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ORIGINAL ARTICLE

Electro-encephalogram based brain–computer interface: improved performance by mental practice and concentration skills

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Abstract Mental imagination is the essential part of the most EEG-based communication systems. Thus, the quality of mental rehearsal, the degree of imagined effort, and mind controllability should have a major effect on the performance of electro-encephalogram (EEG) based brain-computer interface (BCI). It is now well established that mental practice using motor imagery improves motor skills. The effects of mental practice on motor skill learning are the result of practice on central motor programming. According to this view, it seems logical that mental practice should modify the neuronal activity in the primary sensorimotor areas and consequently change the performance of EEG-based BCI. For developing a practical BCI system, recognizing the resting state with eyes opened and the imagined voluntary movement is important. For this purpose, the mind should be able to focus on a single goal for a period of time, without deviation to another context. In this work, we are going to examine the role of mental practice and concentration skills on the EEG control during imaginative hand movements. The results show that the mental practice and concentration can generally improve the classification accuracy of the EEG patterns. It is found that mental training has a significant effect on the classification accuracy over the primary motor cortex and frontal area.

Keywords EEG · Neural Network · Brain-Computer interface · Mental Practice · Meditation

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1 Introduction

For several years, many efforts have been done to use the electro-encephalogram (EEG) as a new communication channel between human brain and computer. This new communication channel is called EEG-based brain–computer interface (BCI). Most of these efforts have been dedicated to the improvement of the accuracy and capacity of this EEG-based communication channel. Several factors may affect the performance of the BCI. These factors include the brain signal used as the input of the BCI, the signal processing methods used for feature selection and classification, cognitive tasks to be intended, and subject training. Different types of brain signals are used to detect the subjects' intention. Thus far, slow cortical potentials [11], oscillatory EEG activity [17, 24, 32], and various types of event-related potentials including readiness potential [5], steady-state visual-evoked potential [25], and P300 [29] have been utilized in different BCI systems. In the present study, we use oscillatory EEG activity associated with hand movement imagination and resting state. In addition to employment of different signal processing approaches [6, 9, 21, 22, 27, 28, 33] some researchers have investigated the role of biofeedback [19] and response verification [31] on EEG control. Biofeedback is a technique that individuals can learn how to change and control their own brainwave activity if they are given immediate feedback in an understandable format [10]. McFarland et al. [19] used the μ-rhythm of the EEG signals over sensorimotor cortex to move a cursor to a target on a screen and assessed the short-term effects of feedback of cursor movement on EEG control [19]. It was reported that the feedback could have inhibitory as well as facilitory effects on EEG control. They suggested that the cursor movement might distract the subject attention to the task. Moreover, the cursor movement might produce EEG responses that interfere with the EEG components, which are used for cursor control.

Certainly, one major advantage of EEG-based BCI is that no physical movement is required. The motor imagery is the essential part of the most EEG-based communication systems. Motor imagery is defined as a dynamic state during which representation of a given motor act is internally rehearsed in working memory without any overt motor output. At this point one important question arises and that is how to imagine. Does the quality of mental rehearsal and the degree of imagined effort affect on the performance of EEG-based BCI?

There is now repeated evidence that mental state has significant effects on spatial-temporal EEG patterns. It has been known the signal changes related to alertness, arousal, focused attention and sustained mental effort, and cognitive state are present in EEG. Low brainwaves are associated with tuning off and lack of concentration, while fast brainwaves are associated with focused attention and sustained mental effort. Pronounced DC-potentials shifts were observed during changes in vigilance states [16]. It has been reported different DC-potential shifts during imagination of face, color, and map [30]. The level of shift was lowest for faces, medium for colors, and highest for the map [30]. Moreover, in practitioners of meditation, EEG recordings showed a distinct pattern including an increase in the power of alpha 1 (8.0–10.0 Hz) and theta 2 (6.0–7.5) band during meditative state of the mind [18]. It has been demonstrated differences on the degree of EEG phase synchronization between artists and non-artists during visual perception or looking at the paintings and imagery of paintings [4]. It was reported that in artists as compared with non-artists, phase synchrony was mostly enhanced during imagery. The degree of synchrony would be correlated with professional training.

In this work, we present a mental training scheme based on mental practice and concentration skills for EEG-based BCI and examine the role of mental training on EEG control.

2 Mental practice and concentration skills

2.1 Mental practice

Mental practice refers to repeating a physical skill in the mind, without any physical movement of the body, with the intent of learning or refinement. There are strong evidences that mental practice has a moderate but extremely reliable effect on performance. Not only can mental imagery improve specific motor skills but also enhance motivation, mental toughness, and controlling arousal. It was suggested that the mental rehearsal duplicates the actual motor pattern that is being rehearsed. It is broadly accepted that motor imagery is directly related to motor physiology. There are a lot of reports that support the hypothesis of common neural mechanisms between motor imagery and motor control with the difference that in the latter case, execution would be blocked at some corticospinal level [7, 12, 13]. From this hypothesis, it can be expected that mental imagery could help the consistency in movement. It is now well established that mental practice using motor imagery improves motor skills [13], but performance efficiency depends on the individual differences and imagery quality. The effects of mental practice on motor skill learning are the result of practice on central motor programming [7]. According to this view, it seems logical that mental practice should modify the neuronal activity in the primary sensorimotor areas and consequently change the performance of EEG-based BCI.

