



ROBOTIC ARM CONTROLLED BY A HYBRID BRAIN COMPUTER INTERFACE

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ABSTRACT

The Hybrid Brain Computer Interface (Hybrid BCI) systems provide an integrated system with different signal sources, as multiple interpretations of brain waves through an electroencephalogram (EEG), as well as muscular signals from electromyography (EMG) and gyroscopic positioning. Many hybrid BCI systems perform not only with high quality devices, longer preparation times but with lower possibility of lightweight portability not just for the acquisition device but for the processing device as well. A hybrid BCI is implemented using a commercial device for the signal measurement known as Emotiv EPOC, focusing on relaxation (alpha wave related) and concentration (Beta and Gamma wave related) as brain waves, winking as muscular application and head movement on the horizontal axis. It was implemented the features extraction methods, Power Spectral Density (PSD), Hjorth Complexity and Mobility (Hjorth Parameters), Petrosian Fractal Dimension (PFD) and the Frobenius Norm. A Support Vector Machine (SVM) classifier was used as the classification method.

Keywords: hybrid BCI, electroencephalography, electromyography, EPOC, power spectral density, petrosian fractal dimension, support vector machine.

INTRODUCTION

A method that interlaces different type of signals such as electroencephalography, electromyography and body movement is known as a hybrid Brain Computer Interface (BCI) [1] which is included in the Human Machine Interfaces (HMI), giving a wider range of possibilities for the user to manipulate the end of the application.

As diverse bio-signals exists, the same is understood for methods to process them, falling into two main categories, synchronous and asynchronous, where the user has the liberty to activate them or with an external stimulus. It is a must for the system to be adaptable and easily accessible, needing just a couple of sessions to completely control the system.

Using a bulky system is always certain to work, but limits the portability, therefore a small standalone system offers a solution, not only as a lower cost like Emotiv EPOC [2] for acquiring the signals and the Raspberry Pi 2 [3] for the processing segment, it offers a faster setup time with only a main drawback on being light on the hardware's capability.

For an appropriate interaction between the user and the end application, a graphical interface is needed, not just for the acquisition segment but for the real time work, which under a standalone system it is necessary to maintain the design to a minimum approach. The main concern on the system limitations applies as well for the processing segment, where the number of stages must be kept short, with interest in features based on the time and frequency variability, linear and nonlinear signals generated mostly from the brain, features extraction methods such as Power Spectral Density [4] and Hjorth Parameters [5] were implemented with the Support Vector Machine (SVM) [6] as the classifier, without the use of other methods like artefact rejection [7], keeping a lower consume on processing and memory power.

The main purpose of a hybrid BCI application is for the end-user to have diverse control on it, which in this case is the manipulation of a robotic arm by moving square and rectangular shaped pieces from a stand point to boxes with their respective shaped grooves.

METHODOLOGY

Hybrid BCI

A typical BCI is conformed of a cycle involving the user, processing segments and an application, as seen in the Figure-1 (M. Ahn M. Lee, J. Choi *et al.* 2014), where the main aspects are mentioned. A user with an active or passive control mostly, an acquiring segment with invasive or non-invasive method, processing which includes pre-processing and selection of the features to be extracted, prediction has the activation of from the user and it is recognized for a prediction or classification method and lastly an application that shows the final stage of a BCI involving medical rehabilitation, video games or virtual reality.

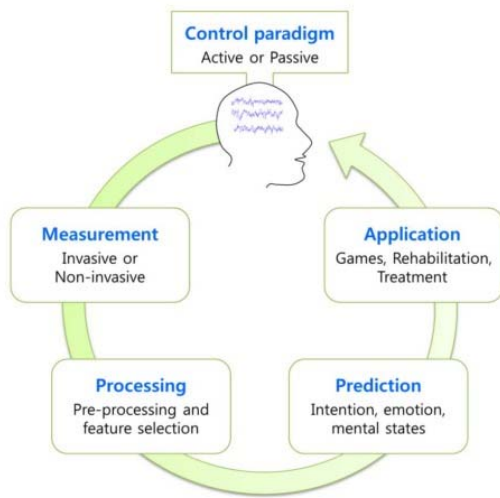


Figure-1. A typical BCI.

