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An online EEG-based brain–computer interface for controlling hand grasp using an adaptive probabilistic neural network

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A R T I C L E   I N F O

A B S T R A C T

This paper presents a new online single-trial EEG-based brain–computer interface (BCI) for controlling hand holding and sequence of hand grasping and opening in an interactive virtual reality environment. The goal of this research is to develop an interaction technique that will allow the BCI to be effective in real-world scenarios for hand grasp control. One of the major challenges in the BCI research is the subject training. Currently, in most online BCI systems, the classifier was trained offline using the data obtained during the experiments without feedback, and used in the next sessions in which the subjects receive feedback. We *investigated* whether the subject could achieve satisfactory online performance without offline training while the subjects receive feedback from the beginning of the experiments during hand movement imagination. Another important issue in designing an online BCI system is the machine learning to classify the brain signal which is characterized by significant day-to-day and subject-to-subject variations and time-varying probability distributions. Due to these variabilities, we introduce the use of an *adaptive probabilistic neural network* (APNN) working in a time-varying environment for classification of EEG signals. The experimental evaluation on ten naïve subjects demonstrated that an average classification accuracy of 75.4% was obtained during the first experiment session (day) after about 3 min of online training without offline training, and 81.4% during the second session (day). The average rates during third and eighth sessions are 79.0% and 84.0%, respectively, using previously calculated classifier during the first sessions, without online training and without the need to calibrate. The results obtained from more than 5000 trials on ten subjects showed that the method could provide a robust performance over different experiment sessions and different subjects.

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1. Introduction

Over the past decade, many efforts have been done to use the electroencephalogram (EEG) as a new communication channel between human brain and computer. This new communication channel is called brain–computer interface (BCI). A variety of BCI systems have been described in the literature mostly differing in the requested mental strategy and in the type of brain signal used for classification. The majority of BCI systems rely on the spontaneous EEG components in the sense that they are not dependent on specific sensory events, such as slow cortical potentials [1,2], mu and/or beta rhythms [3,4], and features extracted from the spontaneous EEG [5–8]. Other types of BCIs are based on the P300 of the visual event-related potential [9–11]. The P300-event-related potential is an evoked response to an external stimulus which presents as a positive deflection at a latency of around 300 ms after the onset of external stimuli. Farwell and Donchin [9] first demonstrate the use of P300 for BCIs in a so-called oddball paradigm. One BCI solution relies on an involuntary response known as the steady-state visual evoked potential (SSVEP) [12–14]. SSVEP is a periodic evoked potential elicited by rapidly repetitive visual stimulation. When a subject focuses attention on such stimulus, EEG activity may be detected over occipital areas at corresponding frequencies. Effective attempts have been done to improve the accuracy and capacity of the BCI systems. In addition to the employment of different signal processing approaches [8,15–18], some researchers have investigated the role of EEG biofeedback [19], response verification [20], and mental training [21] on EEG control.

Although significant progress has been made in the area of brain–computer interface in recent years, the experimental paradigms have been largely designed for cursor movement [3,4] and spelling [22] under certain conditions and mainly for restricted scenarios or demonstration purposes, e.g. [17,23–25]. In our previous work in 2002 [26], we explored the use of single-channel single-trial EEG signals for natural control of prosthetic hand grasp in an amputee subject. The experiments were performed on a below

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elbow amputee subject. The tasks to be discriminated were the imagination of hand grasping, opening, and idle state. An average correct classification rate of 83% was achieved. Recently, in a case study, the use of BCI for a limited control of hand grasp in a tetraplegic subject has been demonstrated [27,28]. The beta activity associated with foot movement imagination [27] and the frequency bands (14–16 and 18–22 Hz) associated with imagination of the left hand movement [28] was used as a triggering signal for control of functional electrical stimulation.

There are several challenges involved in employing BCI for real-world tasks such as hand grasp control. The ability to control the sequence of hand grasping and holding in upper-extremity prosthetic devices is a critical issue. Holding function is accomplished by a BCI state where the user is not involved in any particular mental task and BCI should not carry out any action.

Another important issue in designing a practical BCI is the selection of mental tasks to be imagined. Different types of mental tasks have been used in BCI including left, right, foot, and tongue motor imagery. In many online BCI systems, the mental task is different from the subject's intension which is the action to be controlled by the BCI, e.g. [27–30]. However, it should be noted that it is desirable to select a mental task to be consistent with the desired action to be performed by BCI. The intended movement is to be what the subject imagines.

One of major challenges in BCI research is both subject and classifier training. Currently, in most online BCI systems, the classifier was trained offline using the data obtained during the experiments without feedback, and used in the next sessions in which the subjects receive feedback [22,30–32,50]. Moreover, the experimental paradigms during offline calibration sessions is different from that during online control. This biofeedback affects the spatial–temporal-spectral patterns of EEG activity [33]. Furthermore, the mental training which is performed during BCI sessions will also affect the EEG signals produced during performance of motor imagery. This means that the classifier has to be trained again offline [34]. Vidaurre et al. [23,24] introduced an online BCI using continuously or discontinuously adaptation of an initial classifier to control the horizontal position of a ball falling downward from top of the screen by the imagination of left- or right-hand movements, while online experiments were conducted on naïve and untrained subjects and the subjects received feedback from the beginning of the online experiments. Initial classifier, which was trained offline, was applied in the first trial and then updated continuously or discontinuously. Besides, they provided a static subject-specific classifier for comparison with two continuous and discontinue adaptive systems while 3 nonfeedback runs were used for offline training of classifier and used for classifying subsequent six feedback runs on the same day [24].

Our aim in this work is to test whether the naïve and untrained subjects could achieve satisfactory online performance without offline training of the classifier while the subjects receive feedback from the beginning of the experiments. Two schemes of classification were used: adaptive and static. The adaptive scheme was used during the first sessions (days) with feedback to train the classifier and used the trained classifier for subsequent experiment sessions (days) with no adaptation and no offline calibration.

