SSVEP-EEG Signal Classification based on Emotiv EPOC BCI and Raspberry Pi ⋆

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Abstract: This work presents the experimental design for recording Electroencephalography (EEG) signals in 20 test subjects submitted to Steady-state visually evoked potential (SSVEP). The stimuli were performed with frequencies of 7, 9, 11 and 13 Hz. Furthermore, the implementation of a classification system based on SSVEP-EEG signals from the occipital region of the brain obtained with the Emotiv EPOC device is presented. These data were used to train algorithms based on artificial intelligence in a Raspberry Pi 4 Model B. Finally, this work demonstrates the possibility of classifying with times of up to 1.8 ms in embedded systems with low computational capacity.

Keywords: Brain Computer Interface, SSVEP-EEG, Classification, Machine Learning, Data acquisition, XGBoost

1. INTRODUCTION

In recent years, extensive research has been developed in robotic systems based on brain-computer interface (BCI). These systems provide the user a communication channel that allows obtaining from the strength of brain waves to communicate the user's intention to external devices, transforming into a computer-controlled signal. These studies have focused on improving or replacing physical functions in people with motor disabilities (Alcivar-Molina et al., 2018, Han et al., 2018). In this context, the non-invasive electroencephalography (EEG) techniques have been used widely to capture brain activity to be used as the source data for BCI, mainly by the high time resolution and low-cost method (Chen et al., 2019, Erkan and Akbaba, 2018). Despite that, many BCI applications based on EEG data, the data acquisition is highly noise susceptible, mainly for the low-cost EEG devices such as blinking, relative movement between the scalp and electrodes, impedance changes between the scalp and the surface electrodes, adipose tissue, and hair. To overcome these difficulties, the artificial intelligence (AI) technique has been used to reduce the complexity of noisy data and increase data classification accuracy. Most of the BCI works based on low-cost devices are focused on binary data classification such as the 2D virtual wheelchair control (Huang et al., 2012), or to obtain hand movements directions (Chouhan et al., 2018, Ghaemi et al., 2017), EEG based prosthetic arm (Fuentes-Gonzalez et al., 2021), and much other research works. In this line, some works carried out a process of feature extraction to the filtered EEG signals using temporary windows of data to vectors containing relevant information. This reduction in the dimensionality of the information makes it possible to reduce the computational cost and in some cases improve the accuracy of the classification algorithms (Artoni et al., 2018, Asanza et al., 2017). The classification of EEG signals has made it possible to develop brain-computer interface

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(BCI) applications, assisting people with reduced capacity problems by controlling electronic, robotic, or prosthetic devices, (Asanza et al., 2020). Most of the assistance studies to classify the subject's intention with reduced abilities use EEG data recorded from the region of the motor cortex (Al-Saegh et al., 2021). Alpha waves from the frontal region of the brain (Fischer et al., 2018) or also the Brain activity recorded in the occipital region of the brain during steady-state visually evoked potential (SSVEP) (Shao et al., 2020). Therefore, the main challenges for the EEG BCI devices are the low information transfer rate, the high error rate, and the development of multiclass EEG data classification techniques, especially for data coming from those low-cost devices. Thus, in this work, we propose a methodology to employ machine learning techniques using a low-cost raspberry to capitalize on the advantages of artificial intelligence in order to process the EEG data captured from an Emotive headset device to classify five different subjects' intention to be used in any control devices.

In this work, the acquisition of EEG signals from the occipital region of the brain is performed during visual stimuli applied to the test subjects. Furthermore, an EEG signal pre-processing method is used to remove noise components and a feature extraction mechanism to classify and determine the visual stimulus that the test subject is observing. The pre-processed data is used to extract characteristics for later classification of intentions. Section III details the dataset used. The pre-processing methodology, feature extraction, and clustering algorithms applied are described in section IV. Then, section V shows the results with the different clustering algorithms used with the pre-processed dataset. Finally, section VI summarizes the discussion results and conclusions.