There are many different types of imagery and methods of conducting it [3]. The procedure was used in this work is as follows: first, the subjects were instructed to watch closing or opening a hand. Each action takes about 5 s. It was added details, which make the actions come alive so that it can be really re-lived in the mind. The subjects were asked to note the details of the actions and try to imagine the details, even the lines, marks, and patterns on the hand, during imagination. Then, depending on the cue visual-stimuli, which appears in the monitor of computer, the subject should imagine hand grasping or opening. This step is repeated once a day for several days.

2.2 Concentration procedure

Another important issue in developing an EEG-based BCI is the mind controllability. Through the concentration practice and relaxation skills (i.e., meditation practice), it can improve the controllability of the mind [23]. Concentration is holding the mind to one form or object steadily for a long time. Through mental concentration, the mind is focused on a single goal for a period of time, without jumping from one object to another. The training in concentration is the intentional self-regulation of attention and makes the mind firm and steady. In addition, it has been shown that concentration practice causes the changes in cortical electrical activity [1]. Aftanas et al. [2] reported that meditative experience, characterized by less complex dynamics of the EEG, involves 'switching off' irrelevant networks for the maintenance of focused internalized attention and inhibition of inappropriate information. According to this view, it seems logical that meditation practice should modify the neuronal activity and consequently changes the performance of EEG-based BCI. There are a variety of meditation procedures [23]. The training procedure used in this work is based on mindfulness meditation and is summarized as follows:

1. Sit upright in a comfortable chair.
2. Hold the head up, with attention flowing into the area between the eyebrows and higher brain.
3. Inhale and exhale once or twice to relax. Remaining still for a few moments until you feel centered. Be aware of your natural breathing rhythm. Notice that your breathing is calm and steady.
4. When inhalation occurs naturally, mentally listen to a pleasant word that is agreeable to you. When exhalation occurs, again mentally listen to the word. Feel that the sound of the chosen word is blossoming in mind or your field of awareness. Continue doing this, without effort and without anxiety about results.
5. When a state of conscious, calm awareness is experienced, discontinue listening to the word. Be still continue practice for several minutes until you feel inclined to conclude the practice session.

For best results, it should be practiced for 20 min once or twice a day for at least 30 days.

3 Experiments

The current study utilized a two group experimental design, a mental training group, and a control group, each containing eight subjects. There were three separate experiment days on each subject. The control subjects did not receive any special training. The second and third experiments were conducted for 10 and 20 days after the first experiment. For mental training group, the first experiment on each subject was carried out before any mental training, but the second and third experiments were conducted after 10 and 20 days of mental training, respectively. Mental training consisted of mental and concentration practices. Each subject performed both practices several once a day for several days.

The EEG data of fourteen normal right-handed subjects were recorded at a sampling rate of 256 by Ag/AgCl scalp electrodes placed according to the International 10–20 system. The eye blinks were recorded by placing an electrode on the forehead above the left brow line. The signals were referenced to the right earlobe. During each trial experiment, one task was performed without any warning tone. Depending on the cue visual stimuli, which appeared in the monitor of computer at 2 s, the subject imagines either right-hand grasping or right-hand opening. If the visual stimuli do not appear, the subject does not perform a specific task. Data were recorded for 5 s during each trial experiment and each trial was repeated 50 times for each task.

One of the major problems in developing a real-time BCI is the eye blink artifact suppression. The traditional method of the eye blink suppression is the removal of the segment of EEG data in which eye blinks occur. This scheme is rigid and does not lend itself to adaptation. Moreover, a great number of data is lost. To overcome these problems and to shorten the experimental session, we have already developed an adaptive noise canceller (ANC) filter using artificial neural network for real-time removing the eye blinks interference from the EEG signals [8]. In this work, we used this method for real-time ocular artifact suppression without any visual inspection.

4 Feature extraction and eeg classification

The features are formed from 2-s interval of single-channel EEG data, in the time period 2.2–4.2 s, during each trial of experiment. The window starting 0.2 s after cue presentation is used for classification because it takes time for the subjects to start imagination. However, the classification accuracy is affected by the onset time of the analysis window and it is subject specific [25]. The mean absolute value (MAV), variance, the relative power of beta band to the total power, the relative power of theta band to the total power, and the relative power of alpha band to the total power constitute the features. The periodogram method is used to estimate the power spectral density of EEG signals. Various feature vectors were formed and were fed into the neural network classifier. The multilayer perceptron (MLP) with back-propagation learning rule is used. The MLP network considered in this study consists of two hidden layers each containing hyperbolic tangent units and two output nodes. The classifier is trained to distinguish between rest state and imaginative hand movement. The imaginative hand movement can be hand closing or hand opening. The EEG features associated with resting state, imaginative hand closing, and hand opening constitute both the training and validating data. A fivefold cross-validation procedure is used to validate the accuracy of the classifier. The fivefold cross-validation divides the data into five equally sized disjunct partitions. Each partition is then used once for testing; the other partitions are used for training. Then the results are averaged. During training, the feature vector was randomly selected from the training sets and then fed into the network. The learning process is stopped when it is apparent that the generalization performance has peaked.