The BCI systems translate the brain activity into signals that control the external devices. Thus, event detection and classification of brain signals are an important issue in developing an EEG-based BCI. In this context, effective attempts have been done to improve the classification accuracy and capacity of the BCI systems [35]. However, robust and accurate EEG discrimination still remain a challenge in developing an online EEG-based BCI. The significant considerations in classifier design are computational complexity, generalization performance, and robustness to time-varying envi-

ronment. The pattern recognition strategy should be robust against day-to-day usage.

In this work, we develop a new BCI system based on an adaptive probabilistic neural network working in a non-stationary environment for the first time in the literature for online classification of EEG signals to control the *sequence* of hand grasping and opening in an interactive virtual reality environment.

2. Classification approach

The measured values of EEG signal can be considered realizations of a random variable with a certain distribution. In this case, the pattern classification problem usually reduces to the construction of a model that estimates the class conditional densities $p(x|k)$ of the data and the respective prior probabilities $p(k)$ for each class k. Then, using Bayes' theorem, the posterior probabilities $p(k|x)$ can be computed

$$p(k|x) = \frac{p(x|k)p(k)}{\sum_l p(x|l)p(l)} \tag{1}$$

In order to classify an unknown pattern x, we select the class with the highest posterior probability $p(k|x)$ as suggested by the Bayes' rule. The accuracy of probabilistic classification relies on the accuracy of the probability density function (pdf) estimation, which can be obtained by parametric, nonparametric, or semiparametric methods. Parametric approaches are easy to implement, but the assumed pdf may not always match the original data distribution very well. In the nonparametric approach, it is assumed that a functional form of probability densities is unknown. Many researchers have studied Bayesian classifiers by the estimation of probability density function using artificial neural networks, the so-called probabilistic neural networks (PNNs) [36–42]. The PNNs implement in a parallel fashion nonparametric estimation techniques commonly used in statistics. They are characterized by fast training and convergence to the Bayes-optimal decision surface.

The bayesian classifier based on parametric techniques has been already employed in BCI design [15,43–45]. In this work, we use a probabilistic neural network based on nonparametric approach working in a time-varying environment for online classifying the EEG pattern during motor imagery.

2.1. Probabilistic neural network

The probabilistic neural network (PNN), introduced by Specht [37,38], is based on well-established statistical principles derived from Bayes' decision strategy and nonparametric kernel based estimators of probability density functions and is capable of realizing or approximating the Bayes classifier

$$C(x) = arg \left(\max_{1 \leq j \leq M} \{p_j f_j(x)\} \right) \tag{2}$$

where $x \in R^d$ is a d-dimensional feature vector, $C(x)$ denotes the estimated class of pattern x, p_j is the *a priori* probability of class j $(1 \leq j \leq M)$, and the conditional probability density function of class j is f_j. The object of the PNN is to estimate the values of f_j. This can be done using a nonparametric estimator based on the Parzen kernel in the form

$$\hat{f}_{n_j}(x) = \frac{1}{n_j} \sum_{i=1}^{n_j} K_{n_j}(x, X_i^{(j)}) \tag{3}$$

where $X = \{X_i, Y_i\}$ is the set of n observations, each $X_i \in \Re^d$ is a feature vector, and Y_i is a label indicating the class of pattern X_i. The original set can be partitioned into M independent subsets X^j, so that each subset contains only the data of the corresponding class. n_j denotes

the number of patterns of class j, i.e., $n_j = |X^j|$. The sequence K_n is based on the Parzen kernel in the multidimensional version and takes the following form:

$$K_n(x, u) = h_n^{-d} K\left(\frac{x - u}{h_n}\right) \tag{4}$$

where h_n is a certain sequence of numbers and K is an appropriately selected function. Precise assumptions concerning sequence h_n and function K that ensure the convergence of PNNs were given in [46]. The function K can be presented in the form

$$K(x) = \prod_{i=1}^{d} H(x^{(i)})$$

Then, sequence K_n is expressed by means of formula

$$K_n(x, u) = h_n^{-d} \prod_{i=1}^{d} H\left(\frac{x^{(i)} - u^{(i)}}{h_n}\right). \tag{5}$$

The most popular is the Gaussian kernel given by

$$H(v) = (2\pi)^{-1/2} e^{-1/2 v^2} \tag{6}$$

and

$$K_n(x, u) = h_n^{-d} (2\pi)^{-1/2} \prod_{i=1}^{d} e\left(\frac{x^{(i)} - u^{(i)}}{h_n}\right)^2. \tag{7}$$

The prior probabilities p_j are estimated by

$$\hat{p}_j = \frac{n_j}{n} \tag{8}$$

where n_j is the number of observations from class j, $j = 1, \ldots, M$. Combining (2), (3), and (8) we get the following discriminant function estimate:

$$\hat{d}_{j,n}(x) = \frac{1}{n_j} \sum_{i=1}^{n_j} K_{n_j}(x, X_i^{(j)}) \tag{9}$$

Assign input pattern x to class m in moment n if

$$\hat{d}_{m,n}(x) \hat{d}_{i,n}(x)$$
$$\text{for} \quad i \neq m, i = 1, \ldots, M, \quad n = 1, 2, \ldots \tag{10}$$

2.2. Adaptive probabilistic neural network

The nonparametric method discussed above can be applied only where probability distributions do not change with time. To generalize the above nonparametric pattern classification scheme to non-stationary case, Rutkowski [46] presented a recursive version of the discriminate function estimate (9) as

$$\hat{d}_{m,n+1}(x) = \hat{d}_{m,n}(x) + a_{m,n+1} \left[T_{m,n+1} K_{m,n+1}(x, X_{n+1}) - \hat{d}_{m.n}(x)\right]$$
$$\hat{d}_{m,0} = 0$$
$$T_{m,n} = \begin{cases} 1 & \text{if} \quad Y_n = m \\ 0 & \text{if} \quad Y_n \neq m \end{cases} \text{for} \quad m = 1, \ldots, M, \quad n = 0, 1, 2 \ldots \tag{11}$$

In order the pattern classification rules (10) and (11) to be strongly asymptotically optimal, the sequence $\{K_n\}$ and $\{a_n\}$ have to satisfy certain conditions [46]. In this regard, the sequences $\{K_n\}$ and $\{a_n\}$ have been selected to be of following type

$$h_n = kn^{-H}, \quad k > 0, \quad H > 0$$
$$a_n = n^{-a}$$

We applied the PNN based on the Parzen kernel to discriminate between two tasks ($M = 2$) with the following parameters

$$H = 0.35, \quad k = 5, \quad a = 0.5.$$

Time-varying discriminant functions (10) are estimated by means of the learning procedure (11) using the learning sequence $\{(X_i, Y_i), i = 1, 2, \ldots n\}$. In order to classify pattern $X_{n+K}(K \geq 1)$, it is necessary to store the whole learning set of the length n. Next, when the pattern X_{n+K} to be classified appears, procedure (10) is activated and put $x = X_{n+K}$.