There are multiple methods to measure the brain activities which focused on different approaches, such as Magnetoencephalography (MEG), functional Magnetic Resonance Imaging (fMRI), Electrocorticography (ECoG) or Electroencephalography (EEG). Some of these methods requires a high quality standard equipment to perform, meaning higher costs and complex settings up, however, produces precise information on specific locations of the brain such as the fMRI [8] and with invasive procedures like ECoG, where a grid of electrodes implant are surgically implanted on the surface of the brain [9]. From a user standpoint, a hardware should be easy to wear with no complexity on the operation and drawbacks that could affect the performance, EEG offers the possibility to work over the surface of the scalp, with multiple electrodes offering possibilities on acquiring brain signals from different points of the head and no main concerns on the way of wearing it.

EEG is a reasonable tool to develop BCIs, even though there are some which are categorized as high standard medical equipment with a wide frequency range and multiple EEG channels. Commercial EEGs are not just affordable to anyone but they offer a portable and light solution to the user. In the Figure-2a, shows the popularity of EEG among other types of hardware within the research community; In the Figure-2b, the different types of commercial EEGs, where Emotiv EPOC is the most popular among them.

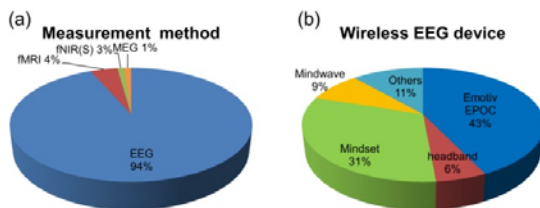


Figure-2. Some popular aspects of measurement methods and EEG devices.

This device offers 14 EEG channels that follow the 10-20 standards, wireless communication with a USB dongle and a suitable design for different head sizes as seen in the Figure-3; some of the specifications can be found in the Table-1 (Emotiv, Inc, 2014), where the system uses 128 Hz of sampling rate with a resolution of 14 bit, enough to perform the basic EEG and EMG signal processing [10].



Figure-3. The EPOC Emotiv.

Table-1. EPOC Emotiv specifications.

Specification key	Specifications
Number of channels	14 channels with CMS/DRL references
Sampling method	Sequential sampling, single ADC
Connectivity	Proprietary Wireless, 2.4 GHz band
Channels Names	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P7, P8, T7, T8, O1, O2
Sampling Rate	128 Hz (2048 Hz Internally)
Resolution	16 bits (14 bits effective) 1 LSB = 0.51uV
Dynamic Range	8400uVpp
Bandwidth	0.2 – 45 Hz, 5 th order Sinc Filter Digital notch filters at 50 Hz and 60 Hz
Battery Life	12 Hours

BCI is focused mainly on improving the interaction of some patients with the environment due to some physical factors or impediments that deter them from having a typical daily life. Other applications aim to provide a type of entertainment for anyone who wants to explore the different aspects of a BCI such as with virtual reality, video games [11] or robotic manipulation [12].

A hybrid BCI system could be structured of different brain signals, nevertheless, using alternative aspects of others physiological signals used in Human Machine Interfaces (HMI), such as Electrooculography (EOG), Electromyography (EMG), head or hands movement, could be categorized as a hybrid BCI [13]. In



this case, three aspects are used, EEG, EMG and Gyroscopic movement.

