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Towards an EEG-based brain-computer interface for online robot control

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Abstract According to New York Times, 5.6 million people in the United States are paralyzed to some degree. Motivated by requirements of these paralyzed patients in controlling assisted-devices that support their mobility, we present a novel EEG-based BCI system, which is composed of an Emotive EPOC neuroheadset, a laptop and a Lego Mindstorms NXT robot in this paper. We provide online learning algorithms that consist of *k-means* clustering and principal component analysis to classify the signals from the headset into corresponding action commands. Moreover, we also discuss how to integrate the Emotiv EPOC headset into the system, and how to integrate the LEGO robot. Finally, we evaluate the proposed online learning algorithms of our BCI system in terms of *precision*, *recall*, and the F-measure, and our results show that the algorithms can accurately classify the subjects' thoughts into corresponding action commands.

Keywords EEG · BCI system · *k-means* clustering algorithm · Principal component analysis

1 Introduction

Wireless sensors have been successfully applied in medicine. Medical applications such as artificial pancreas and wireless pulse oximeter sensors have proved to be fruitful avenues of

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research. Researchers have also applied wireless sensors to aid in improving patient mobility. One of such mobility applications is the use of an electroencephalogram (EEG) headset that allows patients to control a wheelchair with their minds [1, 9, 10, 17, 25, 39]. An EEG-based brain-computer interface (BCI) is a system that enables people to control devices using signals from their scalps, which can be used to assist patients who have highly compromised motor functions, such as completely paralyzed patients with amyotrophic lateral sclerosis. Typically, a BCI is composed of modules of preprocessing, feature extraction, classification and feedback.

Using an EEG headset to control a wheelchair may prove to be challenging: most learning algorithms that collect information from EEG headsets are trained not online but offline. Online algorithm is referred to as that a learning algorithm can directly process a collection of data without pretreatment process and offline training process, while offline algorithm means that the learning algorithm is presented, apriori, with a collection of data that are used to train the hypothesis. This hypothesis remains the same even as new data are encountered. Since a learning algorithm is not able to adjust to the diversity of signals that a patient may produce while using the headset, the static nature of this algorithm limits learning of the hypothesis. Nevertheless, human brain is self-learning, and it can automatically adjust as it receives stimulus or feedback from different systems. Consider an example in which a patient is asked to train an algorithm by thinking about moving the wheelchair forward and backward. During the test, when the patient is asked to create the thought of moving the chair forward, the wheelchair probably cannot distinguish the movement commands, because the learning algorithm is likely to misinterpret the signal [44].

There are a number of related works on the design of BCIs. Birbaumer et al. present the first BCI, a spelling system using slow cortical potentials (SCPs), which is validated with severely disabled patients [2], but SCP BCIs have several disadvantages [3]. Then, BCIs based on event-related (de)synchronization (ERD or ERS) have been widely investigated [4, 21, 30, 32, 33, 35, 40], but some patients cannot use ERD BCIs, because they are unable to modulate sensorimotor rhythms for effective control [18, 22, 31]. BCIs based on steady-state visual evoked potentials (SSVEPs) have also been significantly researched [16, 23, 26, 36, 38], but SSVEP BCIs do not work for some patients [27, 28]. EEG-based BCIs have been studied as well [5, 6, 11, 29, 41], but most of them are not under an online processing. Exploring EEG headsets to control cyber-physical systems is not new. Several researchers have explored this notion of EEG based control, but these applications are extremely inaccurate. Neurofeedback has been used in a variety of training applications. One such application is the focus training in patients suffering from ADHD [5]. However, we believe that our proposed BCI system is able to enhance the accuracy of EEG based control algorithms.

In this paper, we present a novel EEG-based BCI for online robot control, which is a solution to problems of diversity in the signals and dynamic nature of the brain, and can be used for paralyzed patients in controlling assisted-devices that support their mobility. Our prototype of BCI system consists of an Emotive EPOC neuroheadset, a laptop and a Lego Mindstorms NXT robot. More specifically, the Emotiv EPOC headset is a neuro-signal acquisition and processing wireless neuroheadset with 14 saline sensors being able not only to detect brain signals but also users' facial expressions, which uses a set of 14 sensors to tune into electrical signals produced by the brain to detect the participants' thoughts, feelings and expressions in real time. The EPOC is a wireless EEG system with 14 channels. The laptop is used to collect data from the neuroheadset, classify them, and then transmit activity commands to the robot. The robot will perform the corresponding activities according to the received commands. To enable the BCI system to control the robot effectively and accurately, we present online learning algorithms of *k-means* clustering and principal component analysis to classify the signals from the headset into corresponding action commands. In particular, we use a modified version of the online *k-means* clustering algorithm in which cluster centroids are updated dynamically as new examples are received, and explore principal component analysis to perform a reduction in the feature space [34].