3. Experimental setup and data set

3.1. BCI competition 2003-data set III

Before applying the above statistical classification method to online hand grasp control, the algorithm was applied to the data set III of "BCI Competition 2003" which is obtained by Graz group [47]. This data set was recorded from a healthy subject during a feedback session. Three bipolar EEG channels were measured over C3, Cz, and C4. EEG signals were sampled with 128 Hz and was filtered between 0.5 and 30 Hz. The task was to control a feedback bar in one-dimension by imagination of left- or right-hand movements. The experiment included seven runs with 40 trials each. All runs were conducted on the same day with breaks of several minutes in between. The data set consists of 280 trials of 9-s length. The first 2 s were quiet. At $t = 2$ s, an acoustic stimulus indicated the beginning of the trial, and a cross ("+") was displayed for 1 s. Then, at $t = 3$ s, an arrow (left or right) was displayed as a cue stimulus. The subject was asked to use imagination as described above to move the feedback bar into the direction of the cue.

3.2. Online hand grasp control experiments

(1) *Subjects:* The experiments were carried out with ten able-bodied volunteer subjects (five females, five males, aged between 24 and 26). Subject NH was left handed and the rest right handed. The subjects had never participated in BCI-experiments before.

(2) *Recording:* Monopolar EEG signals were recorded at a sampling rate of 256 from positions F3, F4, Fz, Pz, C3, C4, and Cz by Ag/AgCl scalp electrodes placed according to the International 10–20 system and then were filtered with a 0.5–45 Hz bandpass filter. The eye blinks were recorded by placing an electrode on the forehead above the left eyebrow line. All recording channels were referenced to the left earlobe and a ground electrode at the right earlobe. The signals were continuously collected and processed during the experiments, while the subject was free to blink and to move his eyes.

(3) *Experimental paradigm:* The experiment was based on an interactive virtual reality environment. The subjects sat on a relaxing chair with armrests. At the start of trial, an opened hand was displayed on the screen and the subject should try to keep it open for 5 s (i.e., holding phase). This is the holding state in which the subject does not perform any specific mental task. Following the relaxation phase, a ball began to fall and by reaching the ball to the palm, at 7 s, an active feedback phase lasting 5 s was started in which the user should try to grasp the ball by imagination of hand grasping (i.e., closing phase). Upon the detection of motor imagery by the classifier, the hand will be closed sequentially. The sequence of closing was controlled by the output of classifier. Following the closing phase, at 12 s, the color of the ball was changed and a closed hand was displayed. The subject should try to open the hand (i.e., opening phase). Fig. 1 shows the structure of a typical run.

The experiment consisted of 10 sessions for each subject (except for one subject in whom 8 sessions were conducted). Each session was conducted on a different day and consisted
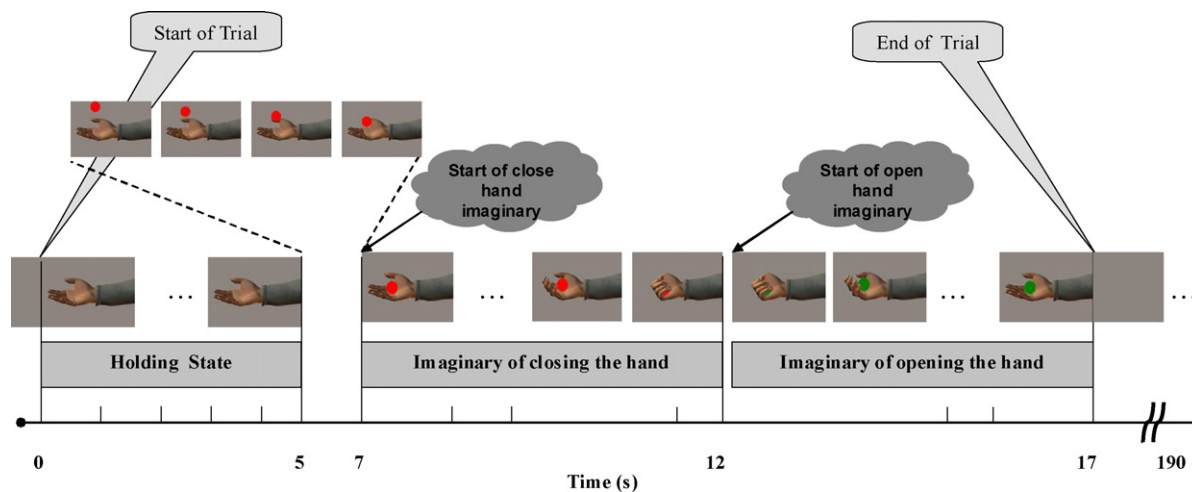
Fig. 1. The structure and the timing of an experimental run during online hand grasp control.

of at least 10 runs. Each run consisted of 5 feedback trials and each run consisted of holding state and imagination of hand grasping and hand opening. A resting period of about 2 min was enforced between each run. The tasks to be *discriminated* were the imagination of hand movement and holding state. The imaginative hand movement can be hand closing or hand opening.

(4) *Hardware and software:* To implement the virtual reality based BCI for hand grasp control on a PC, appropriate and optimized computer software was required. In our case, we used Matlab Simulink (THE MATHWORKS, 1998–2000), Real-Time Workshop (THE MATHWORKS, 1999–2000), and Real-Time Windows Target under Windows XP for online data acquisition, filtering and ocular artifact suppression, feature extraction, classification and providing interactive virtual reality environments. The EEG was recorded with a bipolar EEG-amplifier (g.USBamp, g.tec, Guger Technologies, Graz, Austria).