Types of signals

The EPOC Emotiv offers a frequency range of 0.2 to 45 Hz, which works mainly for the EEG signals such as alpha (8 to 13 Hz), beta (14 to 30 Hz) and gamma (31 to 50 Hz) that are involved with relaxation and concentration [14]. For the case of the magnitude of the signals, the EPOC offers a resolution of 14 bits with 0.51uV as the least significant bit (LSB) with a most significant bit (MSB) of approximately 8.1mV, more than enough for the EEG and EMG signals to be correctly measured. Mostly of the EEG waves have a magnitude of microvolt such as alpha (30 to 50 uV), beta (5 to 20 uV) and gamma (5 to 10 uV) [14]. For the case of the EMG, is an accumulation of motor unit action potentials (MUAPs) that can be found in microvolt as well as in the millivolt region, with a typical magnitude of 0 to 10 mV [15].

From EEG there are many types of signals that can be acquired and depending of the point of view of the user, three main types are found, active, reactive and passive. An active type is when the control is totally from the user; Reactive when an external stimulus is used and passive when the user has no control over it. The most common for each type are motor imagery and mental sates, SSVEP and P300, and feelings respectively [16].

Active control offers freedom to the user without the need of an external stimulus, but due to some difficulty of motor imagery on training and application [17], mental sates are chosen as the EEG method.

The two chosen mental states are relaxation and concentration, which can be activated any moment by the user. Those states can be found at the occipital and frontal lobe respectively [18]. In the Figure-4 (Q. Wang, O. Sourina. 2013), a comparison between the relaxation state and the concentration state can be appreciated, where the relaxation focused mainly on the occipital lobe, indicated by the red portion, with a contrast on the frontal lobe, with a blue portion. The concentration state is showing in the frontal lobe, but in a minuscule portion, with some influence on the occipital lobe, nonetheless, concentration can be found mainly in the frontal channels, and relaxation on the occipital channels.

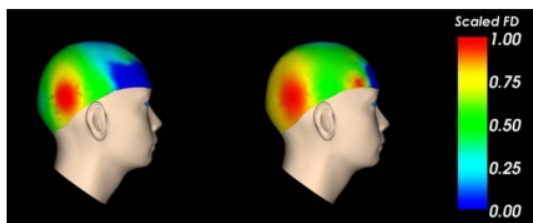


Figure-4. Aspects of mental processing of relaxation and concentration

As seen in the Figure-5 (N. Puzi, R. Jailani, H. Norhazman et al. 2013), indicated by the red circles, the EEG channels used by the EPOC, some are situated on the

occipital lobe, like O1 and O2. For the frontal lobe there are some channels like AF3, AF4, or F7 and F8. The main purpose is to maintain to a minimum the quantity of channels, therefore, one channel is used for each function. For the relaxation state the O2 channel is selected and for the concentration state, the AF3 channel. AF3 is a channel influenced by the concentration and in a position on the head with no hair.

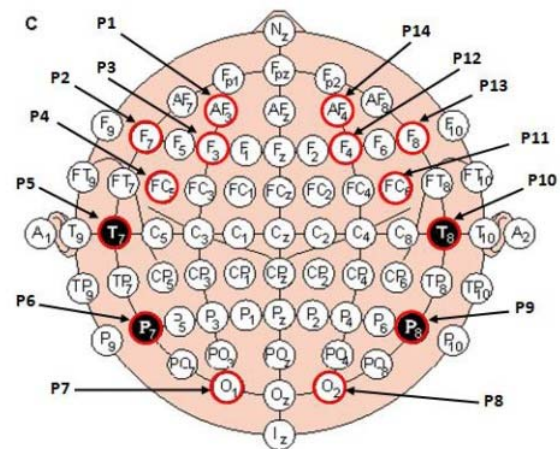


Figure-5. 10-20 EEG system used for the EPOC.

The EPOC Emotiv has an acceptable frequency range and frontal channels for facial expressions to be recorded; many projects use facial expressions like smiling or clenching [20]; In this case, the action of left and right winking is used as the EMG signal.

The channels closer for the winking action are F7, F8 and AF3, AF4, but knowing that AF3 is already used for the concentration state, it can be used as well for the winking action, leaving the right winking to the F8 channel.

For the gyroscope aspect, the EPOC system offers two deflecting sensors in the horizontal and vertical axis, which is ideal for the nod and shake head movements [21]; In this case is used only the shake movement.