2. RELATED WORK

Previous research in this field has made it possible to establish slightly more effective methods to address the different challenges such as acquisition, pre-processing, analysis, and classification of EEG signals.

2.1 Acquisition of SSVEP EEG signals

There is a remarkable tendency in using flickering visual stimuli interfaces, assigning a unique frequency to an action, which allows to recognize the user's intentions. The optimal frequency range for the classification of such signals has been a research topic alone. The existence of different types of brain waves is known now to vary, depending on the individual's cognitive activity and level of attention, (Khosla et al., 2020).

Some studies scan brain *alpha* waves with favorable results, using a frequency band between [8-16] Hz. In these cases the acquisition of SSVEP EEG signals focuses on the activity of the occipital and parietal regions of the subject with a high classification rate (Han et al., 2018). Other authors have extended their research to analize *beta* wave for a range of [5-20] Hz in the front parietal and occipital regions. This requires more computational capacity for the data processing device (Zhang et al., 2015).

2.2 Pre-processing

During the experiment there are different external signal sources that do not originate in the brain, known as artifices. These signals can have a negative influence the waves obtained (Khosla et al., 2020). For this reason, prior to the analysis of the signals obtained in the acquisition step. It is convenient to develop a pre-processing stage to organize the data and eliminate any error.

Among the multiple techniques used to eliminate interference produced by power supply line, DC artifices or unwanted frequency components. The authors apply digital Noch type filters (Chen et al., 2018), Butterworth filter (Erkan and Akbaba, 2018), (Waytowich et al., 2018), Wavelet Denoising methods (Shao et al., 2020), (Chen et al., 2019), etc. Some studies, apply additional algorithms to remove linear data trends (Chen et al., 2018).

2.3 Analysis of SSVEP EEG signals

After data pre-processing, the literature refers to the extraction of features as a way to facilitate the signal analysis in time or frequency domain (Khosla et al., 2020). Recently, features used by authors in EEG signals research have been Signal-to-Noise Ratio (SNR) (Chen et al., 2019), phase Locking Value (PLV) (Han et al., 2018), Minimum Energy Combination (MEC) (Erkan and Akbaba, 2018), Maximum Evoked Response (MER) (Zhang et al., 2015), Amplitud Spectrum (Chen et al., 2015), among others.

In addition, there are standardization methods to obtain values as Z-Score (Erkan and Akbaba, 2018), used to scale features results. This makes possible their comparison and selection of a set of characteristics, that achieves a high rate of accuracy.

2.4 Feature Selection

In prior applications, several feature selection methods are applied, these post-processing methods choose relevant features that contribute to a successful classification of the user's intentions, resulting in an increase in the quality of the later results, (Khosla et al., 2020).

2.5 Classification methods

In the final processing stage, previous research describe different ways to classify features obtained in previous steps. Canonical Correlation Analysis (CCA)-based algorithms have been widely adopted due to the obtained accuracy; previous research through Filter Bank Canonical Correlation Analysis (FBCCA) has achieved 91.78%, accuracy, with a sample of 12 study subjects and the use of 10 electrodes, (Chen et al., 2018). In addition there is Support Vector Machine (SVM), a set of supervised learning algorithms with existing results in 88% of cases, with the help of 9 test subjects, (Zhang et al., 2015).

In recent years there has been a good opening to the use of ANN for this processing stage, a successful classification was achieved in 80% of the tests, in this experiment a Compact Convolutional Neural Network (CCNN) was used, (Waytowich et al., 2018).