Our main contributions can be summarized as follows:

- We present a novel EEG-based BCI for online robot control, which can be used for paralyzed patients in controlling assisted-devices that support their mobility.
- We provide online learning algorithms of *k-means* clustering and principal component analysis to classify signals from a headset into corresponding activity commands.
- We evaluate online learning algorithms of our BCI system in terms of *precision*, *recall*, and the F-measure, and the results show that our algorithms can accurately classify the subjects' thoughts into action commands.

The remainder of this paper is organized as follows: Section 2 covers related works, and Section 3 provides the design of our BCI system including the system motivation, hardware components, and system architecture in detail. Then, we present online learning algorithms of *k-means* clustering and principal component analysis in Section 4, and discuss the communication protocol of BCI system in Section 5. We evaluate our online learning algorithms of the BCI system in Section 6, and conclude the paper in Section 7.

2 Related work

There are a wide range of works on the design of BCIs. We broadly classify these efforts into two categories: BCIs based on event-related (de)synchronization (ERD or ERS) [4, 21, 30, 32, 33, 35, 40], and BCIs based on steady-state visual evoked potentials (SSVEPs) [16, 23, 26, 36, 38]. Then, we discuss some works that use Emotiv EPOC EEG headsets [5, 6, 11, 29, 41].

2.1 BCIs based on event-related (de)synchronization (ERD or ERS)

The authors in [4] report the performance of BCI novices (not from their laboratories) in their first BBCI feedback session in the framework of a broader study. A rigorous investigation of EMG signals demonstrates that the success cannot be ascribed to concurrent EMG activity during motor imagery. In [21], the authors suggest that four people severely disabled by ALS learned to operate a BCI with EEG rhythms recorded over sensorimotor cortex. These results suggest that a sensorimotor rhythm based BCI could help maintain quality of life for people with ALS. The authors of [30] describe how a completely paralyzed patient, diagnosed with severe cerebral palsy, was trained over a period of several months to use an EEG-based BCI for verbal communication. In [32], the authors discuss that motor imagery can modify the neuronal activity in the primary sensorimotor areas in a very similar way as observable with a real executed movement. One part of EEG-based BCI is based on the recording and classification of circumscribed and transient EEG changes during different types of motor imagery such as imagination of left-hand, right-hand, or foot movement. The authors of [35] present an asynchronously controlled three-class brain-computer interface-based spelling device virtual keyboard (VK), operated by spontaneous electroencephalogram and modulated by motor imagery.

However, about 22 % of people cannot use ERD-based BCIs, since some patients are unable to modulate sensorimotor rhythms for effective control [18, 22, 31].

2.2 BCIs based on steady-state visual evoked potentials (SSVEPs)

In [16], the real-time performance of a novel method for detecting SSVEP is evaluated in a BCI spelling task. At the core of this method is a spatial filtering algorithm for extracting SSVEP responses, which in previous offline studies has shown significantly improved classification performance. The authors of [23] present the application of an effective EEG-based BCI design for binary control in a visually elaborate immersive 3D game. The BCI uses the SSVEP generated in response to phase-reversing checkerboard patterns. In [26], a new multistage procedure for a real-time BCI is developed. The developed system allows a BCI user to navigate a small car (or any other object) on the computer screen in real time, in any of the four directions, and to stop it if necessary. The authors of [36] provide an optimization strategy for SSVEP-based BCI, especially in spelling program application. In [38], the authors develop and test two EEG-based BCI for users to control a cursor on a computer display. The system uses an adaptive algorithm, based on kernel partial least squares classification (KPLS), to associate patterns in multichannel EEG frequency spectra with cursor controls.

However, SSVEP-based BCIs do not work for some patients [27, 28].

2.3 Some works on Emotiv EPOC EEG headset

In our experiments, we use the Emotiv EPOC EEG headset. Several researchers have conducted studies using this kind of headset. The authors in [11] conduct a study in which they evaluate scientific validity of results obtained using a commercial EEG headset. Their results are promising, and show that the Emotiv EPOC is a scientifically-viable device. In [12], the authors conduct experiments in which they compare the Emotiv EPOC to a medical device. Nevertheless, their results conflict those in the study of [11]. They found that the Emotiv headset performed significantly worse when compared to the medical system. However, from these studies, it is unclear whether the Emotiv headset provides accurate enough readings to make it a viable device for conducting scientific experiments. In our work, we explore this question and report on our results. Other researchers such as [42], where the authors explore the idea of controlling a NXT Robot using the Emotiv EPOC and NeuroSky headsets. In their experiments, they use the attention level calculated by the software to accelerate and decelerate the robot. However, they did not employ any online learning algorithm or neurofeedback. Applications of learning algorithms to EEG data are not new [7, 20]. In [41], the author in his thesis on raw EEG data classification and applications, uses support vector machines to classify signals obtained from a headset and direct a robot.