(5) *Real-time ocular artifact suppression:* One of the major problems in developing an online EEG-based BCI is the ocular artifact suppression. In this work, during the online experiments, eye blink artifacts were suppressed automatically by using a neural adaptive noise canceller (NANC) proposed in [48]. The structure of adaptive noise canceller is shown in Fig. 2. The primary signal was the measured EEG data from one of the EEG channels. The reference signal was the data recorded from the forehead electrode. Here the adaptive filter was implemented by means of a multi-layer perceptron neural network.

4. Results

4.1. Time–frequency analysis of EEG signals

Event-related desynchronization (ERD) and event-related synchronization (ERS) responses of EEG frequencies during hand grasp control were used to quantify event-related oscillatory EEG responses [49]. The ERD/ERS is defined as relative power decrease (ERD) or power increase (ERS) with respect to a resting period which is usually placed several seconds before trigger onset. To estimate the time–frequency spectral of EEG signals, baseline spectra are estimated from the EEG preceding the motor imagery during holding state. The EEG obtained during each trial experiment is divided into 250-ms short windows, overlapping by 125 ms, 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 trials are then averaged to obtain an average ERSP.

Fig. 3 shows the time–frequency distribution of EEG signals in subject SD during the first and second sessions of the experiment. During the first day, a broad-banded event-related desynchronization (ERD) of mu rhythm in frequency around 10 Hz is observed (Fig. 3(a)). In addition, a weak ERD in the 20-Hz band exists. However, a stronger mu and beta ERD is induced during the second day. Moreover, it is observed that the motor imagination is preceded by event-related synchronization (ERS) of theta and gamma activity which also exits during imagination. Increased gamma oscillations
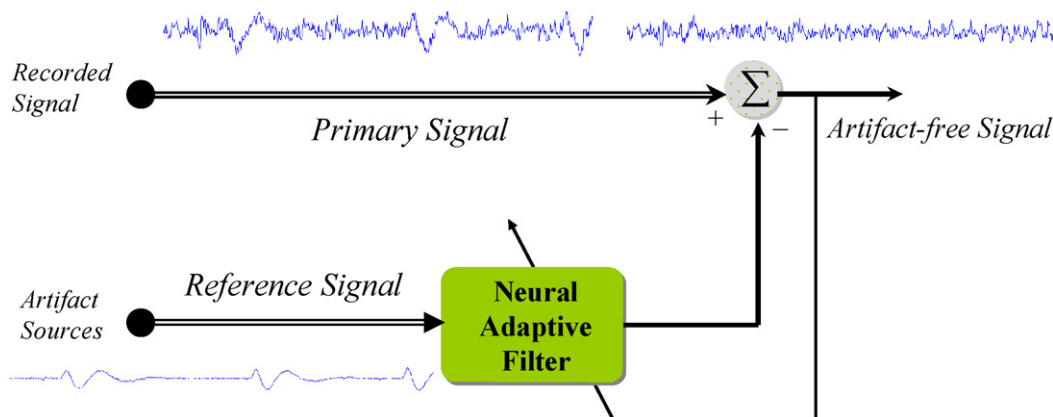

Fig. 2. The structure of the neural adaptive noise canceller used for online ocular artifact suppression.
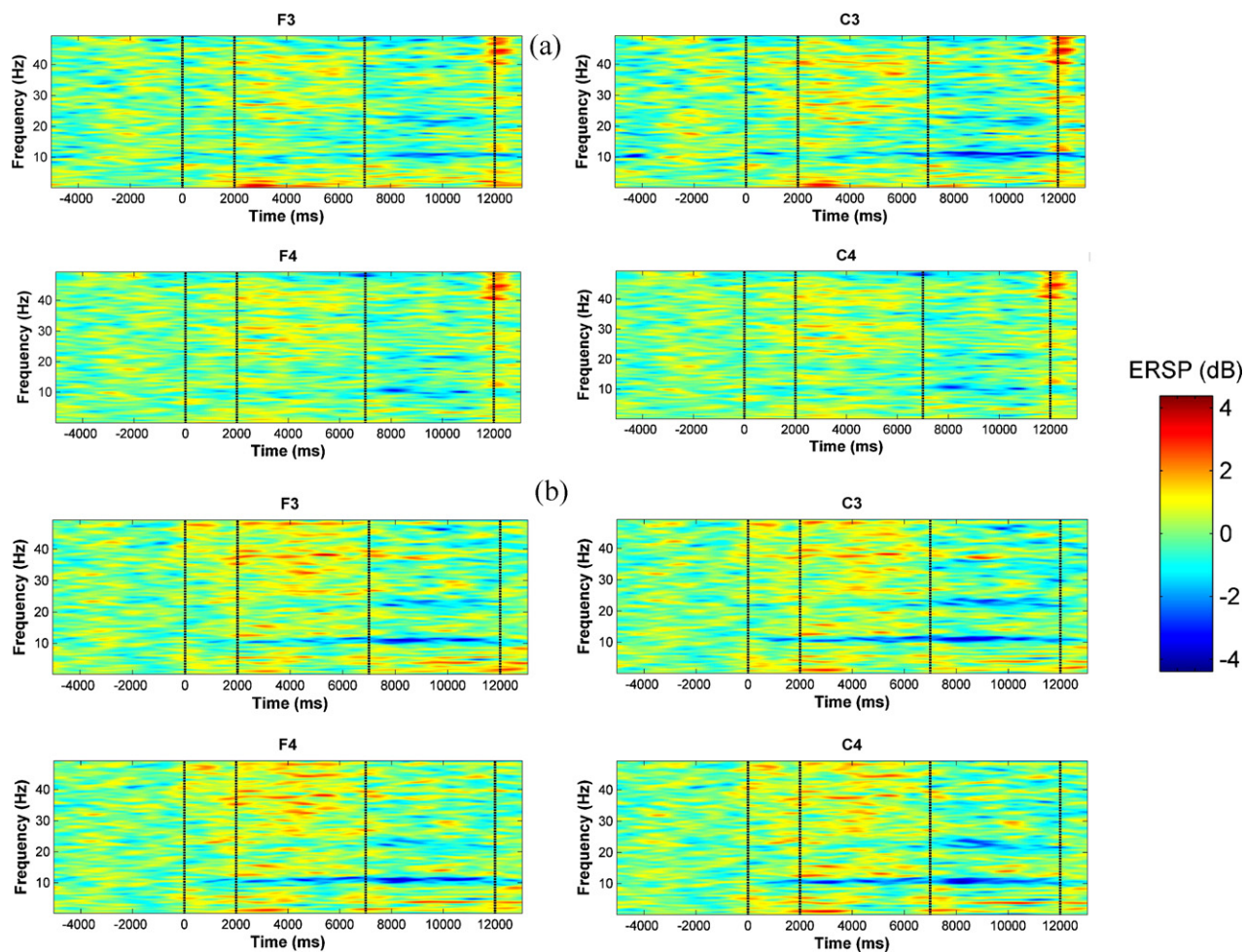
Fig. 3. Time–frequency distribution of EEG signals in subject SD during the first (a) and second (b) session of the experiment. At the beginning of the trial, an opened hand was appeared on the screen and the subject should try to keep it open (i.e., relaxation phase) for 5 s. Following the holding state, a ball began to fall (marked the vertical line at second zero) and by reaching the ball to the palm (marked by the second vertical line), an active feedback phase lasting 5 s was started in which the user should try to grasp the ball by imagination of hand grasping (i.e., closing phase). Following the closing phase (marked by the third vertical line), the color of the ball was changed and a closed hand was displayed. The subject should try to open the hand.

