An online BCI system for reaching control using Gaussian mixture model classifier with adaptive learning

Khatami Firoozabadi S-F, Erfanian A

Brain-Computer Interface Lab., Neural Technology Research Centre, Department of Biomedical Engineering, Iran University of Science and Technology (IUST), Tehran, Iran

Abstract

In this paper, an online BCI is developed for reaching control while the system could be turned on and off by the user using the EEG signals. Reaching control is based on the imagination of reaching task. The time-frequency of the EEG signals shows that there is a broad-banded event-related desynchronization (ERD) in frequency bands around 10 Hz during reaching imagination. The system is turned on and off by closing the eyes for short period of time. Closing the eyes is detected by the EEG signal recorded form visual cortex. The results show that the subject could turn on and off the system and complete the reaching task with an average accuracy of 99.3% and 96.3%, respectively, using Gaussian mixture classifier.

Keywords: *brain-computer interface, online, Gaussian mixture classifier.*

Introduction

Over the past decade, many efforts have been done to improve the accuracy and capacity of the online brain-computer interface (BCI) systems [1]-[3]. Although significant progress has been made in the area of online brain–computer interface in recent years, there are several challenges involved in employing BCI for real-world tasks.

An important issue in designing a practical BCI is the problem of turning the system on/off. In this work, we present a method for robust turning the BCI system on and off by using the EEG signals. Another important issue 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. 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. In this work, we develop an online BCI for reaching control which is based on the imagination of reaching task.

Material and Methods

Subjects and Recording

The experiments were carried out with two able-bodied volunteer subjects. EEG signals were recorded at a sampling rate of 256 from positions C3, C4, O1, and POz by Ag/AgCl scalp electrodes placed according to the International 10-20 system and then were band pass filtered from 2 to 60 Hz. 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.

In this work, eye blink artifacts were suppressed automatically by using a neural adaptive noise canceller (NANC) proposed in [4].

Experimental Paradigm

The proposed online BCI system consists of two classifiers. One classifier (i.e., on/off classifier) is used for turning the system on and off using the data recorded from position O1-POz. The second classifier is used for control of reaching using the data recorded from positions C3 and C4. The classifiers were trained offline in a short offline training session and then used for online experiments.

Offline Training Session: For training the on/off classifier, the data from position O1-POz were recorded while the subject closed her eyes and then opened, each for 5 s, repeatedly**.** The experiments consisted of 6 runs, each with 6 trials. For training the second classifier, the experiments consisted of 5 runs, each with 10 trials. The first 5 s were quiet. At $t = 5s$, a picture of table was shown to the subject. This is the idle state in which the subject does not perform any specific mental task. At $t = 10s$, a glass was appeared on the table in which the user should imagine the reaching.

Online Feedback Session: The experiment was based on an interactive virtual reality environment. The subjects sat on a relaxing chair with armrests.

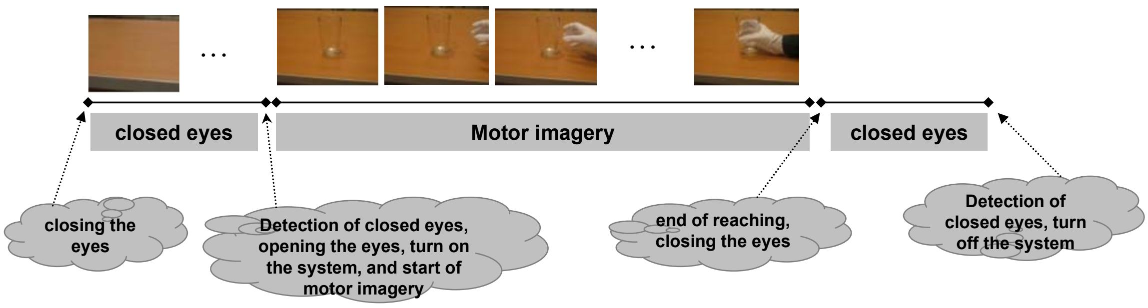

Fig. 1. The structure and the timing of an experimental run during online feedback experiments.