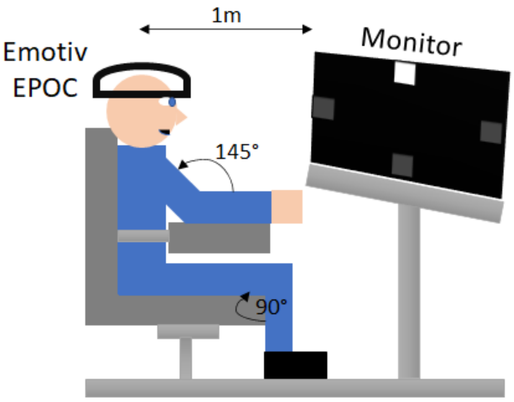

Fig. 1. Run setup during data acquisition

3. DATASET

3.1 Experiment organization

Thanks to the management of the neuroscience research group and the ethics committee of the Tencia University of Machala (UTMACH), twenty adult subjects (no gender discrimination) were recruited between the age of 20 and 35. The subjects were received by the personnel in charge of carrying out the experiment. Staff will avoid wearing brightly colored clothing that distracts subjects' attention during the experiment.

The personnel in charge of the experiment respected the `COVID-19` biosecurity measures , this measures ordered by the Ministry of Public Health of Ecuador's Government include: mandatory use of masks, ventilated experimentation area, contact surfaces properly disinfected, as well as cleaning all utensils used before and after each experiment. *(https://www.salud.gob.ec/medidas-de-proteccion-basicas-contra-el-nuevo-coronavirus/)*

The area where the experiment will be conducted was completely clean, with natural light, white walls without pictures or drawings that distract the subjects' attention. The test environment has air conditioning system at 25 degrees Celsius. During data recording, in some cases low-level noises were reported between 30 and 55 decibels (dB) from sources such as air conditioning and occasionally the vehicle passage that provided very low noise between 10 and 30 db.

Each subject received and signed an informed consent indicating that their participation in this study is strictly voluntary and anonymous. In addition, subjects are informed that the data collected will be confidential and their use is exclusive for research purposes. No personal information was disclosed.

The subjects were asked to sit in a reclining and comfortable armchair with their upper limbs placed on the armrests of the armchair and with an elbow angle of 145 degrees. On the other hand, the lower limbs will be arranged at a 90-degree angle to their thighs. For the experiment, a 17" monitor was placed alined with the eyes of the test subject, at a distance of 1 meter from the head of the subject. This can be seen in Fig. 1.

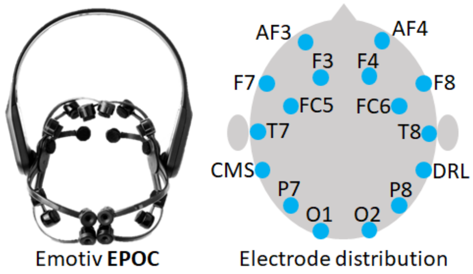

Fig. 2. Emotiv Epoc electrode layout

3.2 Acquisition device

The EEG signal registration *Emotiv Epoc* device was placed in each subject, some of the technical descriptions include a sampling frequency of 128Hz,this device has 14 electrodes and two ground references, distributed in the international system 10 - 20 as shown in the Fig. 2.

During the EEG signal recording process, a conductive gel was used to reduce the impedance between the electrodes and the scalp which significantly improved the integrity of the recorded signals. The details of the electrodes the *Emotiv EPOC* device has are as follows:

- EEG.AF3: Electrode located in the frontal area of the brain in the left hemisphere.
- EEG.F7: Electrode located in the temporal frontal area of the brain in the left hemisphere.
- EEG.F3: Electrode located in the frontal area of the brain in the left hemisphere.
- EEG.FC5: Electrode located in the central frontal area of the brain in the left hemisphere.
- EEG.T7: Electrode located in the temporal area of the brain in the left hemisphere.
- EEG.P7: Electrode located in the parietal area of the brain in the left hemisphere.
- EEG.O1: Electrode located in the occipital area of the brain in the left hemisphere.
- EEG.O2: Electrode located in the occipital area of the brain in the right hemisphere.
- EEG.P8: Electrode located in the parietal area of the brain in the right hemisphere.
- EEG.T8: Electrode located in the temporal area of the brain in the left hemisphere.
- EEG.FC6: Electrode located in the central frontal area of the brain in the right hemisphere.
- EEG.F4: Electrode located in the frontal area of the brain in the right hemisphere.
- EEG.F8: Electrode located in the temporal frontal area of the brain in the right hemisphere.
- EEG.AF4: Electrode located in the frontal area of the brain in the right hemisphere.

