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A Neurofeedback training paradigm for motor imagery based Brain-Computer Interface

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***Abstract*—The performance of motor imagery based brain-computer interface (BCI) is mainly depending on subject's ability of self-modulation EEG signals. A proper training would help naïve subjects to modulate brain activity proficiently. A few works of neurofeedback training showed that the performance was similar by using different feedback type because they did not provide the distinguishing characteristic to train subjects. To improve the performance of neurofeedback training, we presented a training paradigm which provided dissimilar information of imagination strength in visual feedback. The strength based feedback showed the difference in the inter-trials and it would help subjects to follow the right way to modulate brain signals. The experiment results verified the effectiveness of the proposed training paradigm.**

I. Introduction

Recently, motor imagery-based Brain-Computer Interface (MI-BCI) system has received more and more attention [1], [2]. Motor imagery, such as imagination of limb movement, can result in event-related desynchronization (ERD) of mu rhythm in the contralateral sensorimotor cortex, as well as motor execution [3]. The basic principle of MI-BCI is to translate ERD phenomenon into control command. To achieve good performance of MI-BCI, mutual training for the subject and the system should be taken into account concurrently. Some BCI researches have been paid more attention to develop machine learning algorithms, which will achieve high classification accuracy [4], [5]. No matter how outstanding the algorithms are, BCI cannot obtain good performance while subjects fail in self-modulating brain activity. For the naïve subject of BCI, it is difficult to control his or her own EEG patterns. Therefore, it is necessary to provide a suitable training program for naïve subjects, which will help subjects to learn the method of self-modulation at initial stage.

Even though feedback is very important in training procedure, only a few studies have explored how the feedback type affects the learning progress. In [6], Neuper et al compared training performance between realistic feedback and abstract feedback for the same task, and found that there was not much difference. In a typical BCI paradigm, feedback about performance is provided by a continuous or discrete form [7], [8] .In [9], the study reports the advantages of continuous versus discrete feedback. No matter what type of feedback, even continuous feedback, it only stands for a single classification outcome. But for the same class result, there exist different levels of motor imagery. At the initial state of training, naïve subjects will try motor imagery using different ways. If the system can provide imagination strength information to subjects at every time, which instructs them to do motor imagery following the right way with high strength.

The goal of this paper was to develop a neurofeedback program based on imagination strength information feedback. In this study, a linear support vector machine (SVM) [10] was used to discriminate between EEG patterns associated with left and right motor imagery. The value of output probability(P) as feedback signals can well reflect the current brain activity. Meanwhile, in BCI training, feedback must be as attractive as possible so as to avoid frustration. In the feedback screen, a ball in water sink will move with output probability based step. To present more rich visual feedback, the water's color will change when the ball reached different height. The experimental results demonstrated effectiveness of the proposed training paradigm.

II. Methods

A. subjects

Nine healthy subjects and a progressive muscular atrophy (PMA) patients (aged=22.3 ± 1.63; 8 males, 2 females), participated in this study. All were right-handed and had no BCI experience. They gave informed consent before the experiment started. After completion of the whole experiments, they were payed for their participation. All participants were divided into experiment group and control group randomly.

B. The EEG Signal Recording and Preprocessing

The EEG signals were recorded using a 16-channel g.USBamp system, with electrodes placed according to the international 10-20 system.13 channels were chosen(FC3 FCZ FC4 C5 C3 C1 CZ C2 C4 C6 CP3 CPZ CP4), the reference and ground electrodes were respectively fixed on Fz and the left earlobe. All channel signals were acquired at a sampling frequency of 256Hz by passing a bandpass filter within 5-30 Hz.