in parallel with theta oscillations have been also observed during voluntary movement performance [50]. Mensh et al. [51] demonstrated that incorporating gamma-band activity, could enhance the performance of EEG-based BCI. Enhanced gamma oscillations, which has been associated with attentional and intentional states, may be related to increased information transfer (high integration between the brain areas) in order to finalize the imagery task.

Fig. 4 shows the ERS/ERD maps for the subject HG1 during the second, sixth, and seventh experiment sessions. In this subject, a clear short-lasting theta ERS activity before and after imagination of hand was observed. A more interesting ERS/ERD pattern observed in subject HG1 is that a strong gamma ERS was appeared during the imagination, while theta ERS appeared before and after imagination. ERD responses of mu rhythms and ERD/ERS in beta bands during hand motor imagery have been already reported [52,53], but the motivation of current study was to investigate the changes of ERD/ERS patterns during consecutive sessions of BCI-experiments. For this purpose, we used two-way analysis of variance (ANOVA) to test the effect of sessions on the ERD responses of mu and beta rhythms. To apply ANOVA test, two groups were constituted. Group 1 constituted the ERD values in mu (beta) band during 10 runs of the first session for all subjects, and group 2 the ERD values in mu (beta) band during last session of experiment. Comparing the ERD responses during the first and last sessions, the results show that BCI experiment sessions have significant effect on the mu ERD

responses ($p < 0.0118$), with significant level of 0.05, but effect on beta ERD is not significant ($p < 0.0834$).

The results indicate that the subject training occurs during consecutive experimental sessions could change and enhance the ERS/ERD patterns. Hence, the classifier designed for BCI system must be robust against these session-to-session variations.

4.2. Online hand grasp control

The EEG data was continuously recorded and filtered and the eye blink artifacts were removed online during each run of experiment. The features were extracted from 1-s sliding windows with 100 ms overlap and classified. Every 0.5 s, strict majority voting was applied to the 5 classification results to determine the class and to generate the control signal. The feature set was formed from the spectral power of EEG signals recorded from positions F3 and C3 for right-handed subjects (and form F4 and C4 for left-handed subject) in theta (4–8 Hz), alpha (8–14 Hz), lower beta (15–24 Hz), upper beta (25–32 Hz), and gamma (33–40 Hz) frequency bands.

The sequence of closing (opening) consisted of ten steps. Upon the detection of motor imagery during each 0.5 s, the hand will be closed (opened) one step. If the motor imagery is correctly detected during all steps, the hand will be closed (opened) completely. At 12 s, a closed hand was shown to the subject and he/she should try open the hand by imagination of hand opening.
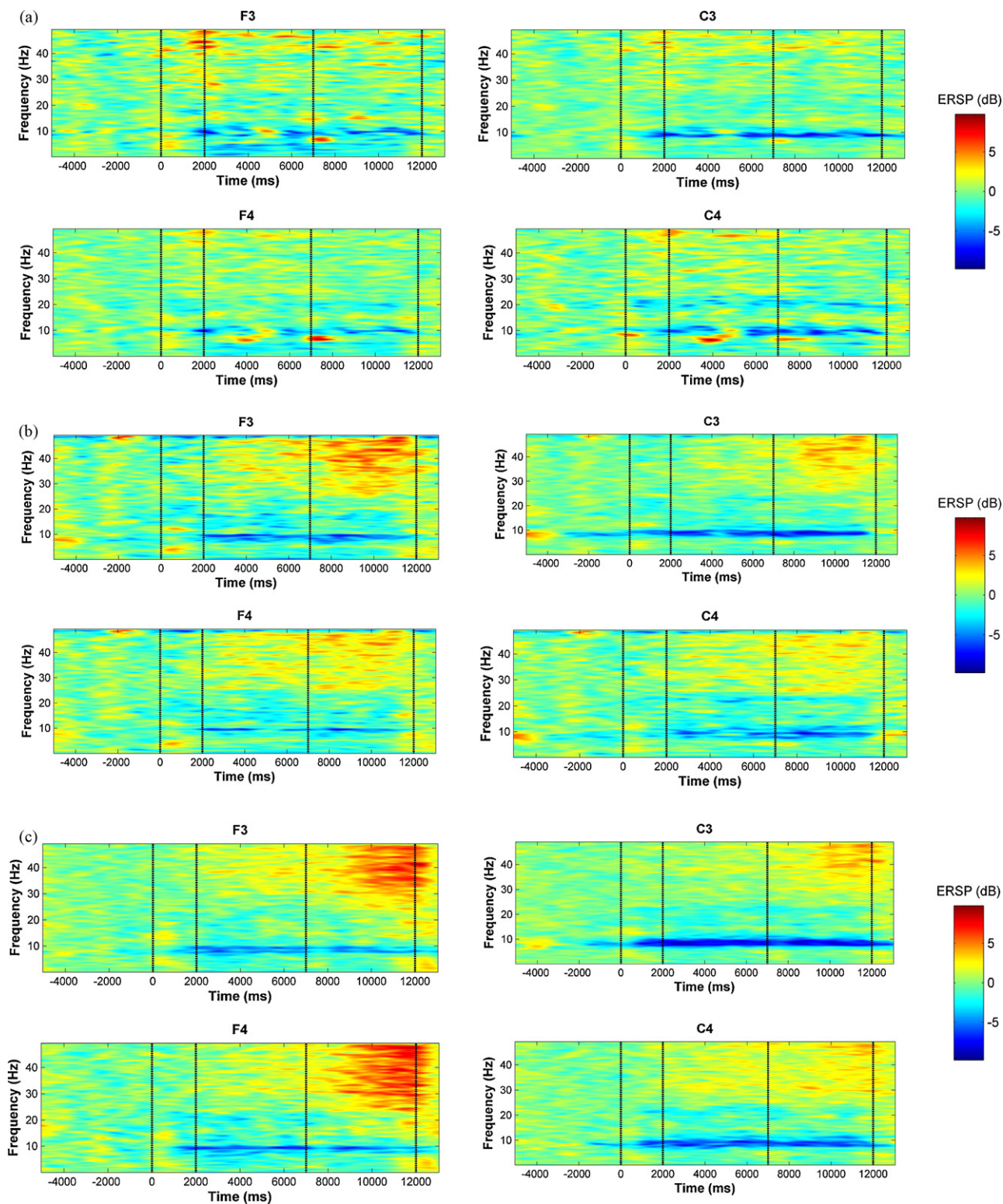
Fig. 4. The ERS/ERD maps for the subject HG1 during the second (a), sixth (b), and seventh (c) sessions of experiment.