Pre-processing

The first step is to remove the DC offset from the signals in spite of using a filter to do so, indicated by [22] and [23]. It is recommended to use a simple adjustment of the offset by removing the average value and multiplying it by the LSB to give the signal in microvolt.

The EPOC has a Band Pass Filter already applied to the signals; therefore a High Pass Filter is used at 2 Hz 5th order Digital Butterworth, to avoid any possible remaining noise. There is no artefact rejection system used, as applied by [24] to avoid any extra memory consumption.

The size of the window must be relatively small to avoid any heavy processing of multiple values. In some cases different window values from 2 to 16 seconds have been examined, with better results on balancing the speed and value extraction with 2 and 4 seconds [25]. A window



of less than 2 seconds wide is used when a quick reaction characteristic such as SSVEP can be applied, similarly to P300 which values of reaction time are needed to be instant on less than a second; In this case a window of 2 seconds is used in the online process and 4 seconds in the data collection for the relaxation and concentration, and 2 seconds for the winking action.

Another aspect of preparation is the normalization of the signal, where it is a must as a pre-processing step [26]; it basically centres it to the mean and component wise scales it to the unit variance. This aspect is only applied for the EEG signals; it helps to separate any aspect that can be found in an EMG signal, in which normalization is not applied to avoid any removing of features of the winking action.

Features extraction

To classify and differentiate the actions of the user, the understanding of signal's characteristic is a must. Having multiple options of feature extracting functions, the quantity per action depends on the complexity and difficulty of detecting the signals. Others use a technique of converting them to a subspace delimiting the dimension of the characteristics related to the spatial patterns, but it imply to increase the consumption of processing memory, therefore the features are kept to a minimum, with 2 characteristics or dimension for simpler action like winking and relaxation and 3 dimensions for concentration.

There are many types of function for extracting characteristics from the biological signals with certain aspects which helps the classifier. Some functions are linear such as Power Spectral Density (PSD) that are used [27], and the Frobenius Norm, but are not enough for more complex brain signals like concentration, where nonlinearity features are needed to distinguish the action from others like Hjorth Parameters and Petrosian Fractal Dimension (PFD) [28].

The chosen functions can be seen in the Table-2 with their respective actions, where for relaxation and winking, linear and quasilinear functions are used but for concentration a nonlinear aspect is applied in order to extract another aspect of the action that may not be easily observable with the linear or quasilinear functions [29].

Table-2. Description of the features extraction functions.

Relaxation	
Power Spectral Density ratio	Linear
Hjorth Mobility	Quasilinear
Concentration	
Power Spectral Density ratio	Linear
Hjorth Mobility	Quasilinear
Petrosian Fractal Dimension	Nonlinear
Winking	
Frobenius Norm Hjorth Complexity	Linear
	Quasilinear

The samples were taken in one session of 1 hour approximately; for relaxation, the user with the closed eyes entered a relaxing state for 128 seconds with 8 seconds active interval, 5 times. For the concentration, a 26 minutes session is used with 100 seconds active interval. For the winking action a 300 seconds session is used with 2 seconds active interval.

In the Table-3, it can be appreciated the three actions with their offline and online window's sizes, the total of the trial in seconds and the quantity of the samples used to train the classifiers. Concentration needed more samples than the others due to the difficulty of detecting it.

Table-3. Some aspects of action's data.

Action	Offline window size (s)	Online window size (s)	Trial (s)	Samples quantity
Relaxation	4	2	640	75
Concentration	4	2	1600	192
Winking	2	2	300	75

To understand better the actions of relaxation and concentration, a spectrogram plotting function was used, where in first sight, in the Figure-6, the relaxation action shows a reddish bold line at 10 Hz followed by the resting segment, each line represent a moment of activation from the user when is relaxing with the eyes closed.

