Classification of EEG from Black Color Stimuli to Command a Remote-Controlled Car: Ongoing Study

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***Abstract*—In this manuscript, we present a pilot study to use the black color stimuli and resting state to wirelessly control a remote-controlled car. Power Spectral Density (PSD) was calculated on EEG signals to extract features and Multilayer Perceptron (MLP) was proposed to classify the EEG features using a 5-fold cross validation. Our results reported that best score classification was on 100% for Delta band using six electrodes and they allow to control a remote-controlled car. This approach is compared to other BCI paradigm and machine learning algorithms so that our results outperformed others works.**

I. Introduction

A Brain-Computer Interface (BCI) is a system which is able to record, analyze, classify the brain signal in order to control an external device or a computer. So, people with severe motor disabilities benefit from these technologies and enhance their quality of life. The electroencephalographic signals (EEG) is the most suitable and common way to register brain signals to BCI. The EEG signals contains the summation of all the neural activity while a subject develops different kind of mental activities such as cognitive tasks [1], attentional task [2] , motor imagery tasks [3], etc.

The EEG-based BCIs reported various applications such as speller [4], controlled robots [5], just to name a few. Regarding BCI to control robots, this technology allows the subject to control a robot while he develops a mental state. The state-of-the-art are reported that Brain-controlled manipulators and mobile robots are two kinds of brain-controlled robots for disabled people [6].

In the scientific literature, in [7], the authors developed a tele-operation control which is able to coordinate multiple mobile robots by means of Brain-Computer Interface using SSVEP visual Stimuli. The authors achieved an average classification accuracy that is more than 85%.

The blink eye approach is useful to control mobile robot by means of EEG signals. In [8] people suffer from motor disabilities were able to control a mobile robot using the eye blink strength which was processing with Discrete Wavelet Transform (DWT). Also, in [9], the amplitude level of EEG signals related to blink eyes is used to command a robotic gripper. In [10], a mobile robot built on Arduino platform was controlled using brain signals. The band power features and support vector machine (SVM) were applied to analyze EEG signals. The authors achieved a score classification of 96%.

In [11], a low-cost robot car is controlled using a BCI with SSVEP paradigm. The best classification accuracy was 92.2% using a Linear Discriminant Analysis (LDA). Also, in [12] different level of power spectrum was analyzed to control a robot car using a SSVEP and the results achieved 70% of accuracy.

The disadvantage of MI is that the subject require long training for enhance a performance. Also, The SSVEP could be exhausting for the subjects during the experiment [13]. For this reason, different mental states to control a mobile robot should be studied.

On the other hand, recently studies have reported the effect of color stimuli on brain signals and try to determine how decode this information using EEG signals [14], [15], [16]. This approach can be used how paradigm to build a Brain-Computer Interface.

In [14], the authors recorded EEG signals for four different color stimuli (red, yellow, green, blue). They proposed a Power Spectral Density as feature extraction and using a Interval-Type-II fuzzy space classifier in order to classify the EEG signal. The authors achieved a score classification of 85.23% for red color. Furthermore, a frequency analysis approach was proposed in [15] to decode and understand the brain signal during different colors stimuli (green, red, blue, yellow). The results reported that green, red, blue and yellow colors point out maximum frequency approximate in 2.5, 1.2, 1.6 and 0.65 Hz respectively. So, this results suggest that low frequencies are related to color stimuli. The advantage of color stimuli is that the subject does not require long training for reaching a performance.

This work presents a pilot study to use two mental state: black color stimuli and resting state in order to control a remote-controlled car built from the Arduino platform . Different brains band were analyzed using Spectral Power Density (PSD) and these features were classified by means of Multilayer Perceptron (MLP). In this work, a 5-fold cross validation and several topologies of MLP were tested.

This work is presented as follows. In section II the experimental protocol and EEG acquisition are presented. In section III, the methods are presented, including the preprocessing methods, features extraction, Multiplayer Perceptrons (theory and classification scheme) and remote-controlled car controlled setup. The results and discussion are presented in section IV. Finally, conclusions and future work are presented in section V.