After preprocessing, Common Spatial Pattern (CSP) [11] was applied to extract the feature and a linear SVM classifier was used to discriminate the EEG patterns between left hand

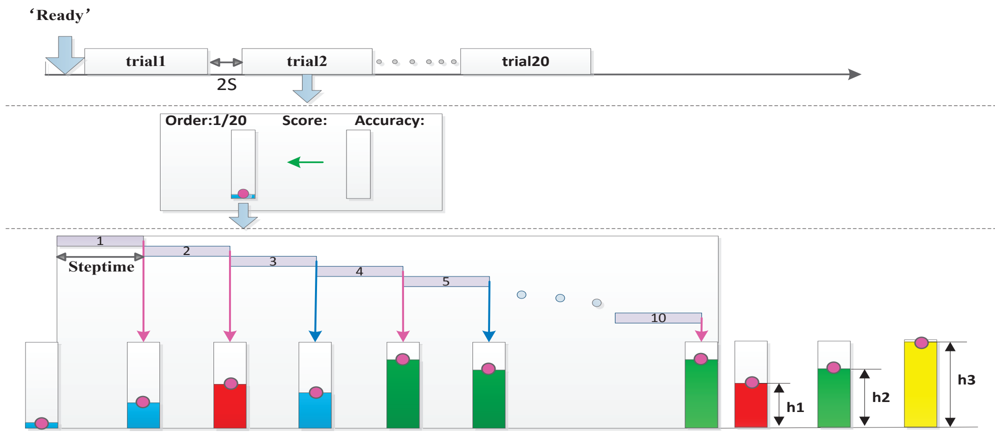


Fig. 1. Illustration of experiment paradigm. A run was shown in Upper panel. In middle panel, a trail of left hand imagination was displayed. Order meaned which trial was being conducted. Score and accuracy showed the cumulated score and number of right trails of finished trials respectively. A left hand imagination trail was enlarged in Lower panel. A trial lasted 3s and was divided into ten subtrials. The red arrow was on behalf of the correct classification while the blue arrow stands for the incorrect classification. The water's color will change following different height.

and right hand motor imagery. At the beginning of training, subjects can not output stable EEG pattern. To instruct subjects, it is necessary to present proper feedback. Feedback is reflected the result of classification. To display right feedback, the parameters of classification should be adapted with EEG variation [12]. We apply an adaption strategy for classifier in this work. In the course of system training, the training data combined with choose trials from previous runs($i \leq 5$).The proportion P(n) of training trials from previous runs was defined as:

$$P(n) = n/5 \qquad (n = 1, 2, 3, 4, 5) \tag{1}$$

when n from 1 to 5, the P(n) represents the proportion from the previous fifth run to the latest run. If the number of runs is less than five, the proportion is still calculated using equation 1 . Due to the limitation of space, the detail of system training will be discussed in another paper.

C. Experimental paradigm

In this work, all subjects would attend two-class motor imagery tasks (left hand vs right hand).The experiment lasted for fortnight. During the whole experiments, two groups alternately attended experiment every other day. Each subject must complete 2 sessions every day, and in which one session consists of 10 runs. Each run consisted of 20 trials, 10 trials for each class presented in randomized order. Total 2800 trials for each subject were recorded. There were 5 - 10 minutes rest time between two sessions. An experiment lasted about 1.5h including preparing time. The subjects were seated comfortably in an armchair, with their hands resting on the chair's arms or on the table in front of them during the whole trial.

Paradigm for Experiment Group:

In the beginning of the experiment, the cue "ready" displays at the center of screen and two sinks show in left and right side of screen. And then, an arrow will show up randomly pointing either to the left or right, meanwhile, a ball appears in arrow pointed sink. The subject was instructed to imagine to use the same side hand to push up the ball. Each subject had to continuously perform the motor imagery until the arrow was erased. This task time will last 3s, which is divided into 10 step time equally(0.3s for each step). The ball will move up H every step. H's value can be calculated as follow:

