PROPOSAL OF A TELEPRESENCE ROBOT USING BRAIN COMPUTER INTERFACE FOR PEOPLE WITH MOTOR DISABILITIES

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Abstract: This work proposes a Brain Computer Interface (BCI) using upper limbs motor imagery tasks for people with severe motor disabilities, which can be employed to send commands to a telepresence robot. The BCI classifies four classes of motor imagery tasks from upper limbs. The system is composed of the following blocks: a Common Average Reference (CAR) filter for signal preprocessing, a Statistical Features Extractor of Time Series, and a K-Nearest Neighbors classifier. Eight healthy subjects participated in the experimental protocol, and performed the motor imagery tasks: flexion-extension (F-E) of the right arm, F-E of the left arm, F-E of both arms, and arms relaxed. The system obtained a success rate of 88% with a kappa coefficient of 83% for four classes of motor intentions. The results suggest the feasibility of the BCI proposed to classify motor imagery tasks, which can be used as commands to control the telepresence robot.

***Keywords**: Telepresence robot, BCI, motor imaginary task.*

Introduction

In the world there are many people with severe neurological or muscular diseases, such as brainstem stroke, spinal cord injury, amyotrophic lateral sclerosis (ALS), muscular dystrophies and cerebral palsy. For these people, simple tasks such as a standing up or using the computer become a challenge [1]. Because of these disabilities, interfaces that use speech or movements of the limbs become hard to be executed. Many studies are being done to create an alternative interaction interface for these people in order to send messages or commands. A field of study that has gained great importance in this direction is the BCI (Brain-Computer Interface) [1], [2].

Brain-computer interfaces are systems constituted by hardware and software that recognizes patterns in brain activities. These patterns are translated in signals that can control external devices. Thus, this technology allows severely paralyzed patients the possibility of communicate and control devices, to interact thereby, with their surroundings [2]. With the advent of this technology, new paths have appeared in order to improve the quality of life of people with severe motor difficulties. The telepresence robot might be mentioned as an example of such application [3]. That system builds a physical entity ready to interact and explore a real environment, controlled by brain activity signals.

Many researches have developed in this field of study. The work in [4] presents a telepresence system that relies on a synchronous P300-based BCI, to choose the direction of the user's intent. In another work, a system based on this paradigm was developed, to control a guide robot in a museum [5]. In [6] is shown the use of SSVEP paradigm to send control commands to a mobile robot. The work in [7] presents a BCI system based on motor imagination to control a telepresence robot.

The work here proposed also uses this pattern of brain activation for the suggested asynchronous BCI, which does not need an external synchronized signal. In this work, a low cost EEG signal acquisition equipment and low complexity computational algorithms to extract features and classify are also used for four imaginary motor activities: flexion-extension (F-E) of the right arm, F-E of the left arm, F-E of both arms, and arms relaxed. The BCI is composed for low cost algorithm of the processing of the following blocks: a Common Average Reference (CAR) filter for signal preprocessing [8], a Statistical Features of Time Series and a K-Nearest Neighbors classifier [9].

Materials and Methods

— Dataset

This research uses EEG data captured of eight healthy volunteers to obtain a preliminary assessment of the proposed BCI system, for controlling the telepresence robot. This dataset contains EEG signals captured from users during four sessions without feedback. The session of each user is six minutes long. The subjects performed a given motor imaginary task for about ten seconds and then remained in a relaxed state for about ten seconds.

EEG signals were recorded with the Emotiv EPOC™ (Figure 1) device using a neuroheadset with 14 integrated electrodes located at standard positions of the International 10-20 system (AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1 and O2). EEG channels were sampled with 128 Hz at 0.51μV, which is the least significant bit voltage resolution. A research ethics committee has approved this study (registry number CEP-048/08).

Figure 1: The Emotiv EPOC device.

— Telepresence robot

The research robotic platform Pioneer 3DX, developed by Mobile Robot Inc., was used in the construction of the telepresence robot (Figure 2). The Pioneer 3DX is a sturdy robot composed of two-wheeled differential traction. The platform also has ultrasonic sensors, SICK LMS-200 laser, batteries, wheel encoders, a microcontroller and an onboard computer. The programming environment was executed in Ubuntu 12.04 LTS, where was installed a set of software development toolkit ARIA (Advanced Robot Interface for Applications), a library that hides the microcontroller routines by high-level functions developed in C++. The client-server communication architecture is used in the system through TCP/IP connections.

