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Original Article

EEG Based Brain Computer Interface for Controlling a Robot Arm Movement Through Thought

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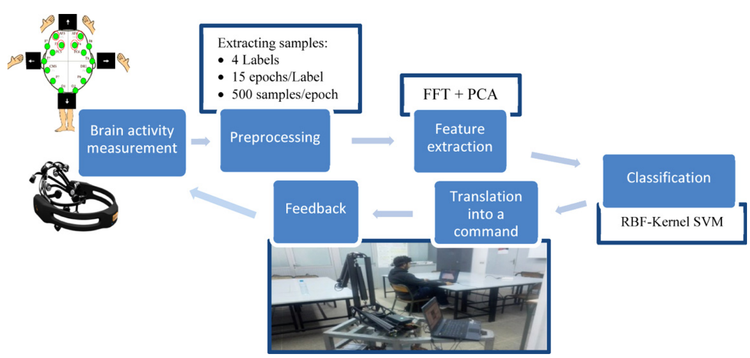
Highlights

- The use of Brain Computer Interface to help a handicapped user to find an object.
- Use of electroencephalogram based on four mental tasks to control the robot arm.
- The system enabled the control of the robot achieving an averaged accuracy of 85.45%.

Graphical abstract



Abstract

Background: The Brain Computer Interfaces (BCI) are devices allowing direct communication between the brain of a user and a machine. This technology can be used by disabled people in order to improve their independence and maximize their capabilities such as finding an object in the environment. Such devices can be realized by the non-invasive measurement of information from the cortex by electroencephalography (EEG).
Methods: Our work proposes a novel BCI system that consists of controlling a robot arm based on the user's thought. Four subjects (1 female and 3 males) aged between 20 and 29 years have participated to our experiment. They have been instructed to imagine the execution of movements of the right hand, the left hand, both right and left hands or the movement of the feet depending on the protocol established.

EMOTIV EPOC headset was used to record neuronal electrical activities from the subject's scalp, these activities were then sent to the computer for analysis. Feature extraction was performed using the Principal Component Analysis (PCA) method combined with the Fast Fourier transform (FFT) spectrum within the frequency band responsible for sensorimotor rhythms (8 Hz–22 Hz).

These features were then fed into a Support Vector Machine (SVM) classifier based on a Radial Base Function (RBF) whose outputs were translated into commands to control the robot arm.
Results: The proposed BCI enabled the control of the robot arm in the four directions: right, left, up and down, achieving an averaged accuracy of 85.45% across all the subjects.
Conclusion: The results obtained would encourage, with further developments, the use of the proposed BCI to perform more complex tasks such as execution of successive movements or stopping the execution once a searched object is detected. This would provide a useful assistance means for people with motor impairment.

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Keywords: Brain–machine interface; Electroencephalography; Emotiv Epoc headset; Fast Fourier transform; Principal component analysis; Support vector machine

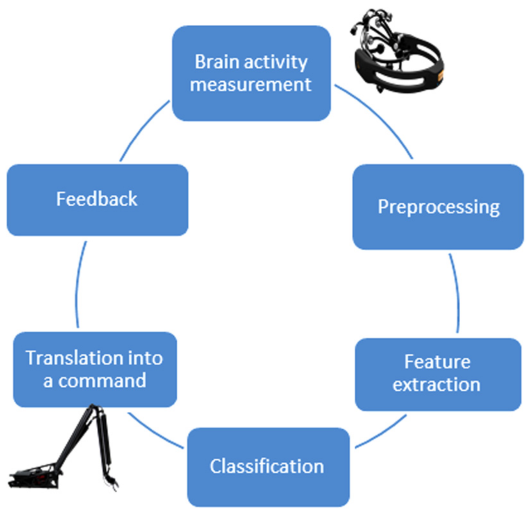

Fig. 1. Brain computer interface system.

1. Introduction

Our brain controls the various functions of the body. Each area of the brain is responsible for a specific function, such as arm and leg movements, vision, hearing and intelligence. The spinal cord is an organ that has a lot of functionality in our nervous system among them the transmission of control messages to the muscles, damage to this organ causes in paralysis. Therefore, patients who are suffering from this severe problem such as motor disabilities cannot handle the simplest daily routines and they need a great deal of support to improve their ability to carry out and move on with normal life. As a result, this problem has an impact on a person's quality of life and adds a high cost for the residential care packages since an assistance is always needed to serve patient.