Two schemes of classification process were used here for virtual hand grasp control: supervised adaptive and static classification. In supervised adaptive scheme, the classifier was continuously updated while the static classifier was not. Adaptive scheme was used to train the classifier online during the first sessions given up-to-date feedback to the subjects without any offline training. Then, the trained classifier was used for subsequent sessions using static scheme without any calibration. *To compute the accuracy of classification*, performed action was compared to the desired action during each 0.5 s.

Fig. 5 shows the results of online hand grasp control during different runs of the first session for all subjects where the adaptive classifier was used for all runs of the session. The subjects had never participated in BCI-experiments before and were able to reach a
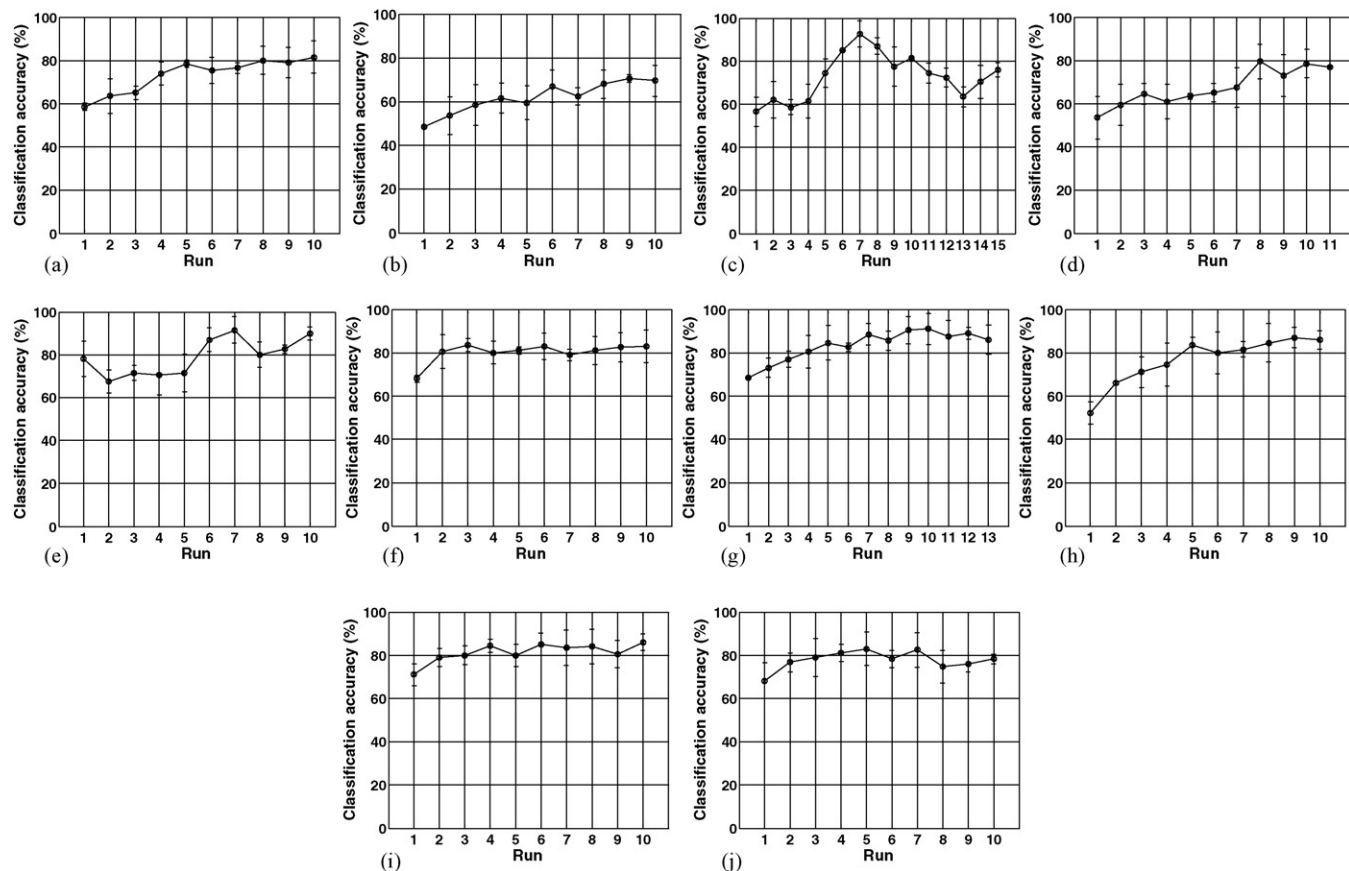
Fig. 5. The classification accuracies obtained during different runs of the first session for the subjects HG1 (a), FP (b), NH1 (c), AS (d), AZ (e), HG2 (f), NH2 (g), MA (h), MH (i), KM (j), where the adaptive classifier was used for all runs of the session.

classification accuracy rate between 70.5% and 92.5% in the first session without offline training. Interesting observation is that in all subjects, except subject FP, an accuracy rate more than 80.0% was obtained after the first few runs during the first session and the performance is robust for the subsequent runs.