Figure 2: Telepresence robotic navigation (TRON).

A structure was built to attach a monitor, a webcam and four 12V lead-acid batteries. Two batteries were used to power the monitor and the other two to provide power to the laser LMS. The batteries were connected in parallel to maintain a longer system operation.

— Signal preprocessing

Common Average Reference (CAR) is a method for providing an inactive reference. The underlying principle of this filter type is the mean calculation of all EEG channels and its subtraction from selected output channels.

$$V_i^{Car} = V_i^{ER} - \frac{1}{N}\sum_1^N V_j^{ER} \qquad (1)$$

Where V_i^{ER} is the potential between the ith electrode and the reference and N is the total number of electrodes.

Often, noise signals appear on common space regions and then picked up by multiple electrodes. Therefore, by averaging a set of measurements, the signal-to-noise ratio can be increased and, thereby, improving the speed and accuracy of the BCI.

— Statistical Features of Time Series

For EEG signals, a number of typically measured statistics can be used to extract basic information about the signal as features for the classifier algorithm. For the preliminary proposed BCI were computed the following statistical features:

$$F_n = \frac{\sum_{n=1}^{N-1}|X_{n+1} - X_n|}{N-1} \qquad (2)$$

$$F_n = \frac{\sum_{n=2}^{N-2}|X_{n+2} - X_n|}{N-2} \qquad (3)$$

Where X_n represents the value of the n^{th} sample of the raw signal.

— k-Nearest Neighbours Classifier

The k-Nearest Neighbours (K-NN) is a relatively simple method of classifying patterns, which consists of assigning a class to an unknown element using the class of the majority of its nearest neighbours, according to a particular distance metric (in feature space) [9].

The Euclidean distance was used in this work, which is obtained by equation (4):

$$D_j = \sqrt{\sum_{i=1}^{N}(x_i - y_{ij})^2} \qquad (4)$$

Where D_j is j^{th} distance value; x_i represents i^{th} value of feature; y_{ij} represents the feature value in ij position; N is the features vector dimension.

— Performance Measurement

Several measures of performance have been proposed in BCI in [10] and [11] such as:

- Accuracy is the percentage of correctly classified feature vectors.
- Information Transfer Rate (ITR) is a standard measure of the amount of information transferred per unit of time. ITR is defined by equation 5:

$$ITR = \frac{log_2(N) + Plog_2(P) + (1-P)log_2\left(\frac{1-P}{N-1}\right)}{c} \qquad (5)$$

Where N is the number of classes, c is the time per selection and P is the success rate of correct classifications. The unit for ITR is bits per second (bits/s), but it can be converted in minutes.

- Cohen's Kappa coefficient is a parameter that represents the concordance between the targets and the prediction values. In this sense, the index here used was proposed for Cohen. The Kappa coefficient is defined in equation 6:

$$Kappa = \frac{p - p_0}{1 - p_0} \quad (6)$$

Where p is the probability of performing a correct classification, p_0 is the level of chance and denotes the accuracy under the assumption that all agreement occurred by chance.

- Sensitivity and specificity: theses metrics in BCI research are used to measure in-sample proportions of correctly classified positive targets (true positives) and the proportion of correctly rejecting a negative result (true negatives).

$$Sensitivity = \frac{T_p}{T_p+F_n} \quad (7)$$

$$Specificity = \frac{T_n}{T_n+F_p} \quad (8)$$

Where T_p and T_n refers to a true positive and negative event; $F_p$and F_n to a false negative and positive event.

Results and Discussion

Tables 1 and 2 show the results of the evaluation indexes of the BCI for the eight users.

Table 1: Performance using the indexes of accuracy, kappa coefficient and ITR.

Users	Accuracy Two classes	Accuracy Four classes	Kappa	ITR [bits/min]
1	0,96	0,92	0,90	11,49
2	0,96	0,92	0,89	11,48
3	0,95	0,91	0,88	11,41
4	0,89	0,77	0,70	10,87
5	0,91	0,81	0,75	11,01
6	0,86	0,72	0,63	10,71
7	1,00	1,00	1,00	12,00
8	0,98	0,95	0,93	11,64
Avg.	**0,94**	**0,88**	**0,83**	**11,32**

Table 2: Sensitivity and specificity index measured.