As a solution the Brain Computer Interfaces are devices allowing direct communication between the brain of a user and a machine, these systems can be used in patient assistance or rehabilitation and require a closed-loop process, most of time composed of six steps (Fig. 1): brain activity measurement, preprocessing, feature extraction, classification, translation into a command and feedback.

Numerous works which Brain Computer Interfaces have been used in controlling robotic platforms can be found in the literature.

Moreover since 1960, researchers [1] introduced the term cyborg and the idea to control an electronic system using brain activity. In 1973 researchers [2] tested the first real experiment on humans. The latter had an electronic control system via brain activity measured by EEG.

The past few years various ways in controlling robotic platforms for people suffering from a diverse range of impairments were investigated. Guger and his colleagues had already shown that it is possible for patients suffering from 'locked-in syndrome', spinal cord injury or damaged regions of the brain responsible for the body movement to control a hand prosthesis by thought without the use of invasive techniques [3,4], another systems were proposed and applied for people with disability in order to control a wheelchair or robot arms [5,6].

BCIs appeared in the computer gaming domain, they have been applied in the virtual simulations, such as games or virtual tours. Pfurtscheller, Leeb and his collaborators [7,8] developed an application in which the subject can move in a virtual street by imagining the movement of the feet to move forward and movement of the right hand to stop. Then researchers start developing various novel applications with relatively low cost non-invasive EEG equipment and software development kits (SDKs). Furthermore, gaming technology has been assisted by virtual and augmented reality systems, making hybrid BCI systems for enhancing the user experience, study and improvement of brain-computer interaction [9].

In fact, what was once science fiction became a reality with the Brain Computer Interface. This approach became possible through the use of technology and mathematical method describing certain physical processes occurring in the brain and corresponding to specific mental tasks. Wavelet-based feature extraction algorithms were introduced in [10]. Power Spectral Density (PSD) [11], Band Powers (BP) [12], Adaptive Auto Regressive (AAR) [13], were also used for feature extraction. A great variety of classification methods was also used to design BCI systems. Linear Discriminant Analysis [14], Support Vector Machine (SVM) [15], and Hidden Markov Model [16] are some examples of widely used classifiers in this field. Classification of mental tasks has been introduced in several works ([17–19]), however, just a few applications in real time have been reported in the literature. Recently, Hortal designed a BCI for controlling an industrial robot arm through mental tasks [20] in which the system performed SVM classification of four mental states to control in real time the movements of the robot with an accuracy achieving 70%. The mental activities consisted of motor tasks involving two imagined movements of both hands separately and two concentration tasks which consisted of a mental recitation of the alphabet backward and a mental count down from 20 to 0. This work had been tested with two volunteers only.

The current work focuses on a non-invasive and spontaneous BCI based on the use of EEG biosignals elicited through mental tasks to control the movements of a robot arm with the goal to help handicapped people find a specific object in the environment. The BCI consists of two steps. Firstly, an Off-line BCI with four mental motor tasks is used to train a volunteer and brain activities recorded are analyzed and processed for feature extraction. Secondly, a real time BCI based on RBF Kernel

Fig. 2. The experimental environment.

Fig. 3. Emotiv Epoc headset.

SVM classifier is implemented to allow the user to control, with the same imagined tasks, a robot arm in the four directions: right, left, up and down. The system is assessed on the basis of the performance obtained with four volunteers who participated to the experiment that was high compared to existing systems which makes our system optimized considering the execution time and its reliability.

The rest of the article is structured as follows. Section 2 presents a description of our system. Sections 3 presents the two experimental prototypes that were implemented. Finally, section 4 illustrates primarily results and discussion and section 5 presents conclusions and perspectives.

2. Materials

Controlling a robot arm is accomplished in this work through a BCI using four mental motor tasks performed by a user imagining the movement of the right and the left hand separately, the movement of both hands and that of the feet. For each task, brain signals are measured using an acquisition system that records EEG from the users scalp, then processed and classified. The output of the classifier controls the movement of the robot arm in the four directions based on the user thoughts. The user can see the decisions of the system in real time via a monitor displaying the streaming of a webcam embarked on the robot arm.

As shown in Fig. 2, the experimental setting uses five components: EMOTIV EPOC headset, a personal computer for acquisition and feedback, Advanced Robotic Manipulator by Invenscience (Arm 2.0), Trustcam's Spotlight Webcam, and a second personal computer for controlling the arm.