5 Results

The brain potentials obtained by ensemble averaging of 50 trial artifact-free EEG data during imagining hand grasping and hand opening are shown in Fig. 1a, b, respectively. The same information is shown in Fig. 1c and d after the mental training. The event-related potentials and DC-potential shifts associated with motor imagery are quite evident in these figures. The subsequent DC-shifts after the beginning of imagination are related to creating and maintaining mental imagery. Figure 2a, b show the time-frequency distribution of EEG signals during hand movement imagination before and after mental training, respectively. Event-related spectral perturbation (ERSP) analysis [15] was used for spectral analysis of the EEG signals. To compute an ERSP, baseline spectra are estimated from the EEG preceding the visual cue. The EEG obtained during each trial experiment is divided into short, overlapping data windows, and a moving average of the amplitude spectra of these is created. The obtained spectra are then normalized by dividing by the mean baseline spectra. Normalized spectral for many

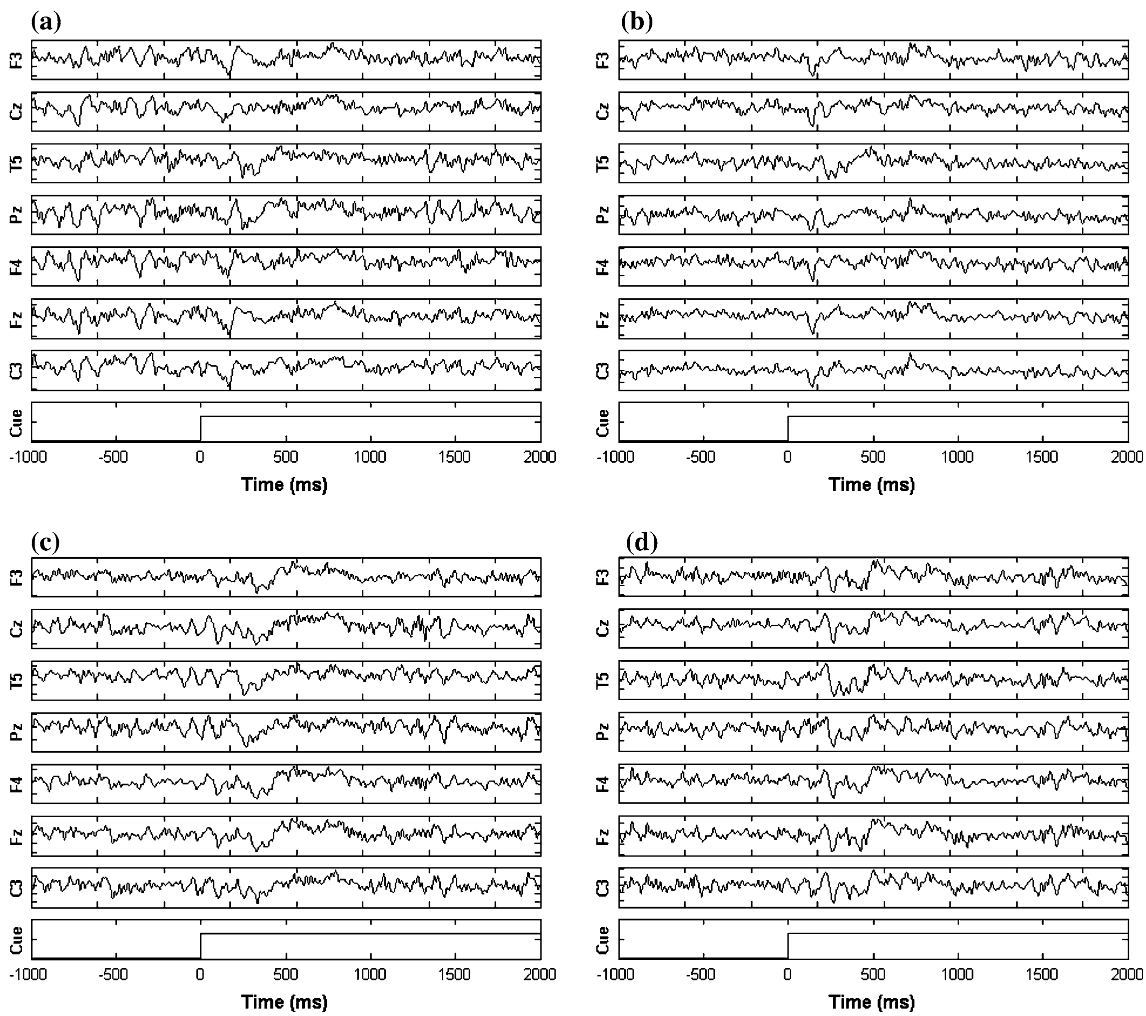

Fig. 1 Ensemble averaging of 50 trials artifact-free EEG data during imagination of hand closing (**a**) and opening (**b**) before mental training; **c** and **d** the same information as in (**a**) and (**b**), respectively, after mental training