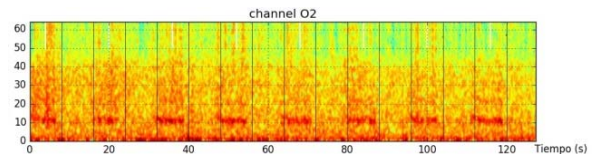


Figure-6. Spectrogram of relaxation (Channel O2).

The Figure-7 shows the result of concentration, in this case it was used the successive subtraction of a random number higher than 200, by subtracting 3 from it each time for the whole active segment [30], different from the online process where concentrating to a specific point for a time can generate similar results. It can be appreciated that the active segments have small reddish dots from a frequency range of 10 to 40 Hz, in some cases at the non-active segments some are visible due to the user concentrating when it was time for resting or be distracted, nevertheless, the concentration can be easily observable when is applied at longer times of trials.

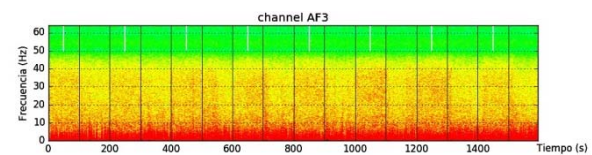


Figure-7. Spectrogram of concentration (Channel AF3).

For a different view of analysing concentration, a convolution and coherence (Normalized Cross Spectral Density) is applied to observe the active frequency range,



where in Figure-8(a), the similitude on the channels AF3 and AF4 remarks frequency ranges of 10 to 18 Hz and 22 to 30 Hz, which in Figure-8(b), with the coherence between the signals have higher relationship between 22 to 30 Hz approximately, indicating that concentration is found in that range mostly.

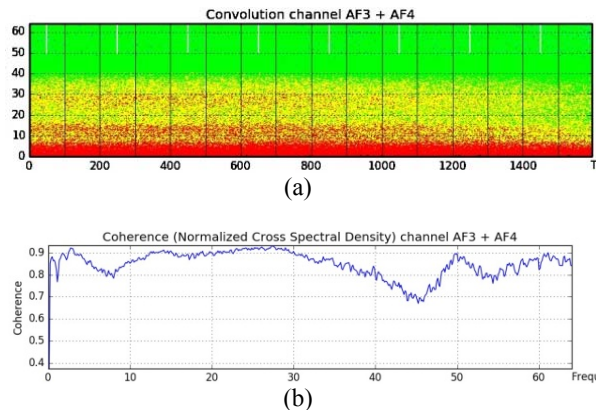


Figure-8. Concentration convolution and coherence analysis plot.

The winking action can be seen in the Figure-9, where the left winking (channel AF3) is stronger in magnitude than the right winking (channel F8) despite both electrodes being positioned closer to the eyes, it shows that the user has stronger winking with the left eye than the right.

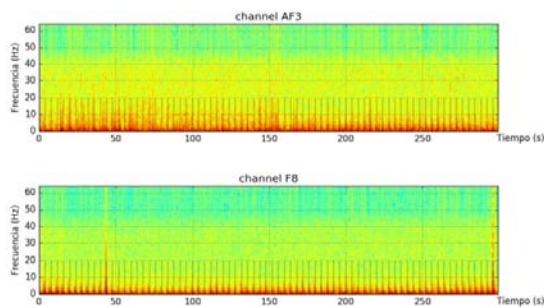


Figure-9. Spectrogram of left and right winking (Channels AF3 and F8).

To visualize the extracted features, the box plot is used for each action with their respective extracting function. This method helps to analyse a vast of quantity of samples with different classes or action and compare their tendency, majority and median values.

The Figure-10, shows the case for the relaxation, where the action or the active samples are easily differentiable from the non-active ones in the Alpha Ratio, that it's the Power Spectral Density ratio for alpha frequency range, with scalar values given by the algorithm; contrary to the Hjorth Mobility where it can be distinguish from offline but not so much with the standard action.