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II. Experimental procedure

A. Participants

In this work, the dataset was recorded from a healthy subject aged 23 years old during he develops two mental activities. Then, the EEG data was recorded from one subject who sat in a comfortable chair during watching a black image (color stimuli) and resting condition with eyes-closed. An acoustic stimulus indicates the beginning of the trial and a message was displayed for 1s to indicate the mental activity. After that the EEG data was recorded during 10 seconds per trial. According to protocol of the experiment consist of 3 sessions with 20 trials each which was separated by break of 3 minutes. In summary, 60 trials were recorded from 3 sessions and 30 trials for each task. During the recording EEG data, the subject was forbidden to talk and move his hands and legs.

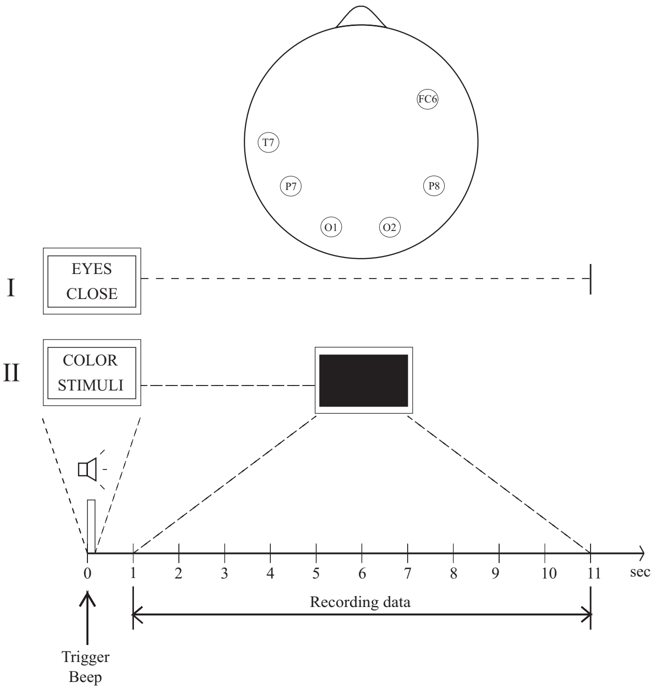

Fig. 1: Timing protocol of experiment.

B. EEG acquisition

A wearable electroencephalography (EEG) of the brand EMOTIV was used to record the EEG signals. In this work, six dry electrodes (FC6, P8, O2, O1, P7 and T7) were available and thet were placed in accordance with the international 10/20 system.

The brain signals were sampled at 128 Hz and Emotiv Test Bench was used to save the data for offline analysis which was analyzed using Matlab R2016a. The experiment setup can be seen in Fig. 2.

Fig. 2: Subject during BCI experiments.

III. Methods

In this section, we present the preprocessing, preprocessing and describe the MLP approach. Furthermore, the details of remote-controlled car are presented.

A. Preprocessing

An Elliptic filter of order five was used to filter twice (once forward and reverse) the EEG data to remove phase distortion effects and eliminate the artifacts. In this work, we analyzed the pass band spectral range of $1-4Hz$ (Delta), $4-8Hz$ (Theta), $8-15Hz$ (Alfa) and $15-30Hz$ (Beta). The order of bandpass filterwas calculated to obtain a -30 dB for frequencies 0.5 Hz.

B. Feature Extraction

We calculate a Spectral Power Density (PSD) over each trial, brain band and electrodes to characterize EEG signals. We create two approaches of raw features: (i) five higher peaks of PSD (5-PSD) and (ii) five higher peaks of PSD and five higher peaks of histogram with 20 bins from PSD (5-Hist-PSD). These new parameters represent the features of each mental activity so feature extraction process converted EEG data into a new data set.