At the start of the trial, a picture of table is shown to the subject. At this time, the subject should turn on the system by closing the eyes. Upon the detection of eye closing by the on/off classifier, a glass on the table is appeared and a short beep alerts the subject. Following the hearing the beep, the second classifier is activated, the subject opens her eyes and begins to imagine the reaching movement. The second classifier controls the movement of the virtual hand. Upon the detection of the hand movement imagination by the second classifier, the virtual hand is moved towards the glass. After reaching the hand to the glass, the second classifier is deactivated and the subject should try to turn off the system by closing the eyes. The experiment consisted of 7 sessions for subject EA and 3 sessions for subject ZB. Each session was conducted on a different day and consisted of 20 feedback trials.

Feature Selection

In this work, we use mutual information criterion for selecting optimal subset of the original feature set. Original features are formed from 1-s sliding window of EEG data. The original feature set was formed from the 1Hz frequency components. Then, we use minimal-redundancy-maximal-relevance criterion (mRMR) [5] to select features with maximal dependency to the target class and minimal redundancy among themselves.

Gaussian Mixture Model Classifier

In terms of classifying an observed vector x into one of the C given classes, the *a posteriori* probability $p(c|x)$ is examined, and the class with the highest one is determined according to the Bayes' rule. Gaussian mixture models (GMMs) are a valuable statistical tool for modeling densities. They are flexible enough to approximate any given density with high accuracy.

In the GMM, a pdf is represented by the weighted sum of a finite number of components with Gaussian densities. Then the pdf estimation problem reduces to estimation of the parameters included in each component. For a N-class problem pattern recognition system, we could have a set of GMMs associated with N classes. For a feature vector denoted as $x \in \Re^d$, the mixture density for the nth model is defined as

$$p^n(x) = \sum_{m=1}^{M_k} \alpha_{k,m} g(x; \mu^{(k,m)}, \Sigma^{(k,m)}) \tag{1}$$

$$g(x;\mu^{(k,m)},\Sigma^{(k,m)}) = (2\pi)^{-d/2} \, |\Sigma^{(k,m)}|^{-1/2} \times \exp\left[-\frac{1}{2}(x-\mu^{(k,m)}) \times (\Sigma^{(k,m)})^{-1}(x-\mu^{(k,m)})\right]$$

where $g(x;\mu^{k,m},\sum^{k,m})$ is the d-dimensional Gaussian distribution. $M^k(1,\ldots,K)$ denotes the member of mixture components of the class k; $a_{k,m}$ is the mixture weight of each component $\{k,m\}$; and $\mu^{k,m}$ and $\sum^{k,m}$ represent, respectively, the mean vector and covariance matrix of each component $\{k,m\}$.

The complete Gaussian mixture density is parameterized by the mixture weights, mean vectors, and covariance matrices from all components densities. For a GMM-based classification system, the goal of the model training is to estimate the parameters of the GMM. In this paper, we use unsupervised learning algorithm proposed in [6] for model selection and learning of Gaussian mixtures.

Results

Offline Training Sessions

Fig. 2 shows the time–frequency distribution of EEG signals in subject ZB during closing and opening the eyes. A broad-banded event-related synchronization (ERS) in frequencies around 10 and 20 Hz was appeared during closing the eyes.

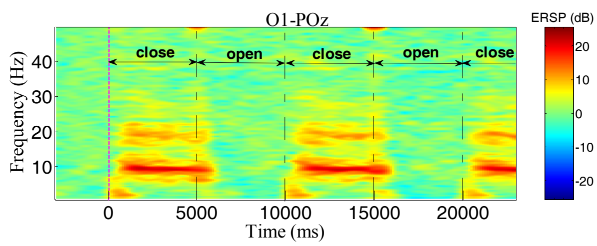

Fig. 2. Time–frequency distribution of EEG signals in subject ZB during closing and opening the eyes.

Table 1. Average accuracy of eye closing and motor imagery detection during offline training sessions.