$$H = P \times L \times steptime/tasktime \tag{2}$$

where P is the output probability of SVM per step, L is the height of the sink. If the outcome of classifier is in accord with arrow pointed direction, the ball will go up H. Otherwise, the ball will drop down H. The ball will not drop if it is already at the bottom of the sink. There still exist other factor, such as concentration, motivation, frustration and fatigue, which will affect the subject's EEG signals [15]. In this paradigm, we set rich visual feedback to encourage subjects. We marked the sink's half height, three-quarter height and total height h1, h2, h3, respectively. During a trial, if the ball arrives at certain height (h1, h2 or h3) at any time, the water-color will be changed from blue to red(h1) or green(h2), or yellow(h3),as shown in Fig.1. Afterwards at the end of a trial, the performance of each trial will be measured by classifier again, and different score("60","80","100") is also recorded according to the above different height. After a short pause (2s), the next trial starts (Fig 1 shown the structure of proposed paradigm.).

Paradigm for Control Group:

In this paradigm, a normal training paradigm was used to train subjects. After the cue disappearing, the subject would do

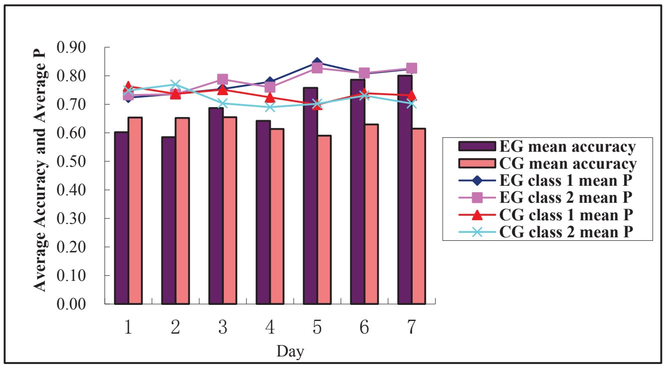
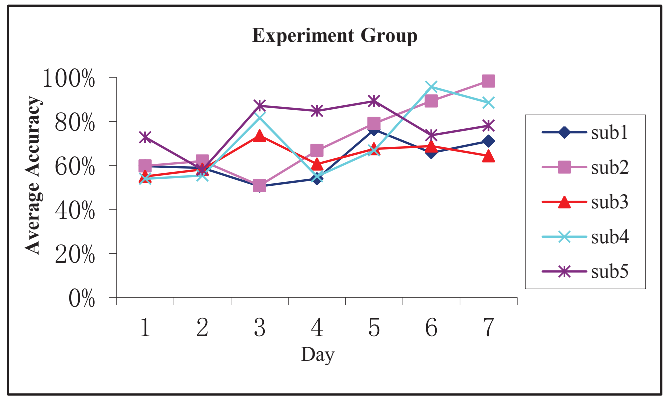
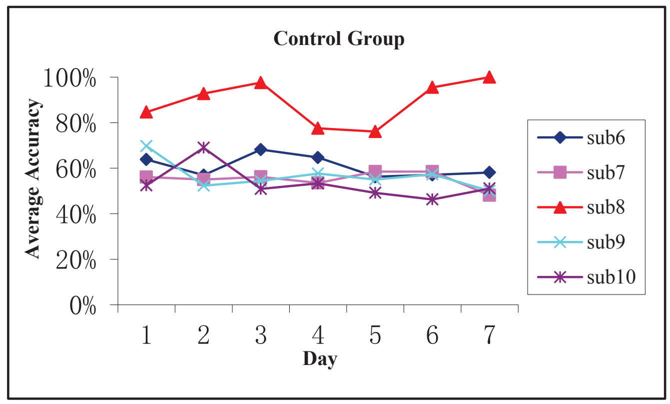


Fig. 2. The training performance of experiment group (EG) and control group (CG).The histogram showed the average accuracy and the curve showed the average output probability p for each class of both group.



(a)



(b)

Fig. 3. Average accuracy of every day for each subject.

motor imagine of left/right hand according to an arrow pointed direction. The task time is also 3s, which consists of ten equal step time. If the classification is right, the ball will ascend H' height, or else, the ball will descend H', water-color keep blue and without score reward in the whole session. H' is designed as:

$$H' = L \times steptime/tasktime \qquad (3)$$

where L, steptime and tasktime have the same meanings as description in equation (2).