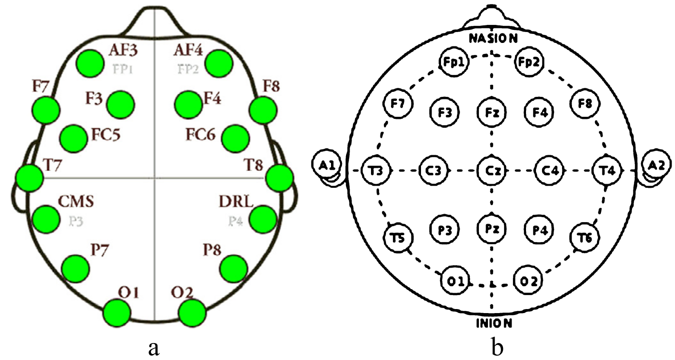

Fig. 4. a: Electrodes of Emotiv Epoc headset. b: Electrodes positions according to the 10–20 system.

2.1. Data Acquisition system

The raw EEG signal was recorded using the EMOTIV EPOC headset shown in Fig. 3 consisting of 14 electrodes (Fig. 4a) whose locations do not correspond exactly to the positions of the standard 10–20 system (Fig. 4b). Since the C3 and C4 positions can cover a region of the motor cortex, they are the preferred placement of the electrodes for exploiting Event Related De-synchronization (ERD) and Event Related Synchronization (ERS) as reported by Pfurtscheller [21,22]. Consequently, the headset was tilted around the axis passing through the reference electrodes located behind ears [23] so that F3 and F4 can cover the positions of C3 and C4. Also, we used AF3 and AF4 electrodes to eliminate the artifacts such as EMG and EOG artifacts and the two reference electrodes. An inbuilt notch filter at 50 Hz and 60 Hz removes power line noise. Data were then amplified and digitized with a sampling frequency of 128 Hz.

2.2. Robot environment

The robotic system used is a computer-assisted manipulator. The purpose of such a system is to help the subject detecting or finding the object he needs in the environment. It consists of (Fig. 2):

– A robot arm (Arm 2.0) fixed on a metal support, it is an articulated robot with six degrees of freedom (referred as the base), the shoulder, the elbow, the wrist rotation, the wrist transition and the clamp. The robot performs the movements of the base and the elbow controlled by the thought of the subject.
– An embedded camera is positioned on the wrist of the robot arm in order to stream the environment.
– A computerized system that allows the transfer of data between the robot arm and the acquisition system based on the TCP/IP communication, which sends the camera streaming to the computer of the acquisition system and receives the order from it.

2.3. Experimental protocol

Four users aged between 20 and 29 years (3 males, 1 female) volunteered to participate in the experiment. All subjects were

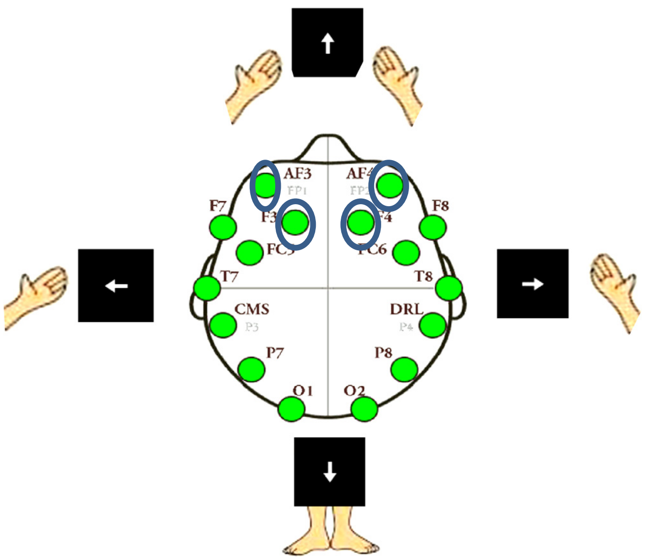

Fig. 5. The alphabet created between the user and the robot arm.

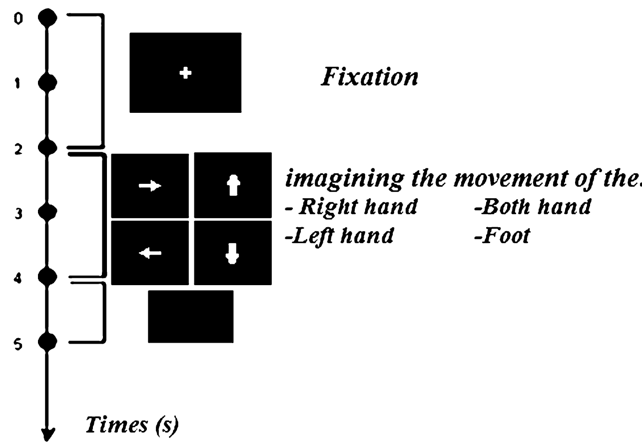

Fig. 6. Offline acquisition protocol.