C. Multilayer Perceptrons

The classification stage was carried out by a Multilayer Perceptron (MLP) which is feedforward Artificial Neural Network (ANN). A supervised learning called back propagation algorithm is used to training the MLP. This network is able to learn how link input data into a desired target by mean of training process. So, it requires a know dataset with input data and corresponding targets for training process. According of the theory, more dataset is desirable to reach a suitable classification model. The MLP use hidden layers with non-linear activation and at least with one hidden layer it is able to map input data and target [17].

In this work, MLP was used to classify EEG data related to two mental states. Different topologies with two-layer hidden were tested and we selected the best topologies. For both layers hidden, the numbers of neurons were calculated by means of

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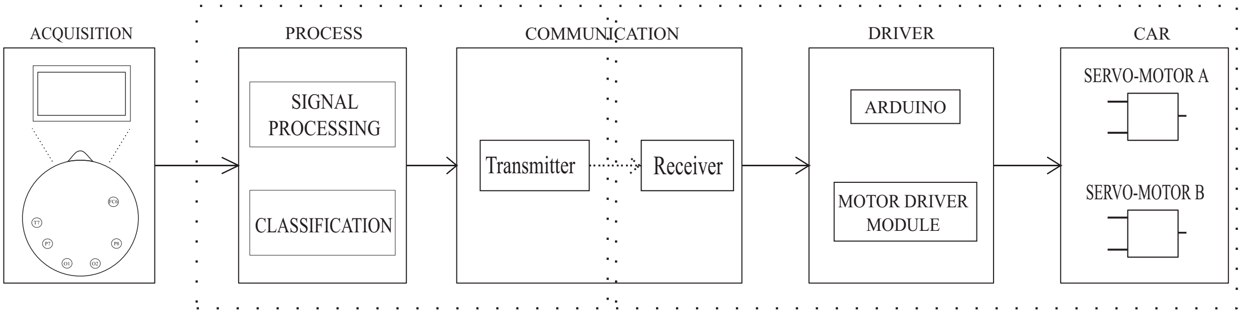

Fig. 3: Architecture of remote-controlled car setup.

all combinations since 5 until 100 neurons in multiples of 5 neurons. A 5-fold cross validation was used because EEG data was grouped in four sessions of training and one for testing. In order to avoid the overfitting problem, MLP was trained with different number of epochs. Finally, the performance of MLP was calculated using a score classification.

D. Remote-Controlled Car Setup

The training processes of MLP was carried out in a computer using MATLAB and testing data was converted into commands to control our Arduino car. We constructed a remote-controlled car using Arduimo plataform due to it is cheaper than other technologies. Also, the motor driver module which is composed of a H bridge, bluetooth circuit to transmit data from computer until Arudino plataform and two engines connected to the wheels were used to built our Arduino car. From Fig. 3, we can see that diagram block which describe the BCI contolled our Arduino car. The testing data were processed in MATLAB and the outputs were sent by means of bluetooth to Arduimo plataform. This commands executed two instructions as can be seen in Table I.

TABLE I: MOTION OF REMOTE-CONTROLLED CAR

Output	Robot's motion	Mental state
0	Backward	Resting state
1	Forward	Watching a black image

IV. Results

In this study, we analyzed the classification accuracy of EEG signals from two mental states using different MLP topologies under the condition of 5-fold cross validation. According to Table II, we can see the performance of classification accuracy for the MLP with different topologies, electrodes and brains bands. Also the last column tabulates the numbers of neurons for each hidden layer. We analyzed different combinations of electrodes in order to achieve a maximum classification accuracy. Better results were reached using six electrodes (FC6,P8,O2,O1,P7,T7) for both approaches. Our first approach reported that best classification accuracy was 100% for Delta band using six electrodes (FC6,P8,O2,O1,P7,T7). The MLP topology in this result was 5 neurons in first layer (FL) and second layer (SL), respectively. The results of our second approach reached a maximum score classification of 96.67% using the Beta band and six electrodes (FC6,P8,O2,O1,P7,T7).