III. Result

A. On-line training performance comparison

In order to evaluate the training performance between experiment group and control group, we calculated the average classification accuracy (ACA) of each group. As shown in Fig.2, there exists an obviously ascending trend in experiment group. At the first four day, the ACA varied around 60% level. From the fifth day, the performance had a prominent improvement. But for control group, the performance varied around 60% at whole training period. In this work, we applied linear SVM as classifier, which would output a probability P for each predict result. To evaluate the performance between left and right hand imagination, the mean output probability of each class was shown in Fig.2 for both groups. It was found that only experiment group had improved the performance of two-class simultaneous.

To show variation of the training performance among subjects, ACA of each day was calculated for each subject. In Fig. 3(a), most subjects showed a good ascending curve except for subject 5. On the contrary, there was no distinct improvement trend for subjects of control group (Fig. 3(b)). Subject8 , who had achieved good performance at initial state, was a special case. Some people, like as subject 8 who had a good feeling of controlling motor imagery, could reach a well performance in any training program.

B. statistic analysis

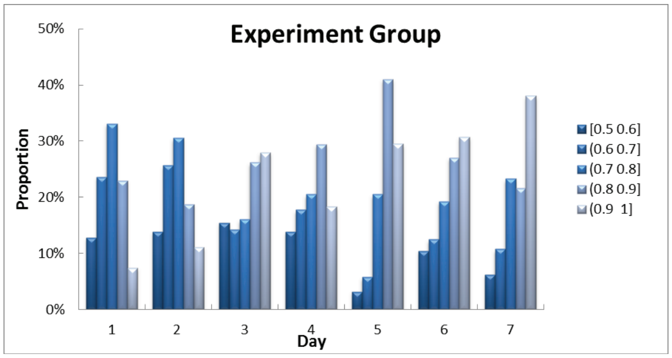
The statistic analysis was used to test whether there was an obvious improvement in recognition performance after using experiment paradigm. A t-test was adopted to evaluate the overall performance of two paradigms. In Table I, results of the t-test suggested the recognition accuracy of experiment group was significantly higher than that of control group in the last four days especially.

TABLE I
THE SIGNIFICANT DIFFERENCES FOR RECOGNITION ACCURACY IN TWO PARADIGMS.

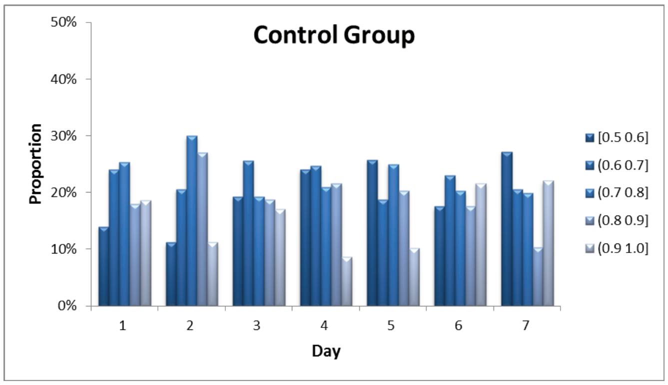
Day	1	2	3	4
p_value	0.0657	0.0017	0.0889	0.1257
Day	5	6	7	1-7
P_value	< 0.0001	0.0001	< 0.0001	< 0.0001

IV. Discussion and Conclusion

In motor imagery based BCI system, subject is asked to do motor imagery while no real body movement. To let a BCI system work well, two aspects should be consider simultaneous: signal processing algorithm and training of subjects. In the past, more works have focused on developing signal processing algorithm. Recently, researchers began to pay attention to training. In [13], Neuper and Pfurtscheller reviewed basic principle and method of neurofeedback training in BCI. To train naïve subjects, suitable training paradigm is



(a) Experiment group



(b) Control group

Fig. 4. The distribution of P over whole training procedure

very important. In this paper, we focused on how to build appropriate neurofeedback based training program at initial several training sessions.