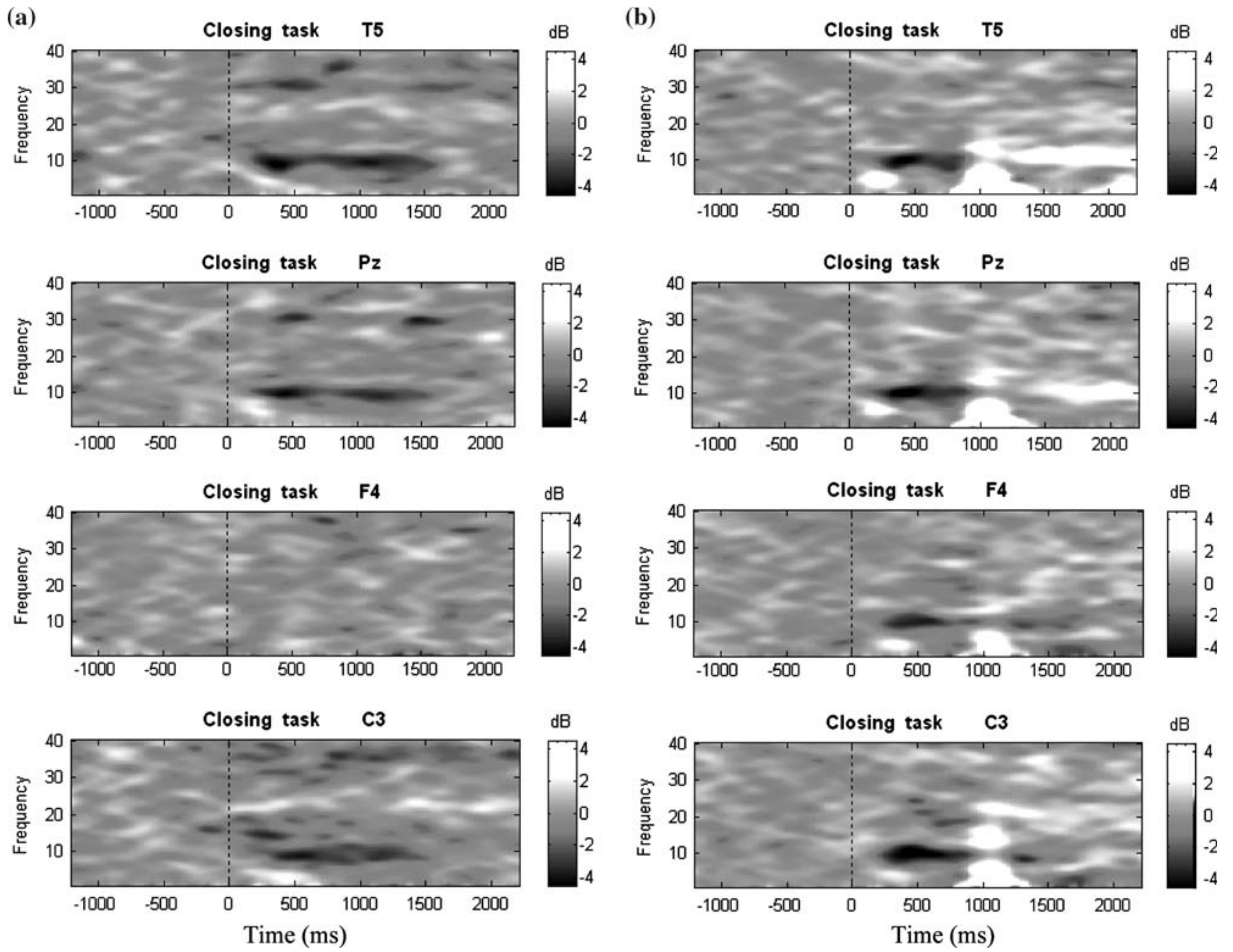

Fig. 2 Mean event-related spectral perturbation of the EEG signals during hand movement imagination for one experiment session before (**a**) and after (**b**) mental training

trials are then averaged to obtain an average ERSP [15]. It is observed that the delta band activity increases following the visual cue. Mental training causes a significant increase in the delta and theta activity in a time interval from 900 to 1,400 ms. Moreover, it is observed that alpha activity is significantly suppressed after mental training. These observations suggest that the mental training may enhance the slow EEG responses. However, further studies should be done to clarify the effect of imagined effort on the spatial-temporal EEG.