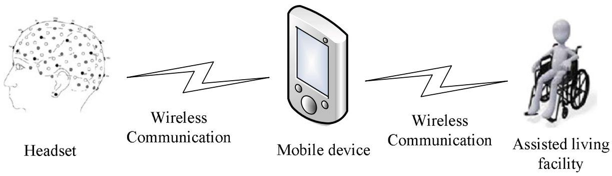


Fig. 1 Motivation of our BCI system

3 BCI system overview and architecture

In this section, we first discuss the motivation of our BCI system, then describe the hardware components of the system, and finally detail our BCI system architecture.

3.1 System motivation

Our BCI system design is motivated by requirements of paralyzed patients in controlling assisted-devices that support their mobility, as illustrated in Fig. 1. Data generated from neuroheadsets (such as Emotive EPOC) on the patients' brains are reported by wireless to mobile devices (such as smartphones or laptops) on which classification decisions are made in real time, and then mobile devices transmit the decision demand to assisted living facilities (such as wheelchairs) by wireless as well [19, 43]. Our BCI system must be able to accurately and effectively classify typical moving directions for daily activities, such as moving forward, moving backward, turning left, and turning right. Such activity recognition is quite useful for paralyzed patients to implement what they are thinking and where they intend to go, because they can manipulate assisted living facilities through their conscious thoughts.

3.2 Hardware of our system

To achieve accurate and efficient activity recognition for neuroheadsets and mobile devices, we provide an extensive hardware support system, which we describe in this section.

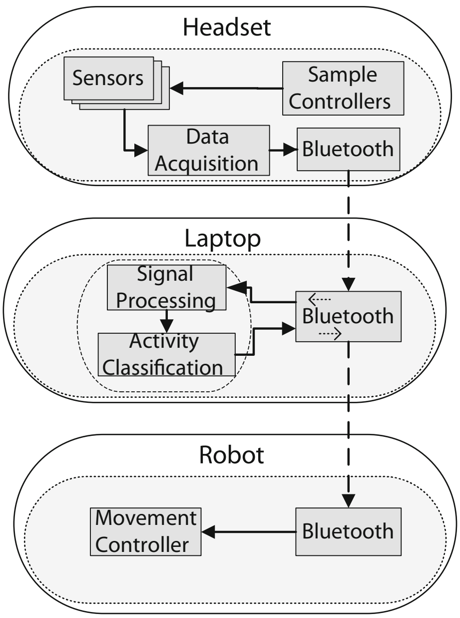
Our BCI prototype consists of an Emotive EPOC neuroheadset, a laptop and a Lego Mindstorms NXT robot, as illustrated in Fig. 2. More specifically, the Emotiv EPOC headset is a neuro-signal acquisition and processing wireless neuroheadset with 14 saline sensors being able not only to detect brain signals but also participants' facial expressions, which uses a set of 14 sensors to tune into electrical signals produced by human brains to detect the users' thoughts, feelings and expressions in real time [14]. The EPOC is a 14-channel wireless EEG system with channel names of AF3, AF4, F3, F4, F7, F8, FC5, FC6, P3 (CMS), P4 (DRL), P7, P8, T7, T8, O1, O2 [13, 15]. The laptop is used to collect data from the neuroheadset, classify them, and then transmit activity commands to a robot. The robot will perform the corresponding activities according to received commands [8, 24]. In the system, the EPOC neuroheadset first generates data by sensors sampling electrical signals on human brains, and then transmits raw data to the laptop via Bluetooth. Then, the laptop executes online learning algorithms to classify these brain signals into corresponding action commands, and then sends these commands to the NXT robot via Bluetooth. Finally, with action commands, the robot will perform the basic maneuvering (such as moving forwards, moving backwards, turning left, and turning right).