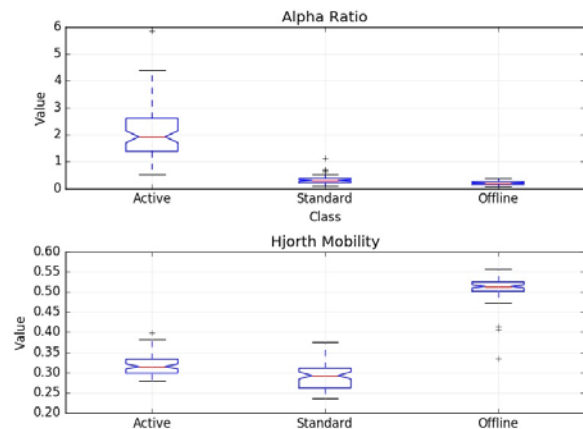


Figure-10. Relaxation's features box plot

The non-active samples have a standard action which involves the user to fix the mind into a blank state with the eyes open; and an offline action, that basically is leaving the EPOC system on a flat surface and sending the raw data; It is useful to understand what kind of noise could influence the real active samples and save them for future classification of non-active samples.

The Figure-11 shows the three features extraction functions for the concentration, which beta ratio is the PSDr for beta frequency range, PFD and Hjorth Mobility. The non-active classes for concentration are standard, offline, EOG and Winking; standard and offline are the same type as for relaxation; EOG are samples taken when the user moves the eyes from left to right within the respective time window; lastly, the EMG-Wink is related to the winking action, in this case is taken as an artefact, so that the classifier can detect and differentiate correctly the concentration action.

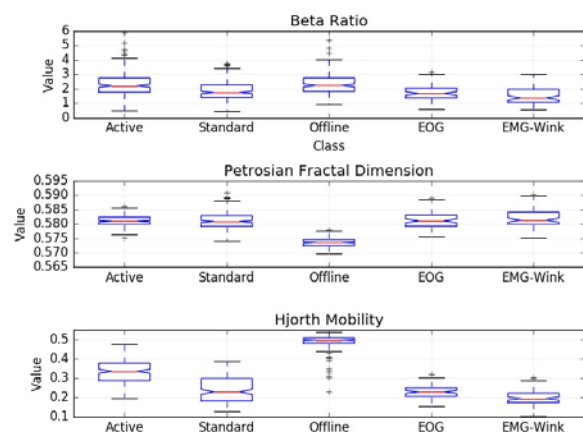


Figure-11. Concentration's features box plot.

For the case of Beta ratio, the active class is not easily distinguishable from standard and offline; for PFD active is similar to standard, EOG and winking, but for Hjorth Mobility, active class is more observable from all the others non-active classes.



For the winking action, Figure-12 and Figure-13, shows the winking for the right and left eyes, where they look similar to each other, with the difference that for the right winking in the Hjorth Complexity, the active class is similar to the EOG, due to the user having less control over the right winking, opposite to the left winking which has better results.

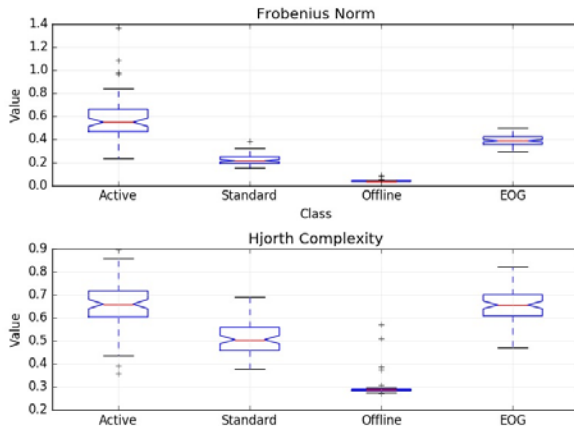


Figure-12. Right winking's features box plot.