Figure 3 shows the results of the single-channel EEG classification during imagination of hand movement and resting state by using MLP networks, for different feature vectors and five subjects from mental training group, before and after mental training. It is observed that a clear improvement is obtained over all channels in subjects BM, EA, FI, and ME after mental training. Table 1 summarizes the results of classification accuracy of the EEG signals at the position C3 before and after mental training. After mental training, accuracy, as high as 98% is achieved in subject ME at the primary motor cortex (C3). It is worthy to note that the rate of improvement on the EEG classification accuracy in different subjects is not the same. This effect may depend upon the quality of mental rehearsal, which is an intrinsic personality feature.

In order to find out whether the performance of the BCI before and after mental training is actually different, we used two-way analysis of variance (ANOVA) [34]. To apply the ANOVA test, we constitute three sessions. Session 1 constitutes the BCI performance for all subjects before mental training, session two after 10 days, and session three after 20 days of mental training. The variable ‘‘BCI performance over the sessions’’ is the within-subject factor. The second factor is the subjects. Table 2 summarizes the results of the test for each EEG channel with significance level of

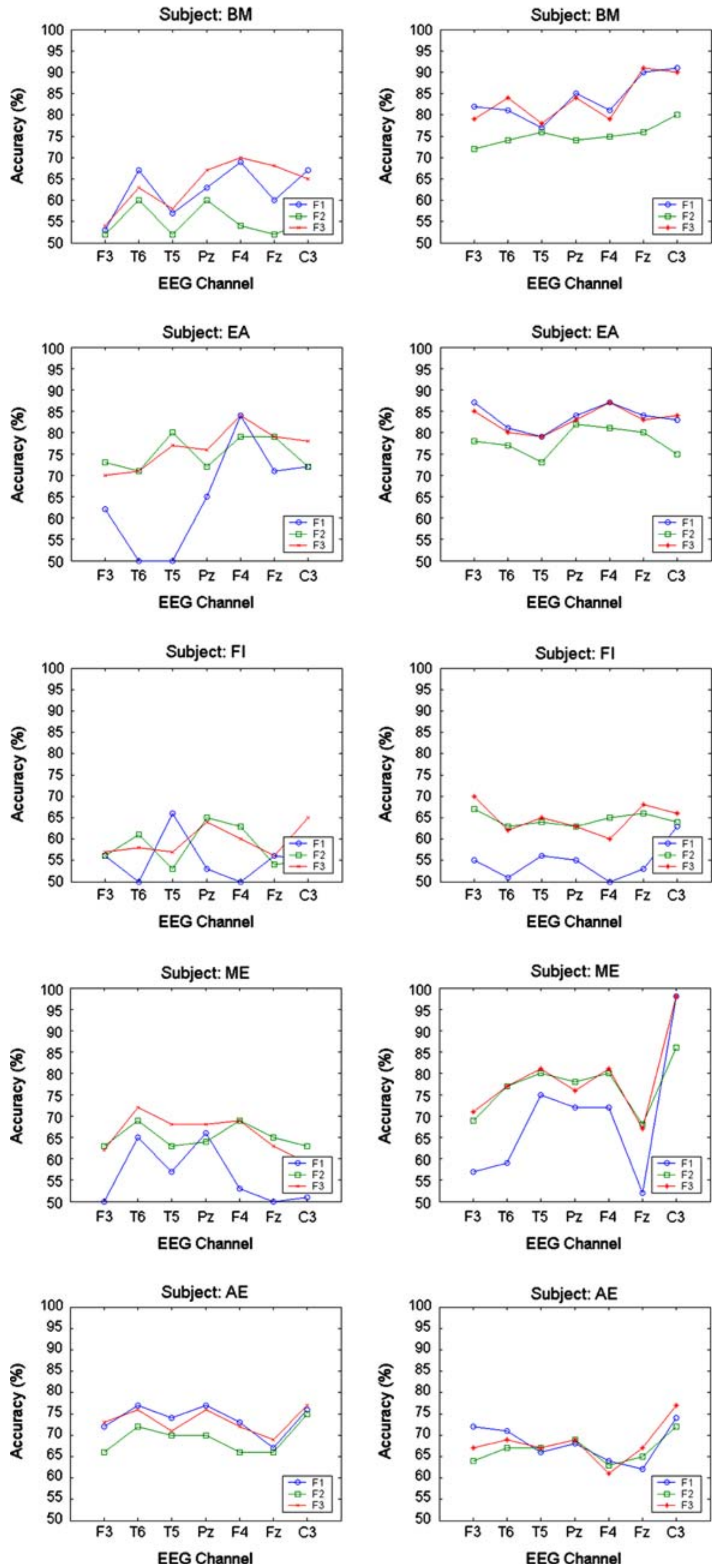

Fig. 3 Single-channel EEG classification accuracies during imagination of hand movement and resting state, for different EEG channels, different feature vectors (F1: *MAV, Var*; F2: $P_\alpha\ P_\beta\ P_\theta$, F3: *MAV, Var,* $P_\alpha\ P_\beta\ P_\theta$), and subjects BM, EA, FI, ME, and AE before (*left plots*) and after (*right plots*) mental training