Fig. 2 Prototype of our BCI system

3.3 System architecture

In order to show a detailed description, we illustrate our system architecture in Fig. 3. As illustrated in Fig. 3, our system resides solely on EPOC headset sensors and on a laptop installed online learning algorithms. The EPOC headset, containing 14 sensors of different modalities, is attached on-head. The sensors on the headset start sampling brain signals by turning on the sample controller, at a user configured rate. The headset communicates wirelessly with the laptop via a built-in Bluetooth (dotted lines), which aggregates data from each sensor and then transmits them to the laptop for online learning. On the laptop, the aggregated data are first processed by the signal processing module and then fed into the activity classification system to make a classification decision. The signal processor, *k-means* clustering, is to gather readings from the headset and associates them with corresponding actions. The classifier, principle component analysis, is initially trained with each predefined activity ground truth. With classification results, the laptop sends the corresponding commands to the robot via Bluetooth. The robot performs the corresponding activity by movement controller. We now describe the core of our system architecture:

Fig. 3 Architecture of our BCI system



Data acquisition We use the API provided by the SDK for the Emotiv EPOC headset to acquire data from sensors [13]. With the API, we just read in raw data values of each sensor, convert them to a vector, and pass it to the online learning algorithms for processing and classification.

Signal processing We use *k-means* clustering, an online clustering algorithm, as our signal processor that resides on a laptop. *k*-means clustering aims to partition *n* observations into *k* clusters in which each observation belongs to the cluster with the nearest *mean*, serving as a prototype of the cluster. Note that online algorithm is referred to as the algorithm can directly process the data without offline training process. With this approach, we are able to associate each of the fourteen readings generated by the headset with a closest action.

Activity classification We explore principal component analysis (PCA), an ensemble online learning algorithm, as our activity recognition classifier which resides entirely on a laptop as well. PCA uses orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. With PCA, we can select the most suitable features by performing a reduction in the feature space.

Movement controller With the received action command, the robot performs the corresponding activities.

4 Online learning algorithms

To begin, we first use an online *k-means* clustering algorithm to associate input vectors with a nearest centroid (or action), and then explore principal component analysis algorithm to perform a reduction in the feature space.

4.1 Online *k-means* clustering

The core of our activity classification approach uses the online ensemble learning, specifically *k-means* clustering. In this section, we explain how we adapt *k-means* to run on a laptop for use with a headset. We choose *k-means* clustering algorithm to process outputs of the Emotiv EPOC headset. Since the headset has 14 sensors on it, we will receive 14 signal values for each reading, that is, each value corresponds to a sensor. Then we perceive each reading as a vector, which is used as the input of the *k-means* clustering algorithm. We discuss the online *k-means* clustering algorithm in Algorithm 1. In Algorithm 1, we define a set of activities $c = \{c_1, c_2, ..., c_k\}$, initially referred to as centroids, and a vector $v = [v_1, v_2, ..., v_s]$, which correspond to the headset sensors of 14 readings. Since there is a significant diversity between clusters, we first adjust the centroid values c for each activity by enforcing a distance requirement on the placement of the original centroids, where ϵ represents the diversity value and is learned in an online processing. We then convert signal values from each sensor on the headset into a vector $v = [v_1, v_2, ..., v_s]$, where each element represents the reading of one sensor. Then, the vector is processed by alternating between two steps. Finally, we obtain a centroid c associated with thoughts to an action.

Algorithm 1 Online *k-means* Clustering Algorithm

Input: Signal values
Output: Centroid c associated with thoughts to an action

Assign initial values to centroids $c = \{c_1, c_2, ..., c_k\}$ //k corresponds to the number of actions (such as move forwards, move backwards, turn left, turn right, where $k = 4$)
for $i = 1$ *to* $k - 1$ **do**
    $c_{i+1} = c_i + c_i \times \epsilon \times i$ // ϵ represents the diversity value, which is learned in an online processing
end
while *signal values* **do**
    Represent signal values as a vector $v = [v_1, v_2, ..., v_s]$ // s corresponds to the number of sensors (for instance, Emotiv EPOC headset has 14 sensors, where $s = 14$)
    for $i = 1$ *to* s **do**
        for $j = 1$ *to* k **do**
            $S_i = \{v_p : \| v_p - c_i \|^2 \leq \| v_p - c_j \|^2\}$ // Assignment step
            $c_i = \frac{1}{S_i} \times \sum_{v_l \in S_i} v_l, (\forall l, l \leq s)$ // Update step
        end
    end
    Return c
end

For instance, we plot the signals collected from the EEG headset by using *k-means* clustering algorithm in Fig. 4.