3.3 Experimental methodology

Twenty healthy right-handed university students at Universidad Tecnica de Machala (UTMACH) were recruited. Before starting the data acquisition, each test subject was given very clear instructions on the tasks to be performed and a short test session was conducted.The tasks that the test subjects performed during the acquisition process are described above, first the subject was asked to visualize

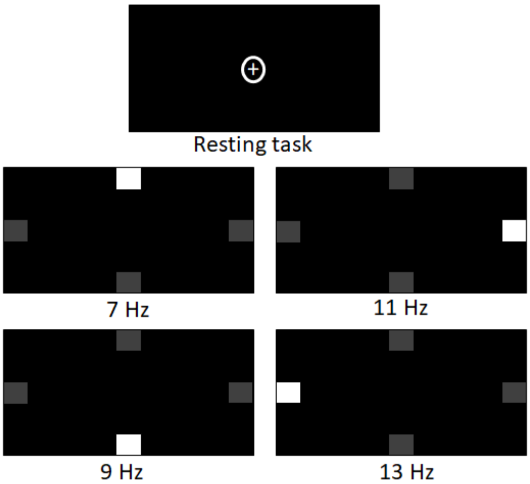

Fig. 3. Visual stimuli used during the experiment

the symbol ⊕ in the center of the screen to record the Resting Task for 3.5 seconds. At that time the test subject only visualizes the center of the fully relaxed monitor without performing any tasks. As shown in the Fig. 3 four visual stimuli with a randonmy duration between 3 and 3.5 seconds each were shown to the test subject. The sequence that includes the four visual stimuli and Resting Task were shown 40 times to each test subject, below are the specifications of the stimuli that indicate the task to be performed by the test subject:

- 7Hz visual stimulus located at the top of the screen, while the rest of the stimuli are dimmed by 80.
- 9Hz visual stimulus located at the bottom of the screen, while the rest of the stimuli are dimmed by 80.
- Visual stimulus of 11 Hz located at the right side of the screen, while the rest of the stimuli are dimmed by 80.
- 13Hz visual stimulus located on the left side of the screen, while the rest of the stimuli are dimmed by 80.

3.4 Recorded data

The number of test subjects who participated voluntarily were twenty, with an average age of 27 ± 3 years old, whose demographic information are as follows:

- Ten of the test subjects were ecuadorian.
- Ten of the test subjects were asian.

Each of the 20 test subjects performed sessions of eleven minutes, during this time, they were shown 40 repetitions of the sequence of the 4 visual stimuli (7 Hz, 9 Hz, 11 Hz and 13 Hz) and Resting Task. The programs used for data acquisition were software `Emotiv PRO` and `Matlab`. `Emotiv PRO` is the program that establishes the connection between the device `Emotiv EPOC` via bluetooth and it saves the records in a *.csv* file for each of the test subject. The `Matlab` software is charge of displaying the visual stimuli presented in Fig. 3 and to synchronize the MarkerValueInt whose values are 1 - 5 where they indicate the moment in which the test subject receives optical stimuli of 7Hz, 9Hz, 11Hz, 13Hz and Resting Task. The Fig. 4 represents the architecture of the programs used during data acquisition.

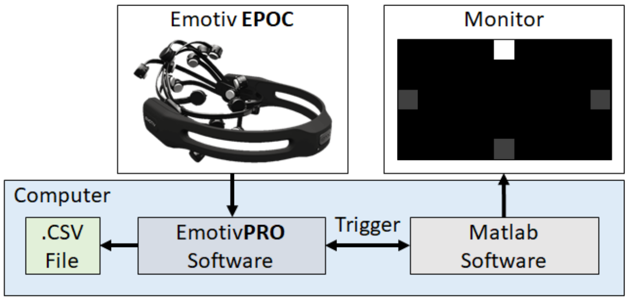

Fig. 4. Structure of the codes used in the acquisition process

This architecture generated a *.csv* for each test subject, these twenty files are located on `1_EmotivData.zip` file, they are published on (Tinoco-Egas et al., 2021) on *IEEE-Dataport*.