Table 1
The alphabet created between the user and the robot arm.

Arrow	The imagining movement	The robot movement
Right	Right hand	The base moves right
Left	Left hand	The base moves left
Up	Right and left hand (at the same time)	The elbow points up
Down	Feet	The elbow points down

free of any history of neurological or psychological disorders. The participants were required to remain still with minimal muscle movement during the experiment.

To control the robot in the four directions, we created an alphabet of four symbols which consist of arrows in four directions right, left, up and down. Once an arrow is presented on the screen of a monitor, the user must think of a movement according to the direction of the arrow. As shown in Fig. 5 and Table 1, there are four options:

– If a right arrow is displayed, the user has to imagine the movement of the right hand that should control the base of robot arm to move to the right.
– If the left arrow is displayed the subject has to imagine the movement of the left hand that should control the base of the robot arm to move to the left.
– If the up arrow is displayed the subject has to imagine the movement of both right and left hand that should control the elbow of the robot arm to move to point up.
– If the down arrow is displayed the subject has to imagine the movement of the feet and that should control the elbow of the robot arm to point down.

Each experimental test takes about 30 minutes, it includes the training phase performed off line and the on-line test. Firstly, a description of the experiment's sequences is introduced to the user and then a period of five minutes is established to allow him (her) to familiarize with the protocol. A white fixation cross is displayed in the center of the monitor for 2 seconds at the beginning, then a cue is randomly presented as a right, left, up and down arrow for 2 seconds. When the cue is presented, the subject was instructed to start imagining a movement of the right hand, the left hand, both the right and the left hand and the movement of the feet based on the displayed arrow direction as described above. Then, a black screen is displayed for 1 second as a resting period (Fig. 6).

2.4. Training

During the training phase, the arrows were displayed 15 times each. The user performed the four imagined movements sixty times which required around five minutes. This was followed by a period of ten minutes to allow the user to rest and get ready for the on-line test aimed at controlling the robot arm based on the user thought.

2.5. On-line control of the robot arm

Using the same setting as in the training phase, the user was fixing the screen where a streaming of the robot's camera was displayed. At the beginning a white fixation cross appeared in the right down corner of the streaming for 2 seconds to inform the user that he has to prepare for a mental task, then this cue changed to a green square for 2 seconds as a start of the imagined movement. When the green square turned red the subject had to stop imagining and he (she) could visualize on real time for 3 seconds the response of his (her) thought through the movement of the robot arm shown on the screen (Fig. 7). For validation, this protocol was repeated ten times by each user for the four movements thought.

3. Methods

Data used in this work were collected from each subject using four electrodes AF3, AF4, F3 and F4. Pre-processing consisted of using differential potentials between data collected with F3 and AF3 and between those collected with F4 and AF4 to eliminate the artefacts. Secondly, a Butterworth stopband filter was applied to remove the power line interference (50 Hz). The set of data analyzed consisted of 60 epochs including data

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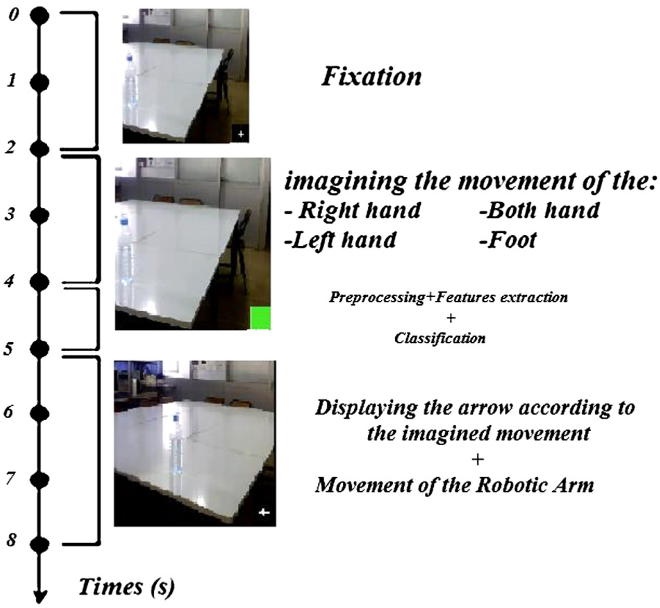

Fig. 7. On-line protocol. (For interpretation of the colors in the figure(s), the reader is referred to the web version of this article.)

corresponding to the four imagined movement represented each by a label of 15 epochs. Each epoch contained 500 samples.