Subjects	Sessions	S1	S2	S3	S7	average
EA	Eye Closing-Opening	94.0%	100%	92.0%	92.0%	94.5%
	Motor Imagery	68.2%	67.0%	74.1%	75.5%	71.2%
ZB	Eye Closing-Opening	100%	100%	86.7%	-----	95.6%
	Motor Imagery	73.0%	79.2%	68.0%	-----	73.4%

Table 2. Number of successful trials for turning on/off and reaching tasks and the average time to complete the task for subject EA during online feedback sessions.

	Sessions	S1	S2	S3	S4	S5	S6	S7	average
On/Off	Number of Successful Trials	20/20	19/20	20/20	20/20	20/20	20/20	20/20	99.3%
	Time (s) to Complete the Task	0.79	1.27	0.70	0.88	0.56	0.82	0.56	0.79
Reaching	Number of Successful Trials	7/7	9/9	7/8	3/4	8/8	10/10	8/8	96.3%
	Time (s) to Complete the Task	18.22	18.34	18.23	18.57	18.41	19.18	18.04	18.43

Table 1 summarizes the results of eye closing-opening during offline training sessions for two subjects. It is observed that an accuracy of 94.5% and 95.6% was obtained for subjects EA and ZB, respectively.

Fig. 3 shows the ERS/ERD maps for the subject ZB during the reaching task. It is clearly observed that a broad-banded event-related desynchronization (ERD) in frequency bands around 10 and 20 Hz is observed during motor imagery.

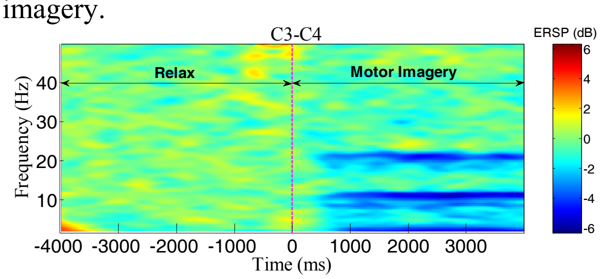

Fig. 3. Time–frequency distribution of EEG signals in subject ZB during motor imagery (i.e., reaching).

The results of motor imagery detection during offline training sessions for two subjects are summarized in Table 1. On average, an accuracy of 71.2% and 73.4% was achieved for subjects EA and ZB, respectively.

Online Feedback Sessions

Table 2 summarizes the results of online experiments for seven days on two subjects. The results indicate that the subject could turn on/off the system 139 out of 140 trials. The average time to complete the task was 2.79 s. The subject could complete the reaching task 132 times out of 140 trials. The average time took to complete the task was 18.43 s.

Discussion and Conclusions

In this paper, an online BCI system was developed for control of reaching while the system automatically could be turned on or turned off by closing the eyes. The closed eye was detected using the EEG signals using GMM-model classifier.

References

[1] K.-H Hazrati M, Erfanian A. An online EEG-based brain-computer interface for controlling hand grasp using an adaptive probabilistic neural network. Med. Eng. Phys., 10: 730-739, 2010.

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

[3] Scherer R, Lee F, Schlogl A. Toward self-paced brain-computer communication: navigation through virtual worlds. IEEE Trans. Biomed. Eng., 55: 675-682, 2008.

[4] Erfanian A, Mahmoudi B. Real-time ocular artifact suppression using recurrent neural network for electro-encephalogram based brain–computer interface. Med. Biol. Eng. Comput., 43: 296–305, 2005.

[5] Peng H, Long F, Ding C. Feature selection based on mutual information: criteria of max-dependency, max-relevance and min-redundancy. IEEE Trans. Pattern Anal. Mach. Intell, 27: 1226-1238, 2005.

[6] Constantinopoulos C and Likas A. Unsupervised of learning guassian mixtures based on variational component splitting, IEEE Trans. Neural Networks, 18: 745-755, 2007.

Author's Address

Fatemeh Khatami Firoozabadi, Abbas Erfanian,
Department of Biomedical Engineering, Iran University of Science and Technology, Iran Neural Technology Research Centre, Tehran, Iran. erfanian@iust.ac.ir