Regarding the first approach, the results of Delta band reported 100% of classification accuracy and these results outperformed Delta band outcomes of the second approach. Although, the Delta band is relate to stages of sleep, it reported the maximum classification accuracy for both approaches [13]. Also, these results are agreement with [14] which reported that low frequecy is realted to color stimuli.

Furthermore, Theta band and Alpha band achieved a maximum score classification of 98.3% and 95% , respectively. For both brain bands, the MLP was built for 5 neurons in first layer (FL) and second layer (SL).

On the other hand, the accuracy performance of 96.67% was reported for Beta band as maximum accuracy using the second approach. This topology was composed of 5 neurons in first layer (FL) and 10 neurons in second layer (SL). These results outperformed the first approach. Note from Table II that the best results were produced using all electrodes, three for each cerebral hemisphere. In summary, Delta band reported better classification accuracy and it outperformed other brain bands. Furthermore, the motion of remote-controlled car for backward and forward is shown in Fig. 4. The distance traveled of remote-controlled car can be tuned, in this case we used 5 centimeters of distance traveled for both motions.

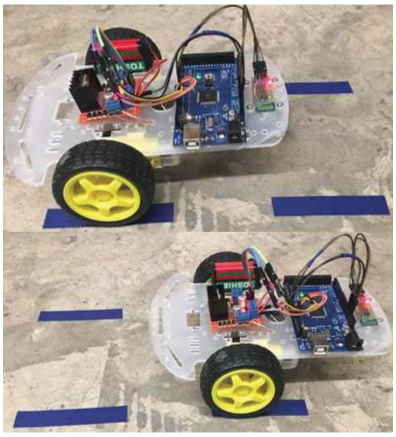

Fig. 4: Motions of remote-controlled car.

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TABLE II: Classification results in terms of accuracy of the classification (ACC).

Electrodes	Band	Processing	Classification		Details
			Train	Test	
FC6-P8-O2-O1-P7-T7	Delta	MLP	100%	100%	FS: 5, SL: 5. Features: Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Delta	MLP	100%	100%	FS: 5, SL: 10. Features: Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Theta	MLP	100%	98.30%	FS: 5, SL: 5. Features: Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Theta	MLP	100%	96.67%	FS: 5, SL: 10. Features: Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Alpha	MLP	100%	95%	FS: 5, SL: 5. Features: Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Alpha	MLP	100%	93.30%	FS: 5, SL: 10. Features: Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Beta	MLP	100%	95%	FS: 5, SL: 10. Features:Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Beta	MLP	100%	95%	FS: 5, SL: 15. Features:Five Higher Peaks of PSD
FC6-P8-O2-O1-P7-T7	Delta	MLP	100%	93.3%	FS: 5, SL: 10. Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Delta	MLP	100%	93.30%	FS: 5, SL: 15. Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Theta	MLP	100%	93.30%	FS: 5, SL: 5. Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Theta	MLP	100%	93.30%	FS: 5, SL: 15.Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Alpha	MLP	100%	93.30%	FS: 5, SL: 10. Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Alpha	MLP	100%	93.30%	FS: 5, SL: 15. Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Beta	MLP	100%	96.67%	FS: 5, SL: 10. Features: Five Higher Peaks of Histogram and (5-PSD)
FC6-P8-O2-O1-P7-T7	Beta	MLP	100%	96.67%	FS: 5, SL: 15. Features: Five Higher Peaks of Histogram and (5-PSD)

V. Conclusions

In this work, a remote-controlled car built on Arduino platform was controlled using two mental activities. Therefore, we analyzed the performance of two mental states (color stimuli and resting state) to develop a BCI. Several topologies of MLP was tested using 5-fold cross validation to find the suitable architecture.

The results reported that best classification accuracy (100%) was obtained using Delta band and six electrodes (FC6,P8,O2,O1,P7,T7) for first approach. Also, our results achieved outcomes which outperformed other works [10] , [12]. So our results demonstrate the feasibility to use color stimuli for controlling a remote-controlled car by means of BCI. As future work, different color stimuli and mental states to control remote-controlled car will be explored and tested.

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