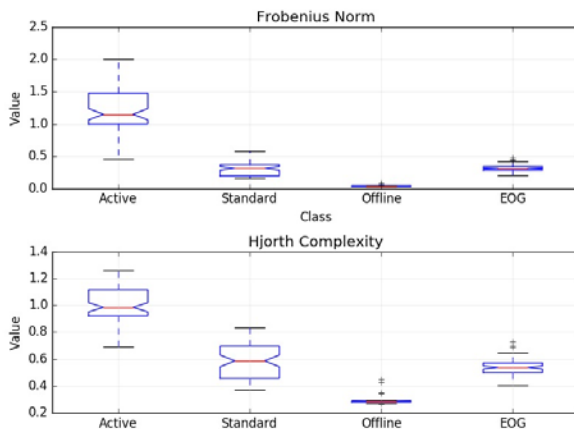


Figure-13. Left winking's features box plot.

Classification

The first step is to mix the samples randomly and separate them into two parts, the data to train the classifier and a test; the distribution for the samples is approximately 65% data and 35% test. The standardization of samples is a must before the application of the classifier, where it removes the mean and scales them to a unit variance.

The chosen classifier is the Support Vector Machine (SVM) which is widely used on bioinformatics due to the exactitude on handling high dimension data [31]. The kernel function used is the Radial Basis Function (RBF), one of the most applicable with the SVM; RBF parameters are γ (gamma) and C , which adjust the quantity of samples to be taken into account and the curvature of the frontiers respectively.

The variation of γ and C can be seen in the Figure-14, for the relaxation action, where the best fit must contain an acceptable degree of samples from the active and non-active; the red dots represent the non-active samples and blue the active samples, therefore their respective coloured shadows indicates the curvature of the classifier, where $\gamma = 10^{-1}$ ($\gamma = 0.1$) gives a circular frontier and $C = 10^2$ ($C = 100$) fits it to be in an adequate distance between the closest samples of active and non-active class; the RBF parameters are the same for all classes.

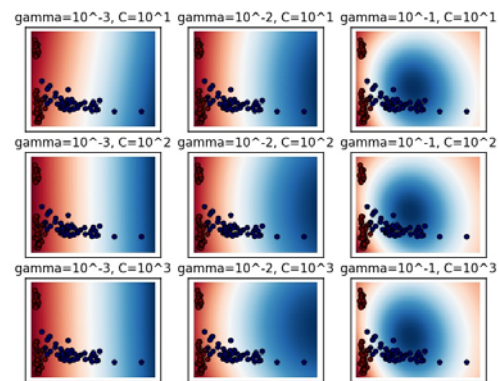


Figure-14. Relaxation's RBF parameters plot

The classifier operates as a binary type, classifying between an active class and a non-active class, where the active class has all the correct actions done by the user and the non-active has the chosen artefacts with a specific number of samples all conforming one single class, instead of using multiple classes, facilitating the use of simple classifiers, one for each action.

The concentration is different as it has tree dimension or classes. The Figure-15 shows the 3D plot, where the blue dots represent the active class and the red the non-active. The use of three dimensions helps to separate the samples correctly, increasing the accuracy of the classifier.

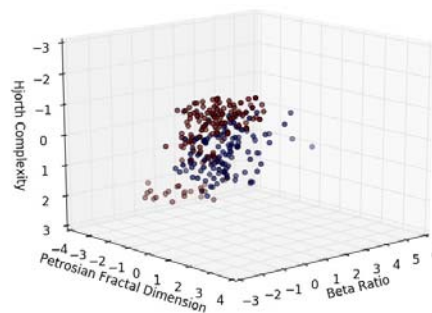


Figure-15. Concentration's RBF parameters plot.

RESULTS

The setup of the experiment has a 5 DoF Robotic arm where the gyroscopic action was given to the waist



movement, the relaxation and concentration to the opening and closing of the tool respectively, and the rotation of the tool for the winking action. All the action are assigns to be as ON/OFF control which when an action is detected the execution is done once, except for the gyroscopic where gradually moves depending of the head position.

The programming language used is Python with the multithreading and multiprocessing functions and Qt for the GUI interface. The hardware for the standalone system is a Raspberry Pi 2, with 900 MHz processor and 1GB of memory and Raspbian as the operating system, sufficient for handling the real time processes.