4. METHODOLOGY

After analyzing the twenty *.csv* files on the folder `1_EmotivData.zip` subject number eleven data was removed from the dataset since it had different acquisition times than the rest of the subjects, this due to the low voltage levels (battery level 1) of the data acquisition equipment that were detected only in this test subject. The nineteen *.csv* files were processed in `Python`, identifying the MarketValueInt (Label), we proceeded to divide into two hundred new *.csv* files (results of forty repetitions and five stimuli) representing two hundred stimulus visualization tasks stored in separate folders: 7Hz, 9Hz, 11Hz, 13Hz and Baseline (resting task). In addition, only the EEG.O1, EEG.O2 electrodes were selected. The recorded information was organized on a folder `2_Raw_Data.zip`, available on (Tinoco-Egas et al., 2021) on *IEEE-Dataport* through the following sub-folders:

- The folder "7Hz" contains 748 *.csv* files.
- The folder "9Hz" contains 754 *.csv* files.
- The folder "11Hz" contains 756 *.csv* files.
- The folder "13Hz" contains 759 *.csv* files.
- The folder "Resting Task" contains 759 *.csv* files.

4.1 Data pre-processing

The aberrant values of each stimuli on `2_Raw_Data.zip` file were delated. To do this, we used the *IQR* (Interquartile Range) method, an aberrant value was considered to be one that was outside the upper and lower limits previously calculated by the aforementioned method, in addition, any value with this condition was replaced by its closest limit. In addition, a Butterworth filter (IIR) of order 20, band pass, with a frequency limit of 5 Hz to 30 Hz was applied to these data, this range includes the frequencies of the visual stimuli comprised of 7 Hz to 13 Hz, the results are on folder `3_Filtered_Data.zip` on (Tinoco-Egas et al., 2021) on *IEEE-Dataport*.

Randomly, the dataset was divided into 70% for training set, 15% for validation set and 15% for testing set. Data augmentation was applied to the training set, adding white noise with different amplitudes to the EEG signal. In this way, we tripled the training set using white noise with amplitudes of 0.5 and 5 (because they gave better results).

4.2 Feature extraction

For feature extraction the algorithm 1 was developed to extract 21 features from the training, validation and test sets: Mean, Mean - weight I, Mean - weight II, Log Detector, Median, Variance, Mean absolute difference, Mean frecuency, Peak frecuency, Variance central frecuency, Maximum PSD, Amplitude Histogram (10 ranges).

Algorithm 1 Feature Extraction Algorithm

```
Result: Extracted features
for folder in DataFolders do
    for files in folder do
        for electrode in electrodes do
            Apply extract_features function to each file.
              Add extracted features to a dataFrame.
        end
    end
    Export dataFrame to csv format
end
```

For feature extraction, the training set without data augmentation and the training set with data augmentation were used separately. Then, in both cases the training set features were normalized using sklearn's `MinMaxScaler` function, as shown in equation 1. Finally, the validation and test sets were normalized with the Min and Max values obtained from the training set.

$$Features(i)' = \frac{Features(i) - min(Features)}{max(Features) - min(Features)} \quad (1)$$

4.3 Classification configuration

The 21 extracted features from the EEG. O1 and EEG.O2 registered data were concatenated, obtaining 42 columns of features that were the input data of the classification algorithms: Support Vector Machine (SVM), Multilayer Perceptron (MLP), Random Forest (RF), k-Nearest Neighbors (KNN) and eXtreme Gradient Boosting (XGBoost) (Yindong et al., 2021).