Table 1 Classification accuracy (%) of the EEG signal for each subject in training group at the position C3 before and after mental training using the feature vector *MAV, Var,* P_α P_β P_θ

Subject	AE	MP	SN	ST	BM	EA	FI	ME	Mean
Before mental training									
Overall	77	59	71	74	65	78	65	59	68
Event	82	66	75	80	59	86	63	40	69
Idle	72	52	67	69	71	70	68	78	68
After mental training									
Overall	77	71	78	65	90	84	66	98	79
Event	96	76	75	73	92	86	83	100	85
Idle	58	67	82	58	88	82	50	97	73

Table 2 Statistical comparison between the performance of single-channel EEG-based BCI before and after mental training with significant level of 0.05

	P value						
EEG channel	F3	T6	T5	Pz	F4	Fz	C3
Session1/session 2	0.0365	0.2029	0.5048	0.0866	0.2597	0.2480	0.1962
Session 1/session 3	0.0001	0.1254	0.0499	0.0486	0.4574	0.0081	0.0001

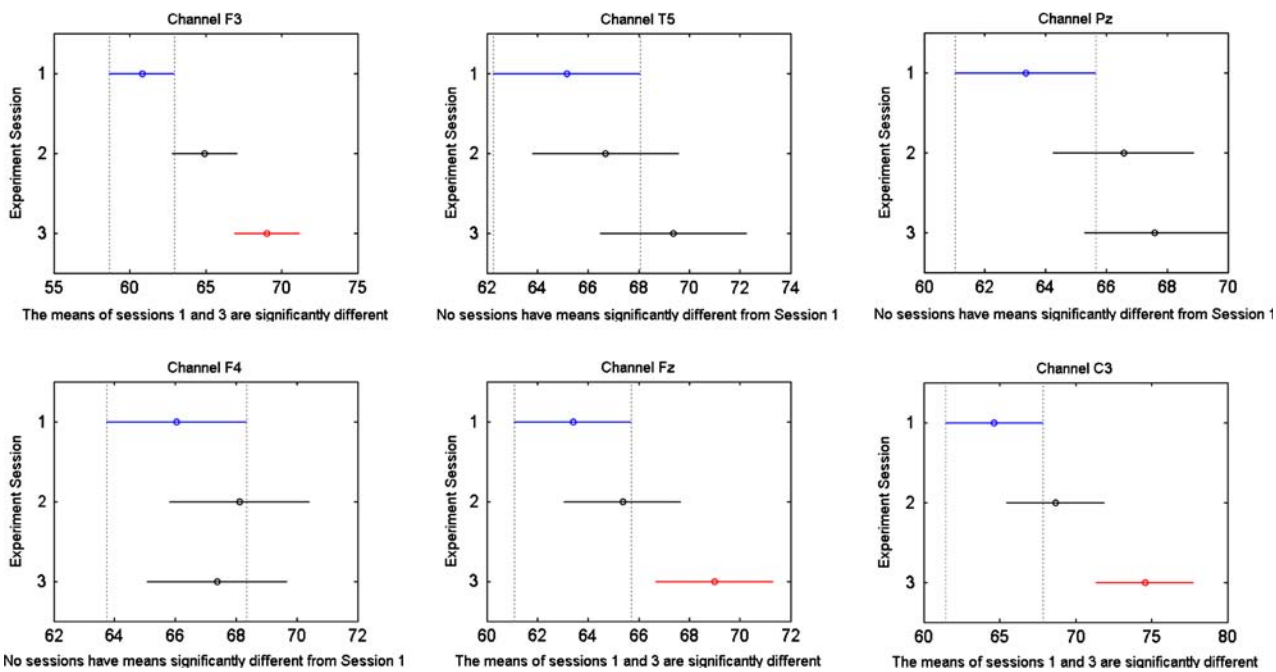

Fig. 4 Estimated means and their 95% confidence intervals of the BCI performance before and after mental training. Session one constitutes the BCI performance before mental training, session two after 10 days, and session three after 20 days of mental training

5%. It is observed that session three is significantly different from session 1 at the frontal positions (F3 and Fz) and especially at the primary motor cortex (C3). It is worthy to note that *P*-value at the positions F3 and C3 is 0.0001, which is highly significant.

To test the mean of classification accuracy over the sessions and determine which pairs of means are significantly different, we used a multiple comparison test based on ANOVA [34]. Figure 4 shows the multiple comparison of the BCI performance before and after mental training for channels F3, T5, Pz, F4, Fz, and C3. It is observed that session 3 is significantly different from session 1 at the positions F3, Fz, and C3.