The Table-4 shows the method applied to 5 users, where relaxation action has more accuracy than concentration despite having an extra class or dimension, nevertheless the process is assertive for most of the users. The cross validation was at 10 fold and the winking and gyroscopic action was used only for a final user whom would manipulate the robotic arm.

Table-4. Results of the classifier for the users.

	User 1(%)	User 2 (%)	User 3 (%)	User 4 (%)	User 5 (%)
Relaxation	98.6	86.6	98.4	99.6	79.6
Concentration	82.7	80.3	81.2	86.8	76.0

The explanation of the test was done only once as the test itself, in order to maintain a simplicity for the user to perform. Some users have stronger alpha wave than others, the same was found for concentration where the user sometimes couldn't enter a relaxing state after a concentrating one fast enough, even though the results were acceptable for being a one session test.

The design of experiment is for the user to move two pieces of different shapes, square and rectangular, to a different position where a box with the same opening shape as the piece is located as quick as possible without making any mistakes; the Figure-16 shows the layout of the experiment.

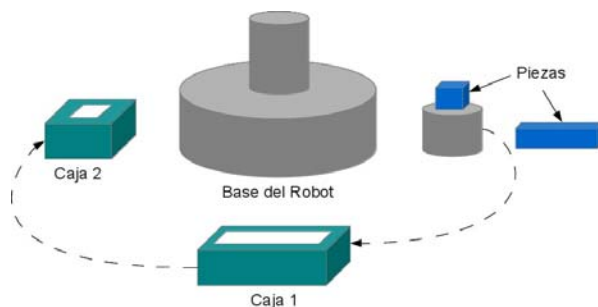


Figure-16. Experiment's layout.

The cycle of the process starts with the user adjusting to a correct rotation of the tool with the winking action; followed by the opening it in order to grab the piece with the relaxation action, then closing it with concentration action. The head movement or gyroscopic

action rotates the waist of the robotic arm in order to position it over the respective box; rotation may be needed to fit the piece into the opening and finally relaxation action in order to drop the piece into the box. Table-5 shows two sessions of the experiment with some trials and the average time for each session and the accuracy of the sessions, where the user demonstrates an acceptable result for the whole experiment.

Table-5. Results of the experiment for one user.

Session	Trials	Average time (s)	Accuracy (%)
1 st	11	34	73
2 nd	13	26	87

CONCLUSIONS

- The project was possible to be adapted into a Raspberry Pi 2 and Python, to manipulate the robotic arm with multiprocessing feature extraction functions, a SVM as a classifier and a graphical interface in real time without any delay and less than 40% of processing consumption.
- Only three channels were used from the EPOC Emotiv to extraction relaxation, concentration, left and right winking actions, making it less heavy and fast for the processing without depending on any artefact rejection.
- Due to the similitude of alpha, beta and gamma waves for relaxation and concentration, and the winking action between users, any person could use the system, without the need of taking sample data and only one training session.
- The concentration can be analyzed easily by performing it on longer periods of time from 10 to 60 seconds where using successive subtractions can increase it, opposite to needing a quick result where by just staring at a fixed point for a couple of seconds.
- For the relaxation on the alpha wave, some users have strong waves compared to others that have it to a minimum, ranging from 9 to 12 Hz, most focusing on 10 Hz, but using the features extraction method of ratio, it was possible to detect for all the users.
- The RBF SVM classifier increases accuracy when an extra dimension or feature is added, nevertheless the processing consumption as well, therefore it must be kept to a minimum for a correct balance between speed and accuracy.
- The best RBF parameters were $C = 100$ and $\gamma = 0.1$, which fit for the relaxation, concentration and as well as for the winking action, without the need of different values for different types of signals.
- The most reliable feature extraction methods were the Hjorth Parameters and the Power Spectral Density ratio, which they offer a wide range of lineal and non-linear brain detections and muscular signals.



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