5. RESULTS ANALYSIS

In this section we will show the confusion matrix of the proposed configuration and analyze the following parameters of the classification algorithms:

- Recall: Probability of classifying true positives. The parameters True Positive `(TP)`, False Negative `(FN)` are used for its calculation, as shown in equation 2:

$$Recall(\%) = \frac{TP}{TP + FN} \quad (2)$$

- Specifity: Probability of classifying true negatives. The parameters True Negative `(TN)`, False Positive `(FP)` are used for its calculation, as shown in equation 3:

$$Specifity(\%) = \frac{TN}{TN + FP} \quad (3)$$

- Accuracy: Results proximity. The parameters True Negative `(TN)`, False Positive `(FP)`, False Negative `(FN)`, True Positive `(TP)` are used for its calculation, as shown in equation 4:

$$Accuracy(\%) = \frac{TN + TP}{TN + FP + FN + TP} \quad (4)$$

- Precision: Dispersion of the obtained set of values. The parameters `True Positive (TP)`, `False Positive (FP)` are used for its calculation, as shown in equation 5:

$$Precision(\%) = \frac{TP}{FP + TP} \quad (5)$$

Binary classes combinations were as follows: (0) 7Hz and 9 Hz; (1) 7Hz and 11 Hz; (2) 7Hz and 13 Hz; (3) 9Hz and 11 Hz; (4) 9Hz and 13 Hz; (5) 11Hz and 13 Hz. With the proposed configurations the results obtained with all classification algorithms are shown in table 1.

Table 1. Average testing classification results obtained with testing set

Algorithm	Accuracy%	Recall%	Precision%	Specifity%
Without data augmentation				
SVM	0.51	0.52	0.34	0.51
MLP	0.52	0.52	0.51	0.52
RF	0.54	0.48	0.54	0.59
KNN	0.51	0.51	0.56	0.51
XGBoost	0.49	0.49	0.52	0.50
With data augmentation				
SVM	0.55	0.55	0.57	0.55
MLP	0.51	0.51	0.55	0.52
RF	0.58	0.59	0.58	0.56
KNN	0.54	0.54	0.53	0.54
XGBoost	0.57	0.56	0.58	0.57

As shown in Table 2, training without data augmentation and classification times were compared using the Raspberry Pi4 B with all classification algorithms.

Table 2. Average training and classification time using the Raspberry Pi4 B

Algorithm	Training (Seg)	Classification (ms)
SVM	9.47	16.58
MLP	32.1	1.8
RF	719.68	20
KNN	0.78	12.16
XGBoost	19.33	7.12

6. DISCUSSION AND CONCLUSIONS

The results showed that using the 21 features for each of the EEG electrodes of the occipital region (O1 and O2) was appropriate, allowing us to reach accuracy values of 58%. Using the training set without data augmentation, among the 5 algorithms that were used are RF and MLP whose accuracy values were 54% and 52%, respectively. The results showed that there were an over-adjustment in the classification algorithms, due to the limited number of examples used during the training process (226). For this reason, it was necessary to use data augmentation for EEG signals with high temporal resolution is possible by adding white noise with small and high amplitudes. The use of this technique allows us to improve the accuracy of the algorithms among which are RF and XGBoost whose accuracy values ware 58% and 57%, respectively. On the other hand, in applications that need real-time responses, the algorithms that reported a shorter classification time were MLP and XGBoost with times of 1.8 and 7.12 milliseconds, respectively.

It is recommended to have an adequate experimental design before proceeding with data registration, in addition to having a proper data preprocessing since it is very important when working with algorithms, because cleaner data will help to improve the classification.

As future works, it is proposed to recruit more subjects that allow us to increase data to eliminate over-adjustment in the algorithms and for these to be able to generalize with new examples. In addition, it is proposed to use Deep Learning techniques (DL) combined with the extraction of spectral images as a characteristic of the temporal behavior of the EEG electrodes. These spectral images would have a high spatial resolution and could be subjected to Data augmentation techniques.

ACKNOWLEDGMENTS

The authors are greatly grateful by the support in EEG data recording given by the ORORESEARCH Research Group (`https://investigacion.utmachala.edu.ec/portal/grupos-investigacion/ororesearch/`).

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