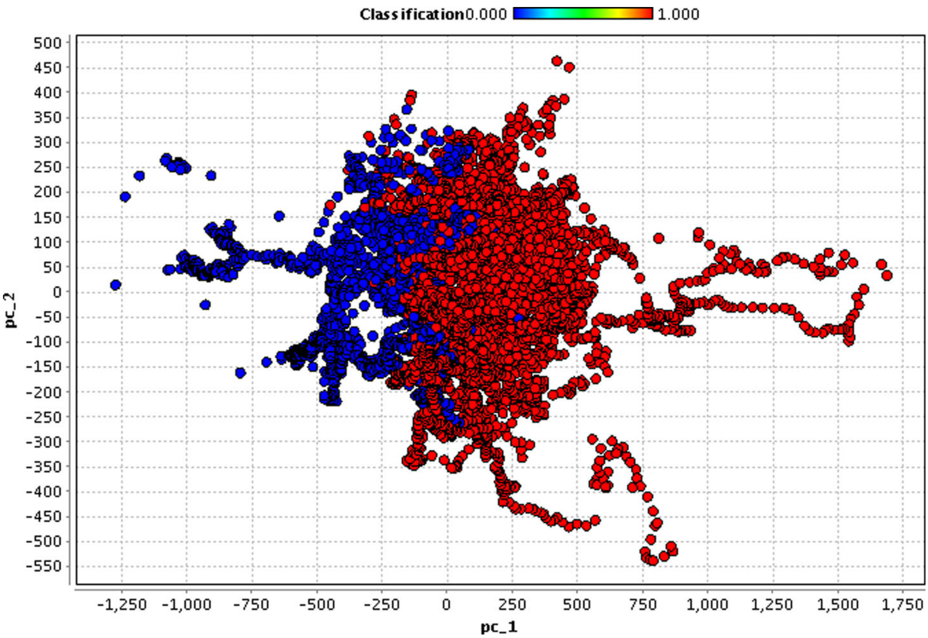


Fig. 4 An instance of *k-means* clustering algorithm for signals collected from the headset

4.2 Principal component analysis

In this section, we perform a dimension reduction of headset readings that converts the 14-dimensional vector to a 2-dimensional vector by exploiting the principal component analysis algorithm, which is detailed in Algorithm 2. As we can see from Algorithm 2, it is comprised of three steps. First, we calculate the co-variance matrix C of the collection cluster centroids c from Algorithm 1. We then calculate the singular value decomposition of the co-variance matrix. Finally, we project each of the 14-dimensional vectors unto the first two eigenvectors of the unitary matrix U, which gives the representation of the points in the reduced space. Note that the input of Algorithm 2 is the output of Algorithm 1, that is, these two algorithms sequentially process the original data.

Algorithm 2 Principal Component Analysis

Input: A matrix of centroid vectors C
Output: A 2-dimensional representation of the centroids P

1 $\sum = \frac{1}{m} C^T C$
2 $[U, S, V] = svd(\sum)$
3 $P = U^{T(1,2)} C$
4 Return P

As a case, we plot the signals collected from the EEG headset on their principal components in Fig. 5. Note that the central cluster part constitutes the real neutral thoughts, while the surrounding part jutting out constitutes other thoughts.

5 Protocol design

In this section, we discuss how to integrate the Emotiv EPOC headset into the system, and how to integrate the LEGO robot as well.

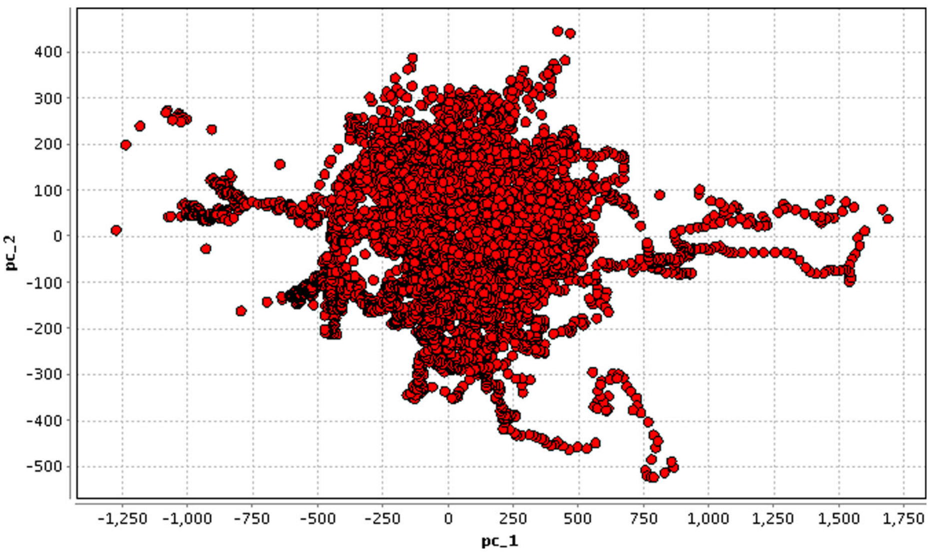


Fig. 5 A case of principal component analysis for signals collected from the headset

5.1 Headset integration

We first require an SDK for the Emotiv EPOC headset, as the sensors are encrypted otherwise. Once obtained and set up, we need to connect the readings to our hybrid *k-means/PCA* programs. To achieve this, we modify our hybrid programs to read in sensor readings using the API provided by the SDK for the Emotiv EPOC headset.