The results of EEG classification for the first and second experiment sessions for control group are shown in Fig. 5. Specific changes in the classification accuracies over the sessions were not observed. Table 3 summarizes the results of classification for the

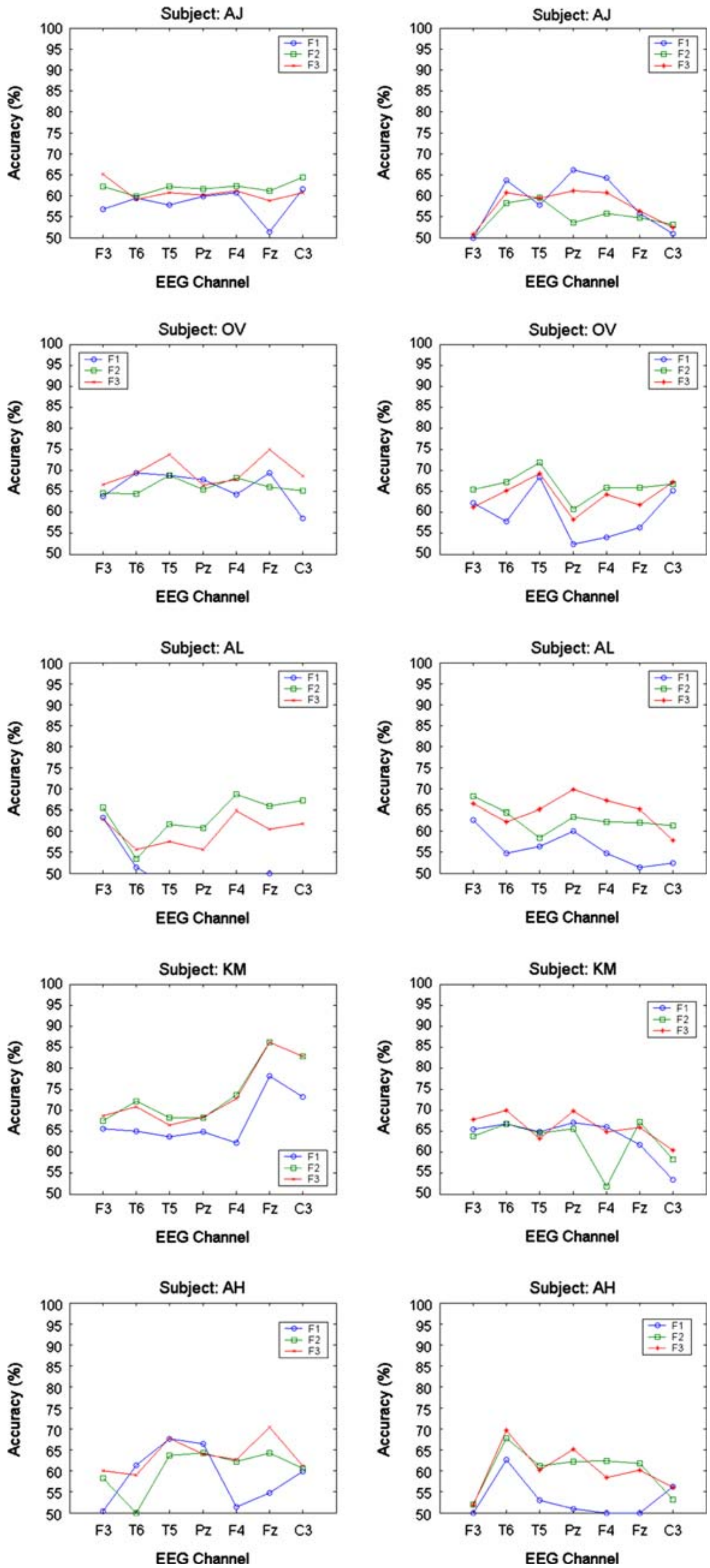

Fig. 5 Single-channel EEG classification accuracies during imagination of hand movement and resting state, for different EEG channels, different feature vectors (F1: *MAV, Var*; F2: $P_\alpha\ P_\beta\ P_\theta$; F3: *MAV, Var,* $P_\alpha\ P_\beta\ P_\theta$), and subjects AJ, OV, AL, KM, and AH from control group for the first (*left plots*) and third (*right plots*) experiment sessions

Table 3 classification accuracy (%) of the EEG signal for each subject in control group at the position C3 for the first and second experimental sessions using the feature vector *MAV, Var,* P_α P_β P_θ

Subject	AH	KM	NH	AV	AJ	OV	AL	ML	Mean
First experimental session									
Overall	61	83	71	75	61	63	62	71	68
Event	76	81	66	73	51	65	76	71	70
Idle	47	85	77	77	71	61	48	72	67
Second experimental session									
Overall	56	61	63	67	52	66	58	69	61
Event	47	53	73	85	51	61	52	55	60
Idle	65	68	54	50	54	71	64	83	63