Table 1 summarizes the average and the best classification rates obtained for all subjects during the first, second, and last experiment sessions. The best accuracies obtained using adaptive classification were 70.5–92.5% (with mean of 84.3%) after 3 min training during the first session of experiment. The average of classification rate over all subject during the first session was 75.4%. During the second session using adaptive classification, the best accuracies were between 81.0% and 93.5% (with mean of 88.2%), while the average rate was 81.4%. The results indicate that the subjects could reach such levels of proficiency after one experiment session using the proposed method.

During third session of experiment, an average accuracy of 79.1% was achieved while classifier calculated during sessions 1 and 2 was used with no adaptation and no calibration for 8 subjects. Average

accuracy over all subjects was 83.6% during eighth session using static scheme.

Fig. 6 shows the average performance over all runs during each session for all subjects using both adaptive and static classification schemes. It is observed that the performance of static scheme is almost the same as that of adaptive. In subject HG1, it is observed that the performance of BCI decreases from 80.05% to 77.90% when the classifier was switched from adaptive to static in the third session and begins to incases during next experimental sessions. During the seventh session, when the classifier was switched from static to adaptive mode, the performance increases from 79.65% to 86.70% and remains the same for the subsequent experiment sessions during static mode of classifier operation. The enhancement in the performance of BCI during the seventh session compared to the sixth session is in accordance with the enhancement in ERS/ERD patterns observed during the seventh experiment session (Fig. 4).

Interesting result observed in Fig. 6 is that the same results obtained for subject HG1 were almost observed in all other subjects. In the last session of experiment, all subject could control the

Table 1
Best[a] and average[b] classification rate obtained during the first, second, and eighth experimental sessions.

Subjects		HG1	FP	NH1	AS	AZ	HG2	NH2	MA	MH	KM	*Mean*
Session 1 (adaptive	Best	81.5	70.5	92.5	78.5	91.0	83.5	90.0	87.0	85.0	83.0	84.3
classification)	Average	73.2	61.9	72.9	67.5	79.1	80.2	83.4	76.6	81.4	77.8	75.4
Session 2 (adaptive	Best	85.0	81.0	93.5	84.5	89.5	91.5	92.0	90.5	86.0	88.0	88.2
classification)	Average	80.1	75.3	85.3	75.5	81.5	85.1	84.3	83.6	80.0	83.4	81.4
Session 8 (static	Best	90.5	82.0	88.5	93.5	96.0	91.5	92.5	93.5	89.0	88.0	90.5
classification)	Average	85.1	80.0	85.8	77.2	89.8	85.7	84.1	83.6	82.6	82.6	83.6

[a] *Best rate:* Mean accuracy over each run was computed and the best run during the session was reported.
[b] *Average rate:* Mean accuracy over all runs of the session was reported.
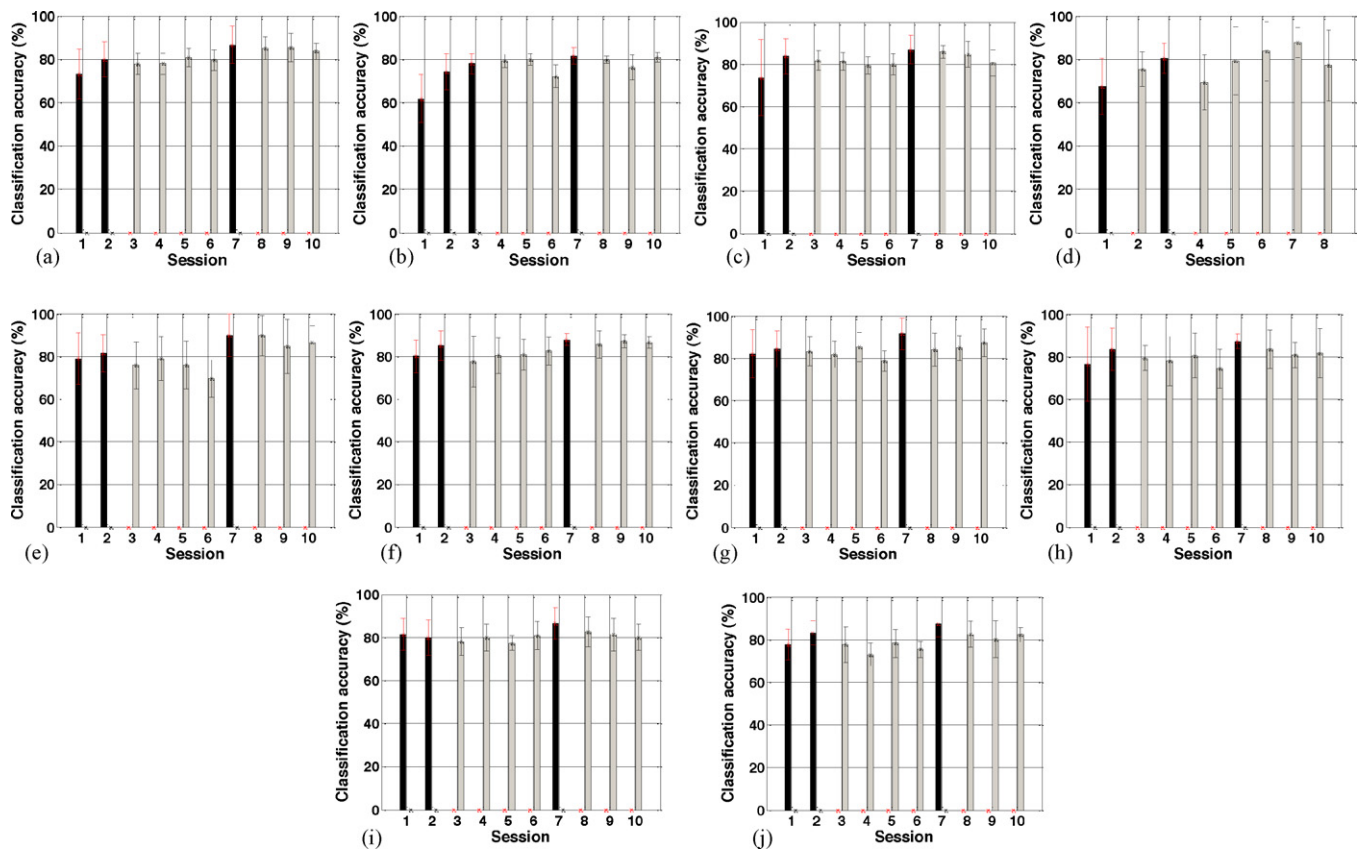
Fig. 6. The average performance obtained during each session for the subjects HG1 (a), FP (b), NH1 (c), AS (d), AZ (e), HG2 (f), NH2 (g), MA (h), MH (i), KM (j), using both adaptive (black) and static (gray) classifications.