Using the API, we enable data acquisition from the headset. Following this, we check the connection and signals of the sensors to make sure that they are of good quality. Then, we can read in the raw signal values of each sensor, convert them to a vector, and pass it to the online *k-means/PCA* algorithms. Once the thought is clustered and the corresponding action command sent to the robot, we then proceed to read in the next thought. Note that we read the next thought until the robot executes the action, instead of the action command being sent to the robot buffer. This is to reduce a backlog of actions sent to the robot, because of a situation that the participant's thought is probably far ahead of the actions before performance which would be extremely difficult to make an association between a thought and an action.

5.2 Robot integration

The LEGO NXT robot is a simple "car" robot that has four commands: moving forwards, moving backwards, turning left, and turning right. Since only one command can be processed at a time, the robot cannot move forwards and turn left at the same time. Using a java package with support for driving the robot via Bluetooth, we write a simple program that has the robot listen for key presses, and when a certain key is pressed, the robot performs the appropriate action. While the robot does not have a buffer for saving inputs, we decide to abandon the use of it.

Once the headset is integrated properly into the hybrid *k-means/PCA* programs, we next focus on having the program connect to a java driver installed on the LEGO robot. Because we already have the LEGO robot set up to respond to certain key presses, we interpret the actions that are sent to the program by the headset as key presses, thereby allowing versatility in testing the headset in other applications that require key presses. We could have the actions directly sent to the LEGO robot, but this would limit functionality in that it only works with the LEGO robot.

Now that the headset and robot integrations are complete, we have a detailed description of BCI protocol: with LEGO robot and headset turned on, a participant wears the headset, and begins to think a thought; by reading in the *k-means/PCA* programs, the thought is clustered to a centroid and the corresponding action is then sent to the robot driver, which simulates a key press for the action; by receiving the action command, the robot executes the action. Note that once the action is executed by the robot, the clustering program will listen for another thought.

6 Performance evaluation

In this section, we first discuss the evaluation setup of the system. Then, we evaluate our online learning algorithms of the BCI system in terms of *precision*, *recall*, and the *F*-measure.

6.1 Evaluation setup

The setup of our BCI system consists of an Emotive EPOC headset, a laptop and a NXT robot. More specifically, the headset samples electrical signals produced by a subject's thoughts in his/her brain in real time. The laptop is used to collect data from the headset, classify them, and then transmit activity commands to the robot. The robot will perform the corresponding activities according to received commands. Subjects (participants) in the experiment are 6 healthy students, who are constituted of 3 men and 3 women with age range of 18-30 years. The personal information of the subjects is summarized in Table 1. All subjects are free of neurological or psychiatric disorders or medications known to adversely affect EEG recording. None has prior experience with EEG recording or BCIs. The nature and purpose of the experiment are explained to each subject before preparation for EEG recording. In the experiment, each subject wears the Emotive EPOC headset on head sitting in a comfortable chair, one meter from the laptop, who is asked to think a moving direction within 5 seconds, and there is a 10-second time interval between thoughts, where the total time for each subject is 2 minutes. Since we have 6 subjects, we have 12-minute data for evaluation. Then, the headset sends the collected data to the laptop via Bluetooth for online processing.

6.2 Accuracy evaluation

To evaluate the accuracy of our BCI system, we first introduce three metrics $precision$, $recall$, and F-measure (or $F1$-score). In a classification task, $precision$ for a class is defined as the number of true positives (i.e. the number of items correctly labeled as belonging to the positive class) divided by the total number of elements labeled as belonging to the positive class (i.e. the sum of true positives and false positives, which are items incorrectly labeled as belonging to the class). $Recall$ is referred to as the number of true positives divided by the total number of elements that actually belong to the positive class (i.e. the sum of true positives and false negatives, which are items which were not labeled as belonging to the positive class but should have been). In our experiment, the F-measure is a weighted harmonic mean of $precision$ and $recall$, where $precision$ is the accuracy to which each cluster is classified, and $recall$ measures the percentage of elements in each cluster that we classified. The formulas for $precision$, $recall$, and F-measure are expressed as: $Precision = \frac{true\ positive}{true\ positive + false\ positive}$, $Recall = \frac{true\ positive}{true\ positive + false\ negative}$, $F_1 = 2 \times \frac{precision \times recall}{precision + recall}$.