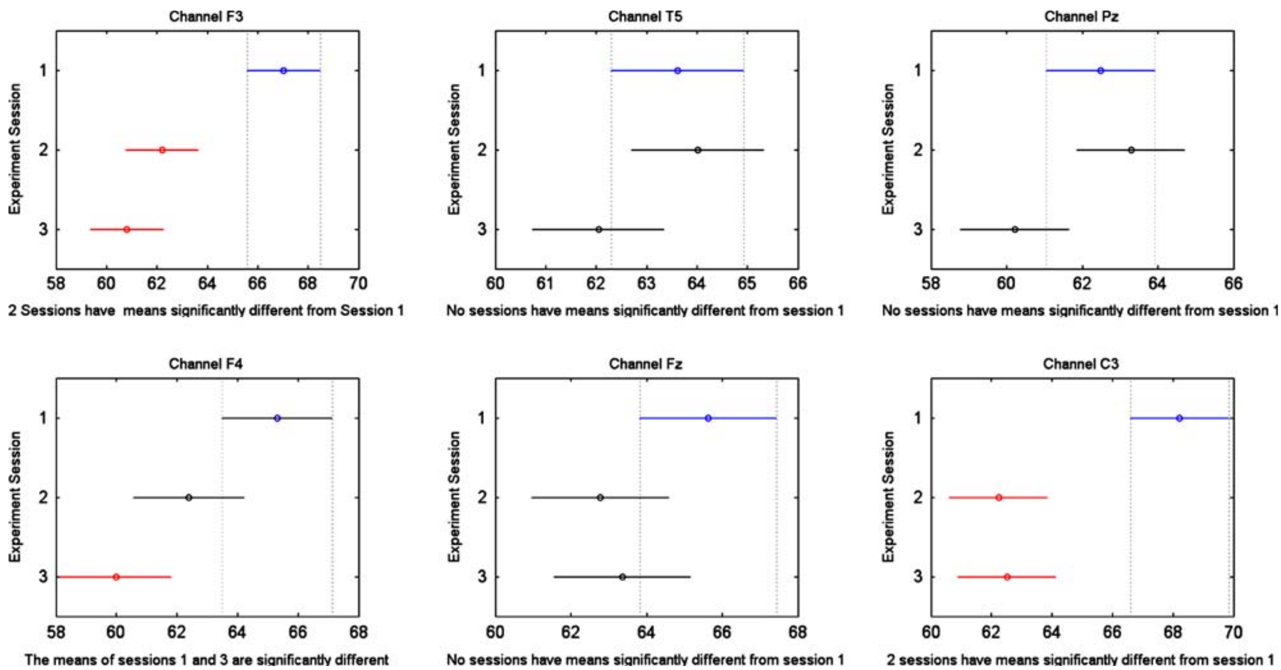

Fig. 6 Multiple comparison of the BCI performance for control group. Session one constitutes the BCI performance for the first day, session two after 10 days, and session three after 20 days of the first day for all subjects in control group

first and second sessions at the position C3 for all subjects in control group. It is observed that the mean classification accuracy during the second session of experiment is decreased with respect to the first session. The mean classification accuracies are 68 and 61% for the first and second sessions, respectively. Figure 6 shows the results of the multiple comparison of the EEG classification accuracies over the three sessions using ANOVA test. It is clearly observed that the classification performance is not improved over the three sessions. It has been already investigated the BCI performance over the time with and without feedback. It was reported that that no overall improvement of the classification accuracy over sessions exits [25]. Also, it was reported [26] after extensive conventional BCI training on three able-bodied subjects, the error-rate over the time displayed a decreasing trend only in the second subject the error-rate showed kept nearly constant in third subject, and in the first subject showed an increasing tendency. Kübler et al. [14] reported that the performance exceeded the 70% accuracy over 20 experiment sessions for a sensorimotor rhythm-based cursor control.

Until now, we investigated the performance of BCI over the experimental sessions for mental training and control group, separately. The results clearly demonstrate that the BCI performance is improved over the sessions for mental training group, but this does not happen for control group. In order to evaluate the effect of mental training on the performance of BCI, two-way analysis of variance is also conducted introducing groups (mental training group and control group) as the between-subject factor. One factor is the experimental sessions and the other is the group. There are eight replicate observations for each group (i.e., eight subjects for each group). This analysis is done for each EEG channel separately. The results show that the mental training has significant effect on the performance over the C3 (P = 0.0089).

6 Discussion

Imagery is the essential part of the most EEG-based communication systems. Thus, the quality of mental rehearsal and the degree of imagined effort should have a major effect on the performance of EEG-based BCI. In this paper, we investigated the role of mental practice and concentration skills on the performance of EEG-based BCI. The results show that the mental training can generally improve the classification accuracy of the EEG pattern during motor imagery. It is found that mental training has a significant effect on the BCI performance over the primary motor cortex (C3) and frontal (F3).

It is observed from Table 2 that the classification accuracy at channel F4 was not significantly improved after mental training. One possible suggestion for this observation is that the effect of mental training on temporal-spectral EEG may not to be the same for different EEG channels and different subjects. Therefore, the relevant features should be selected for each subject and each EEG channel for EEG classification. Investigating the effect of mental training on spatial-temporal-spectral patterns of EEG is one of the key issues for the future research. Moreover, in this work, we investigated the effect of mental training for 10 and 20 days. It will have to be investigated the impact of short-term and long-term mental training on EEG classification.

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