hand movement correctly at the best case between 82.5% and 94.5% (the mean accuracy over the run) and on average between 77.2% and 87.4% (the mean accuracy over the session for each subject).

4.3. BCI competition 2003-data set III

Five 1-s intervals of EEG data of each channel (i.e., C3 and C4) are considered during each trial of experiment. The first window starts 500 ms after cue stimulus and all 1-s windows overlap by 250 ms. The classifiers are trained to differentiate between EEG patterns associated with left- and right-hand movement imagery. The entire feature set are formed from each data window, separately and consisted of the spectral power of EEG signals recorded from positions C4 and C3 in theta, lower alpha, upper alpha lower beta, and upper beta frequency bands. The classifier is trained to differentiate between EEG patterns associated with left- and right-hand movement imagery. From 280 data sets, 140 sets are assigned for training the classifier, while the rest is kept aside for validation purposes. The same data set of "BCI Competition 2003" provided for training and testing are also used here for training and testing, respectively. Table 2 summarizes the classification accuracy obtained using different classification algorithms including linear

discriminant analysis (LDA) [54], quadratic discriminant analysis (QDA) [23], Gaussian mixture models (GMMs) [44], and adaptive probabilistic neural network. It is observed that the best classification accuracy obtained is 90.2% by using APNN. It is worthy to note that the best rate reported in the BCI competition 2003 for this data set is 89.3% [43].

5. Conclusions and discussion

Classification process is an important issue for developing an online BCI for real-time applications. Online training of the classifier is not possible during real-time applications. Therefore, the trained classifier during previous experimental sessions should provide a robust performance during real-time-application with no adaptation and no calibration and should be robust against day-to-day variations and changes in the ERD/ERS responses of EEG signal. Brunner et al. [17] used an initial classifier trained offline using previously recorded data (without feedback) for online classification and reported average accuracies between 49% and 54%, 49% and 54%, and 60% and 67% for first, second, and third sessions, respectively. Vidaurre et al. [24] reported an average accuracy about 74%, 79%, and 84% during the first, second, and third sessions of experiments when an initial classifier computed from 1620 trials was used during online experiments with continuous adaptation. They also provided a subject-specific static baseline for online classification while during each day 3 nonfeedback runs were recorded, then a subject-specific classifier was calculated and used to classify six feedback runs without changing the classifier [24]. They reported an average accuracy about 56%, 58%, and 60% during first, second, and third day of experiment, respectively. The same scheme for classification was used in [32], while a classifier was calculated from the data of a calibration measurement and used for classification

Table 2
Percentile classification accuracy on the BCI competition 2003-data set III using different classification scheme.

Classification scheme	Classification accuracy
74.91%	LDA
83.54%	QDA
87.63%	GMM
90.16%	APNN

during feedback runs without changing the classifier. All recordings (calibration and feedback runs) of one subject have been recorded on the same day (one 'session'). An average accuracy between 53.6% and 93.2% with mean accuracy of 81.6% was reported.

During the present BCI experiment which is based on an interactive virtual reality environment, the subjects received feedback from beginning the experiments without any pre-training. The classifier was trained during the first sessions of experiment and used for online control during the subsequent sessions without adaptation and calibration. The subjects could achieve an average accuracy of 68–83% after about 3 min training during the first experimental session and 80–85% during the second session, while the adaptive classification was used. The average accuracy over all subjects is 75.4% and 81.4% during the first and second session, respectively. During the 8th session, an accuracy of 77.2–89.8% with mean accuracy of 83.8% over ten subjects was obtained using classification with no adaptation.

Mental practice which is occurred during the experimental sessions significantly changes the spatial–temporal patterns of EEG activity. The novel finding reported here is that the subject training occurs during consecutive experimental sessions could change and enhance the ERS/ERD patterns. Moreover, during the performance of a cognitive task, there are many factors outside the motor imagery process that may be affecting the changes in EEG signals. It has been known that the signal changes related to alertness, arousal, focused attention and sustained mental effort, cognitive load, and emotional state of the subject are present in EEG. Therefore, the classifier should be robust against these variations. The major advantages of classifier used in work, is its ability to work in a time-varying and non-stationary environment. The interesting observation is the robust performance of the classifier. The performance almost remains constant when the static classification scheme is used. After a few sessions, when the adaptation becomes active, the performance increases and remains constant for the consequent sessions with static scheme.

The method proposed in this work operates in cue-based (synchronous) communication mode. The extension of the method to asynchronous control applications constitutes the key issue of our current research. Another important issue in developing an online BCI for disable people is the ability to turn the communication device on and off without assistance from others. This is another key issue of our current research.

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Conflict of interest

There are no conflicts of interest for the authors of this study.

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