Comparing with normal training paradigm, experiment group have achieved 80% average classification accuracy after seven days training. Especially, the ACA is appeared a obviously ascending trend. To further study the variation of training processing, we calculated the distribution of average output probability. Fig. 4 showed the change course of imagine strength during training processing. The proportion ,from 0.5 to 1, is divided into five equal interval. Strength of imagination is proportional to output probability (P). Fig. 4(a) showed the distribution of P in experiment group. It is obviously the high P value has a big proportion in course of time. But there is no prominent change in control group, as shown in Fig. 4(b).

In summary, we presented a neurofeedback based training paradigm for Brain-Computer Interface system, which used a rich visual feedback interface to induce subject. The strength information of imagination was included in feedback. Experiment result verified the proposed training paradigm's effectiveness.

Acknowledgment

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References

[1] C. Neuper, GR Müller, A. Kübler, N. Birbaumer, and G. Pfurtscheller. Clinical application of an eeg-based brain–computer interface: a case study in a patient with severe motor impairment. *Clinical neurophysiology*, 114(3):399–409, 2003.

[2] G. Pfurtscheller, C. Neuper, GR Muller, B. Obermaier, G. Krausz, A. Schlogl, R. Scherer, B. Graimann, C. Keinrath, D. Skliris, et al. Graz-bci: state of the art and clinical applications. *Neural Systems and Rehabilitation Engineering, IEEE Transactions on*, 11(2):1–4, 2003.

[3] G. Pfurtscheller and C. Neuper. Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, 89(7):1123–1134, 2001.

[4] K.R. Müller, M. Krauledat, G. Dornhege, G. Curio, and B. Blankertz. Machine learning and applications for brain-computer interfacing. In *Proceedings of the 2007 conference on Human interface: Part I*, pages 705–714. Springer-Verlag, 2007.

[5] K.R. Müller, M. Tangermann, G. Dornhege, M. Krauledat, G. Curio, and B. Blankertz. Machine learning for real-time single-trial eeg-analysis: From brain-computer interfacing to mental state monitoring. *Journal of neuroscience methods*, 167(1):82–90, 2008.

[6] C. Neuper, R. Scherer, S. Wriessnegger, and G. Pfurtscheller. Motor imagery and action observation: modulation of sensorimotor brain rhythms during mental control of a brain-computer interface. *Clinical neurophysiology*, 120(2):239–247, 2009.

[7] D.J. McFarland, L.M. McCane, and J.R. Wolpaw. Eeg-based communication and control: short-term role of feedback. *Rehabilitation Engineering, IEEE Transactions on*, 6(1):7–11, 1998.

[8] B. Blankertz, G. Dornhege, M. Krauledat, K.R. Müller, and G. Curio. The non-invasive berlin brain-computer interface: Fast acquisition of effective performance in untrained subjects. *NeuroImage*, 37(2):539–550, 2007.

[9] C. Neuper, A. Schlögl, and G. Pfurtscheller. Enhancement of left-right sensorimotor eeg differences during feedback-regulated motor imagery. *Journal of Clinical Neurophysiology*, 16(4):373, 1999.

[10] V.N. Vapnik. *The nature of statistical learning theory*. Springer Verlag, 2000.

[11] H. Ramoser, J. Muller-Gerking, and G. Pfurtscheller. Optimal spatial filtering of single trial eeg during imagined hand movement. *Rehabilitation Engineering, IEEE Transactions on*, 8(4):441–446, 2000.

[12] J. Li and L. Zhang. Bilateral adaptation and neurofeedback for brain computer interface system. *Journal of neuroscience methods*, 193(2):373–379, 2010.

[13] C. Neuper and G. Pfurtscheller. Neurofeedback training for bci control. *Brain-Computer Interfaces*, pages 65–78, 2010.