We evaluate our BCI system by comparing the accuracy (F-measure or $F1$-score) of our online learning algorithms with statically-trained algorithms. Note that the statically-trained

Table 1 Personal information of subjects

Gender	Age	Major	Number
Male	21/30	Computer Science	2
Male	26	Mathematics	1
Female	18	Computer Science	1
Female	25	Finance	1
Female	27	Psychology	1

algorithms are the same as online algorithms, but the algorithms need to be trained and the classification is offline. Our accuracy evaluation is comprised of four steps: 1) we write a small program which is able to collect and record the signals from the headset, and save the signal data as a .csv file; 2) collect signals by running the statically-trained algorithm, and record the number of true/false positives and false negatives, respectively; 3) execute our online learning algorithm with inputs of the stored .csv file value; 4) calculate the F-measure for online learning algorithms and the statically-trained algorithms, respectively. We now describe the steps in detail as follows.

Control signal collection Before conducting our experiment, we first gather a collection of signals for the headset as control signals. With these signals, we discover the amount of noise associated with a sensor. Figures 6 and 7 illustrate the collected signals when the headset is put on a table. Note that several of the signals are highly correlated, in terms of noise.

We have now profiled the device for noise. We can determine the lowest value of ϵ in Algorithm 1. The value of ϵ must be greater than maximum noise vector, which ensures that noise from points associated with one cluster does not affect the other. Using the same program as for collecting control signals, we ask subjects to clench their teeth for 5 seconds, and there are 10-second time interval between each clench. We record the number of true positive and false negative, respectively.

Online learning Algorithms The online learning algorithms runs similarly to the statically-training algorithm with inputs of the data collected from the headset by the 6 subjects and outputs of the corresponding classification results. We then calculate the number of true positive and false negative for calculation of F-measure.

***F*-measure calculation** As defined, F-measure is the harmonic mean of $precision$ and $recall$, where $precision$ is the accuracy to which each cluster is classified, and $recall$ measures the percentage of elements that is in each cluster that we classified. We then calculate F-measure based on the equation.

