 C4 CP3 CPZ CP4), the reference and ground electrodes were fixed on Fz and the left earlobe respectively. All the channel signals were acquired at a sampling frequency of 256Hz by passing a bandpass filter within 5-30 Hz.

D. Experiment paradigm

1) Three-class motor imagery training: A high performance of MI BCI system is the foundation of the proposed 2-D control strategy. So every subject should attend a normal three-class MI BCI training program. The number of training session is different for each subject based on their experience. The training session will stop until classification accuracy for every class motor imagery is greater than the threshold (85%). And then the subject is permitted to go on with the next experiment. If the normal motor imagery training is finished, subject will attend two additional runs to train classifier model ,which will be used in cursor control experiment.

2) Center-out paradigm of 2-D cursor control: As mentioned in above section, cursor movement was controlled by two-class motor imagery combination. To test this control strategy, a center-out experiment paradigm was designed ,as shown in Fig.2. In this paradigm, the initial cursor position is placed in the center of the simulation screen. Eight target cursors were distributed equally on a circle with 449 pixels radius. The included angle of the adjacent targets is 45 degree. One target hitting task is defined as a trial. Eight trials are included in a run. Every subject will attend 20 runs in the whole experiment. In each run, eight targets appear in a pseudo random order. Subject is required to control the cursor to hit the target. When the cursor hit the target, this trial would end immediately. To limit the experiment time, the longest trial time is set as 60 seconds. If subject can not hit the target in 60s, this trial also will be terminated.

IV. Result

In the three-class MI training experiment, S1 have achieved accuracy threshold after several runs training. S2 and S3 also finished the training after 2 and 6 sessions training respectively. Before the cursor control experiment, every subject takes two runs (10 trials for each class motor imagery) model training experiment. The model training accuracies are shown in the second column of Table. I.

After the model training program, three subjects joined the center-out online experiments. As shown in Table I, three subjects have finished all 160 trials and the hit rate achieved 100%. To further study the performance of the proposed control strategy, trajectories of all trials are plotted in Fig.3. The first column of Fig. 3 shows the original trajectory and second column show the average trajectory over 20 runs.The trajectory of subject 1 is presented in first row. All eight direction's trajectory showes minor fluctuation around straight line. The average trajectory is very close to straight line. Second row and the third row of Fig. 3 show the trajectory of subject 2 and subject 3 respectively. They also have achieved acceptable performance.

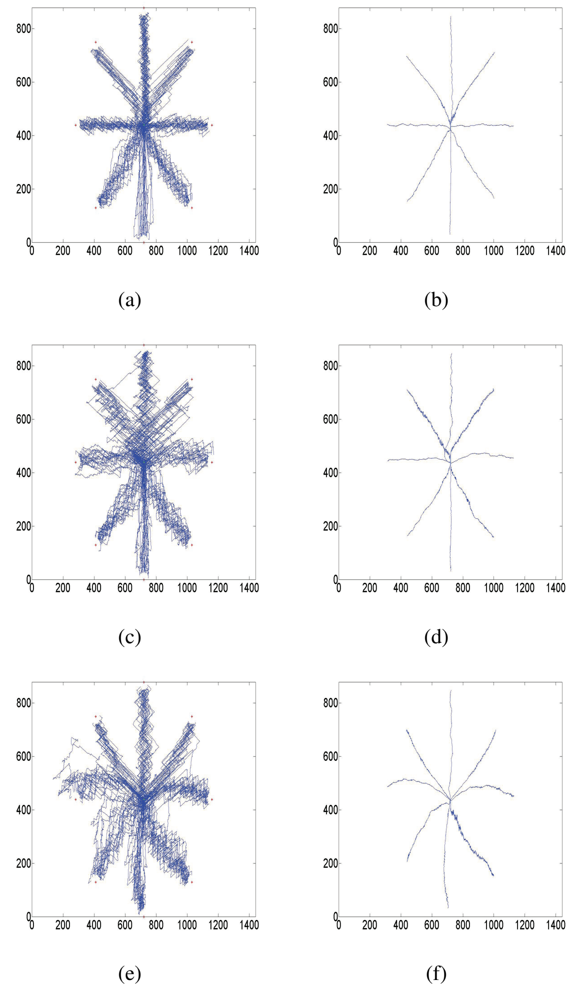

Fig. 3. The trajectories of cursor movement for eight targets.

TABLE I
HIT RATE OF EXPERIMENT

Subject	Model training accuracy(%)	Trials	Hit rate (%)
S1	96.7 %	160	100
S2	98.3 %	160	100
S3	91.7 %	160	100

TABLE II
AVERAGE PROBABILITY OF SUBJECT 1

Direction	Output probability		
	P1	P2	P3
D1	0.0488 ± 0.0685	0.6165 ± 0.3249	0.3347 ± 0.3117
D2	0.2220 ± 0.3540	0.7168 ± 0.3782	0.0612 ± 0.1217
D3	0.4510 ± 0.4080	0.4534 ± 0.4037	0.0956 ± 0.1554
D4	0.7245 ± 0.3881	0.2193 ± 0.3491	0.0616 ± 0.1453
D5	0.6194 ± 0.3638	0.0510 ± 0.0793	0.3298 ± 0.3391
D6	0.4017 ± 0.3516	0.0670 ± 0.0898	0.5313 ± 0.3341
D7	0.1176 ± 0.1698	0.1130 ± 0.1660	0.7690 ± 0.2121
D8	0.0566 ± 0.0827	0.4080 ± 0.3290	0.5354 ± 0.3214

V. Discussion

Generally speaking, no matter what type of BCI is applied, two independent control signals are necessary for 2-D cursor control task. To continuously control cursor using single modality BCI, subject should be intensively trained [3]. On the other hand, hybrid BCI combined two type of mental task to provide multi-dimensional control. However, it is difficult for some subjects to work on two BCI simultaneously. Considering the tradeoff between the intensive training and the complex mental tasks, we proposed a three-class MI BCI based 2-D cursor control strategy. According to the target position, subject should combine two-class motor imagery together to obtain 2-D control command. In theory, we can move cursor to any position . However we can not control the three output probabilities precisely. The sum of three probabilities is equal to one every time. If subject focused on right hand imagery, bigger value of P2 will be obtained while P1 and P3 will be small. What will happen when subject do two-class motor imagery simultaneously? After model training experiment, subjects were asked to do two-class motor imagery test. For example, subjects were asked to imagine moving right and left hand at the same time. This results demonstrate bigger P1 and P2, and very small P3 instead. This suggests that subjects can combine two-class motor imagery, even though they can not control the probability exactly. In other words, they can regulate the moving direction continuously according to the target position by changing combination of the strength of the two-class MI. Table II shows the average probability of the subject 1 for each target. For example, the value of P2 and P3 are bigger than P1 in target 1 which means the subject can control the combination of the two-class motor imagery well.

Fig. 4. Average time for eight target task

However for different target, the complexity of the task is not same. To move the cursor to target 3, P1 and P2 should be as equal as possible. To evaluate the complexity of eight tasks, the average time of the task were calculated in Fig. 4. For all subjects, more time needs to be taken to finish task of target 3 . We found that target 2, 4 ,7 were easily hit by all subjects because these targets were close to P1 , P2 and P3. Subjects only need to mainly focus on one MI to move cursor.

VI. Conclusion

In this paper, we have proposed a promising three-class MI based 2-D cursor control strategy by combining two-class MI to generate new command. For its single-modality based BCI, this strategy is readily applicable and easy to use. The good performance obtained from three well-trained subjects in the 2-D cursor control experiment demonstrate the effectiveness of this strategy.

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