The measurement of an imagined movement at the two channels lasts 2 seconds with a sampling frequency of 128 Hz

$$2 \text{ seconds} * 128 \text{ Hz} * 2 \text{ channels(F3–AF3, F4–AF4)}$$
$$= 500 \text{ samples}$$

Label 1: 500 samples*15 epochs
Label 2: 500 samples*15 epochs
Label 3: 500 samples*15 epochs
Label 4: 500 samples*15 epochs

3.1. Feature extraction

The analysis method is presented in the flowchart below (Fig. 8). Feature extraction was performed through analyzing the EEG signals using the Fourier transform method and combining the Principal Component Analysis method to reduce the dimensionality of the features.

We were mainly interested in frequency components in the range of frequencies between 8 Hz and 22 Hz taking into account that the frequency bands responsible for the sensorimotor rhythms that appear when a person makes or imagines a movement are μ [8 Hz–12 Hz] and β [12 Hz–22 Hz] [24].

Principal component analysis is a statistical algorithm which is widely used for feature extraction and dimensionality reduction. PCA can be defined as a linear projection transforming a number of possibly correlated variables into a smaller number of uncorrelated variables called principal components. The first principal component has the maximum variance, and each succeeding component in turn is orthogonal to the existing components and with the maximum variance. PCA was invented in 1901 by Karl Pearson. It is performed on the Covariance matrix or on the Correlation matrix. These matrices can be calculated from the data matrix. It involves a mathematical procedure called eigen analysis; usually after normalizing (zero-mean) the data matrix for each attribute the analysis can be done by eigenvalue decomposition of a data covariance (or correlation) matrix of a data matrix. The basic goal in PCA is to decorrelate the data by performing an orthogonal projection to remove unwanted components in the signal [25]. In our work, we use PCA to reduce dimensionality of data to 60 samples so that the obtained features matrix for each label was presented as:

Label 1: 60 features *15 epochs
Label 2: 60 features *15 epochs
Label 3: 60 features *15 epochs
Label 4: 60 features *15 epochs

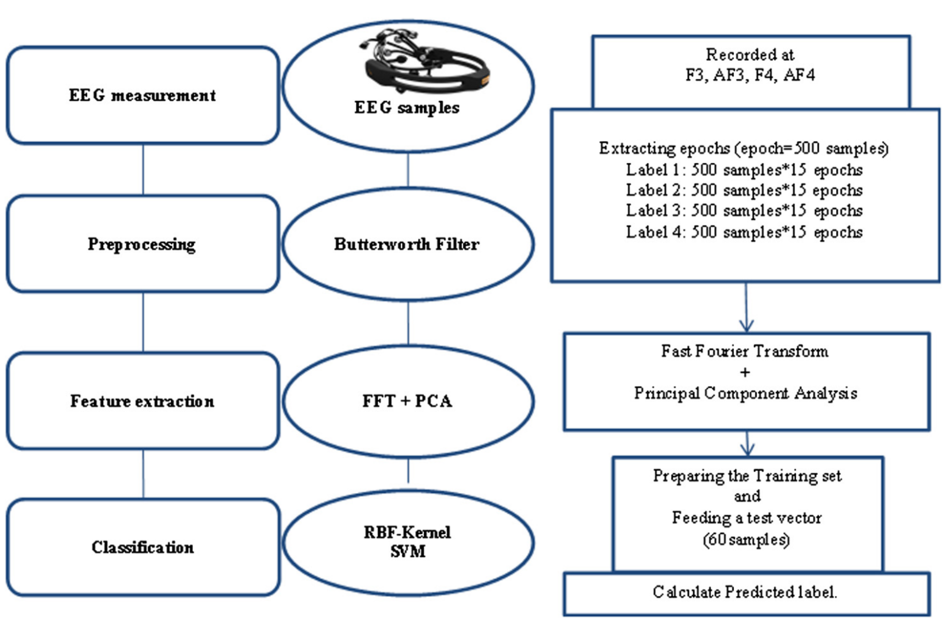

Fig. 8. Chart of analysis methodology of the system.

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Table 2
Success rate of the control of the robot arm (%) obtained with the 4 users. (RH: right hand. LH: left hand. BH: both hands. FT: feet).