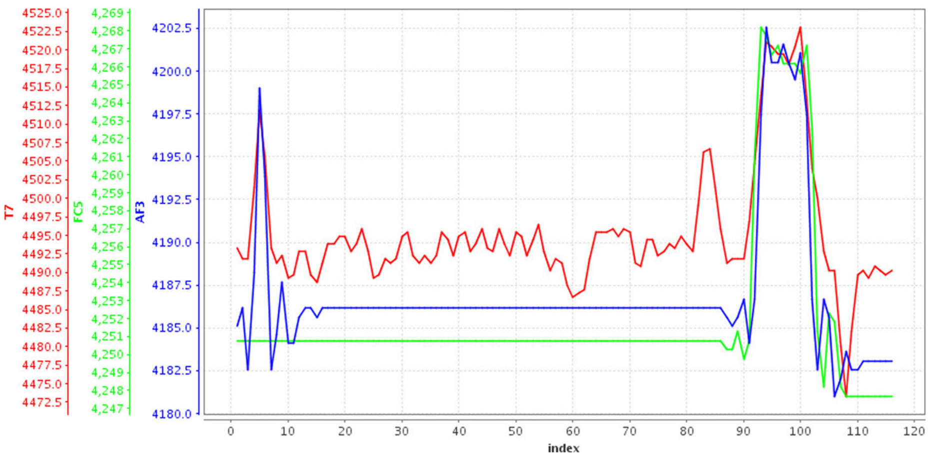


Fig. 6 Signals for the Emotiv Headset for sensors AF3, FC5 and T7

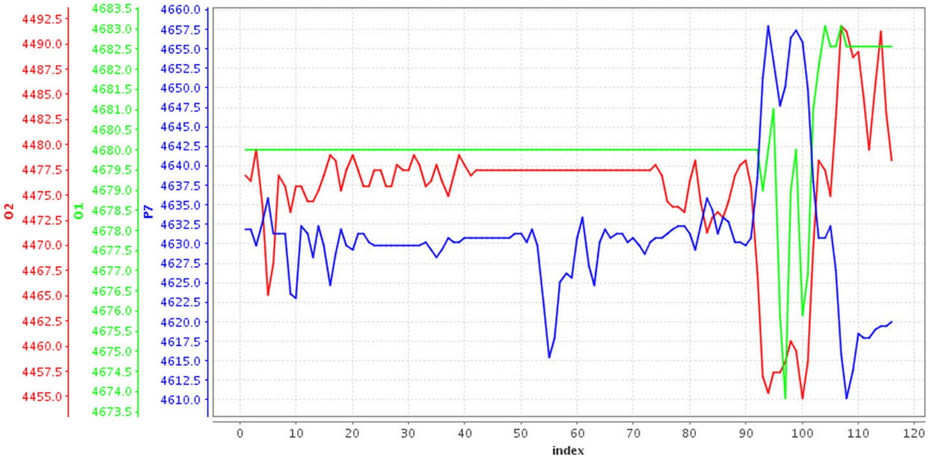


Fig. 7 Signals for the Emotiv Headset for sensors O2, O1 and P7

6.3 Analysis of results

Based on the above evaluation, we analyze the obtained results in this section. In order to show the comparison of online learning algorithms and the static-training algorithms, we first tabulate the true/false positives and false negatives of online learning algorithms in Table 2, and the true/false positives and false negatives of the statically-trained algorithm in Table 3, respectively. Note that the data are collected from 6 subjects with 12 minutes of experiments.

Table 2 True positive and false negative for online training algorithms

EM	GT	TP	FN
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
F	T	FALSE	TRUE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
T	T	TRUE	FALSE

Table 3 True positive and false negative for statically-trained algorithms

EM	GT	TP	FN
T	T	TRUE	FALSE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
F	T	FALSE	TRUE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
F	T	FALSE	TRUE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
T	T	TRUE	FALSE
F	T	FALSE	TRUE

As illustrated, Tables 2 and 3 are composed of four columns: the first column represents the prediction of the Emotiv headset; the second column indicates the ground truth presented by subjects; the third column is the number of true positives; and the last column represents the number of false negatives.

With Tables 2 and 3, we calculate the $precision$ and $recall$, and finally compute the F-measure, for statically-trained algorithms and online learning algorithms, respectively, shown in Table 4. As demonstrated in Table 4, both the algorithms have the same $precision$ 1. Our algorithm has a higher recall ($0.765 = \frac{13}{17}$) than statically-trained algorithms ($0.647 = \frac{11}{17}$), which indicates that our algorithm has a higher accuracy of the activity classification. Moreover, our algorithm has a higher F-measure ($0.867 = 2 \times \frac{1 \times 0.765}{1+0.765}$) than statically-trained algorithms ($0.787 = 2 \times \frac{1 \times 0.647}{1+0.647}$), which verifies the higher accuracy of our algorithm in another perspective.

Figure 8 shows the classification obtained by online training algorithms. As illustrated in Fig. 8, we can distinguish 2 centroids: one is above 0, and the other is below 0. In addition, there is the third centroid around 0. This indicates that our algorithm can accurately classify the received signals into distinguishable centroids.

Table 4 The $precision$, $recall$, and F-measure for the two algorithms

Measure	Static	Online
Precision	1	1
Recall	0.647	0.765
F_1	0.787	0.867

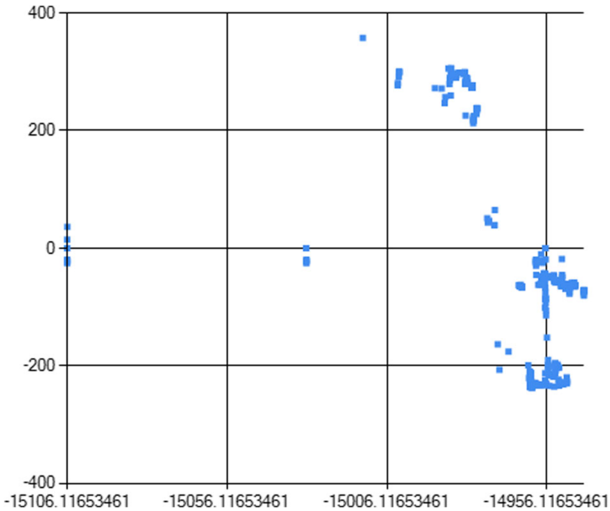


Fig. 8 Positions of the 3 centroids used to conduct the above experiment

7 Conclusions

In this paper, motivated by the paralyzed patients in controlling assisted-devices that support their mobility, we present a novel EEG-based BCI system, which is composed of an Emotive EPOC neuroheadset, a laptop and a Lego Mindstorms NXT robot. We provide online learning algorithms that consist of k-$means$ clustering and principal component analysis to classify the signals from the headset into corresponding action commands. We also discuss how to integrate the Emotiv EPOC headset into the system, and how to integrate the LEGO robot. We evaluate online learning algorithms of our BCI system in terms of $precision$, $recall$, and the F-measure. The results show that our online learning algorithms can accurately classify the participants' thoughts into corresponding actions.

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