Users	Sensitivity	Specificity
1	0,92	0,97
2	0,92	0,97
3	0,91	0,97
4	0,77	0,92
5	0,81	0,94
6	0,72	0,91
7	1,00	1,00
8	0,95	0,98
Avg.	**0,88**	**0,96**

With the given indexes, it is noticeable that some subjects had a good performance (users 1, 2, 3, 7 and 8), while others had indexes just above the acceptable. For a more detailed analysis of these differences, the scalp topographic images were built using data from users 6 and 7, and using R^2 as determination coefficient.

This index calculates how much two signal are similar. The EEG signal captured at the relax state were used as baseline for this comparison. Thus, FC5 and FC6 electrodes were used, because they are the closest electrodes from the sensorimotor cortex region, which is the most activated area during the motor imagery execution.

At figure 5 and 6, the more intense color represents a higher brain activation area.

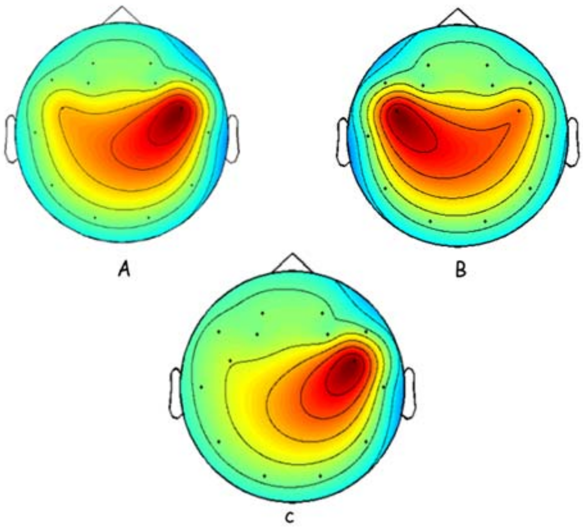

Figure 5: Three different moments of user 6 motor imaginary: (A) Movement imagery of right arm. (B) Movement imagery of left arm. (C) Movement imagery of both arms.

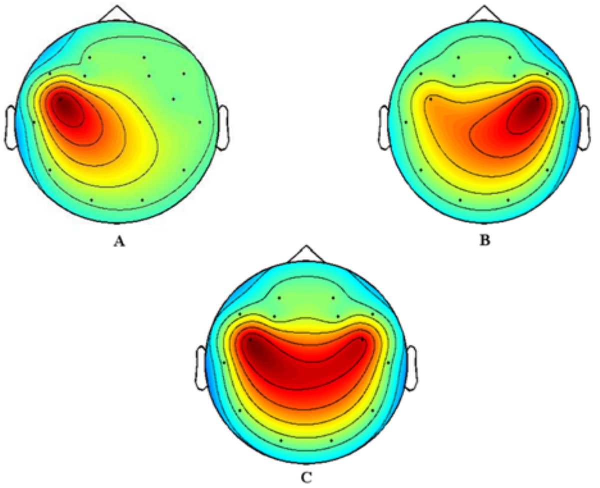

Figure 6: Three different moments of user 7 motor imaginary: (A) Movement imagery of right arm. (B) Movement imagery of left arm. (C) Movement imagery of both arms.

The difference of the test executions by the subjects is clearly noticeable in both figures. It is expected a brain contra-lateral behavior during the motor imagery, i.e., right arm motor imagery activates the left size of the brain and vice-versa [12]. This behavior was acquired by subject 7, where data showed intention patterns quite disparate, making it more effective to classify the characteristics. Subject 6 did not show this behavior. The brain region activated during the motor task was ipsi-lateral. Thus, it is noticeable that Figure 5 (A) and (B) are quite similar, meaning that this subject activates the same region in both motor imagery tests. This makes it more difficult to discriminate this class pattern, negatively impacting the system usability.

Conclusion

The proposed BCI using low cost EEG signal acquisition equipment showed good results using a relatively simple algorithm to extract the features and classify the patterns. The next step is to make a comparison with other low complexity algorithms, which are also used for features extraction and pattern classification, then, integrate the best one into the telepresence robot.

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