User	Class				
	RH	LH	BH	FT	Mean
User 1	93.6	79.5	79.12	89.7	85.48
User 2	82.2	87.7	79.0	84.5	83.35
User 3	87.6	94.5	77.3	92.1	87.87
User 4	89.2	86.5	73.7	91.1	85.12

Table 3
Confusion matrix (%) – User 3 (RH: right hand. LH: left hand. BH: both hands. FT: feet).

True class	Predicted class			
	RH	LH	BH	FT
RH	98.2	0.1	1.7	0.3
LH	0.8	94.7	4.2	0.3
BH	10.5	0.7	88.6	0.2
FT	2.4	0.3	3.8	93.5

Table 4
The performance (%) achieved by user 2 in both cases randomly and successively (RH: right hand. LH: left hand. BH: both hands. FT: feet).

User 2	RH	LH	BH	FT	Mean
Training (1)	82.2	87.7	79.0	84.5	83.3
Training (2)	85.4	86.8	84.2	85.6	85.5

And it defined the training set for real time analysis. Features were then fed into a classifier based on the Radial Base Function Support Vector Machine (RBF-SVM) that calculates the predicted label among the four labels based on the training set.

3.2. Classification

In BCI research, Support Vector Machine (SVM) is regarded as one of the more accurate classifiers [26,27]. To do the classification, SVM makes use of a hyperplane or groups of it in a very high (even infinite) dimensional space to distinguish the different classes to classify. The performance of a given linear SVM depends on a tradeoff parameter C: the C parameter balances the relative importance of minimizing the training error and maximizing the margins between the classes, which directly affect the classifier's generalization ability. The accuracy of the SVM-based classifier depends on the kernel used. In the case of a BCI system, generally a Gaussian kernel or a Radial Base Function (RBF) is applied [28]. Cross-validation basically improves the accuracy of the model by avoiding the overfitting. In K-fold cross validation the data is first partitioned into k equally (or nearly equally) sized segments or folds. In this case, cross-validation is used to choose the best parameters C and gamma of the RBF kernel and to estimate the model performance. In this work, a multiclass strategy was used in the RBF kernel SVM system using 10-folds cross-validation. Best results were obtained for C between 370 and 500 and gamma between 3.5×10^{-5} and 5×10^{-3}.

4. Results and discussion

The results presented in Table 2 are the rates of success obtained by each of the four users in controlling the robot arm by performing each of the four imagined movements. The last column of the table gives the average success rate for each user. These results showed good performance above 85% in average obtained with the four users. Nonetheless, they all showed less accuracy in performing the imagined movement involved both hands as revealed by the confusion matrix whose components are the probability of agreement between the true and the predicted label. Table 3 represents the confusion matrix computed with the user achieving the highest performance (User 3).

These results suggest that the classification accuracy may be affected by the degree of concentration of the user during the training phase. As reported by some users, a loss of concentration is felt when the arrows were displayed randomly. This was confirmed by comparing the performance achieved by user 2 in both cases (1) the four arrows were displayed randomly 15 times each and (2) each type of arrow was displayed successively 15 times. Table 4 shows performance enhancement for all the movements and in particular the movement of both hands as shown in Table 4.

These findings demonstrate capabilities of the proposed BCI in controlling movements in the four directions, left, right up and down based on four motor mental tasks with an overall success rate of 85.45%. As revealed by the confusion matrix the BCI proposed is more efficient (98.2 for the right movement, 94.7 for the left movement) compared to the performance obtained by Hortal (78.4.2 for the right movement, 89.7 for the left movement). In addition feature extraction performed prior classification reduced considerably data dimensionality from 500 to 60 and thus the computation time cost.

5. Conclusion

The current work presents preliminary results in controlling through mental tasks the movements of a robot arm in four directions: right, left, up and down. The system used a brain computer interface that exploits EEG signals recorded for each mental task from the scalp at the locations F3, AF3, F4 and AF4 of the motor cortex. Spectral analysis based on FFT transform combined with PCA method produced optimal features that were fed into an RBF Kernel SVM classifier to discriminate between the four movements. Tests performed with four volunteers showed an accuracy reaching on average 85.45%. Subject training was an essential step; the performance accuracy was impacted by the level of concentration during the movement imagination.

The good rate of success obtained in real time using the four basic movements would encourage, with further developments, the use of the proposed BCI to control the robot arm to perform more complex tasks such as execution of successive movements or stopping the execution once a searched object is detected. This would provide a useful assistance means for people with motor impairment.

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Conflict of interest statement

There is no conflict of interest.

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