Single Trial Classification of Evoked EEG Signals Due to RGB Colors

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Abstract

Recently, the impact of colors on the brain signals has become one of the leading researches in BCI systems. These researches are based on studying the brain behavior after color stimulus, and finding a way to classify its signals offline without considering the real time. Moving to the next step, we present a single trial classification model for EEG signals evoked by RGB colors stimuli, which is not presented in previous studies. In this research, EEG signals were recorded from 7 subjects through BCI2000 toolbox. The Empirical Mode Decomposition (EMD) technique was used at the signal analysis stage. Various feature extraction methods were investigated to find the best and reliable set, including Event-related spectral perturbations (ERSP), Target mean with Feast Fourier Transform (FFT), Wavelet Packet Decomposition (WPD), Auto Regressive model (AR) and EMD residual. A new feature selection method was created based on the peak's time of EEG signal when red and blue colors stimuli are presented. The ERP image was used to find out the peak's time, which was around 300 ms for the red color and around 450 ms for the blue color. The classification was performed using the Support Vector Machine (SVM) classifier, LIBSVM toolbox being used for that purpose. The EMD residual was found to be the most reliable method that gives the highest classification accuracy with an average of 88.5% and with an execution time of only 14 seconds.

Keywords: Brain Computer Interface (BCI), Electroenphesalography (EEG), Event Related Potintials, component (ERP); Emperical Mode Decomposition (EMD), Event-related spectral perturbations (ERSP), Wavelet Packet Decomposition (WPD), Autoregrissive (AR), Fast Fourier Transform (FFT), Support Vector Machine (SVM).

1. Introduction

A brain computer interface (BCI) is an artificial intelligence system that translates the human's thoughts, by using the brain signals, into meaningful commands and actual actions. It enables the person to perform a specific activity without involving any muscle movement. This system is designed especially for disabled individuals. It was used to improve their quality of life and reduce the cost of intensive care (Nicolas-Alonso & Gomez-Gil, 2012).

There are five sequential stages in any BCI system as it follows: signal acquisition, signal analysis, feature extraction, feature classification, and the application interface.

In the signal acquisition stage there can be used two approaches, an invasive and a non-invasive one. The invasive approach needs to inlay microelectrodes inside the skull, which can cause a serious health risk, while the non-invasive approach records the brain signals through a cap that consists of multi-electrodes placed on the scalp, without any risk to the individual (Nicolas-Alonso & Gomez-Gil, 2012).

Electroencephalography (EEG) (Major & Conrad, 2014) is a non-invasive recording approach that is used by most current BCI systems due to its standardisation of the electrode placement, high temporal resolution, relative low cost, high portability, and few risks to the users. EEG comprises a set of signals (Leeb et al., 2008) such as P300 Potentials, Event Related Potentials (ERP), and various rhythms that are classified according to their frequency. P300 potentials are based on the oddball paradigm, which is defined as a random series of event stimuli that contain an infrequently presented set of items (Lalor et al., 2005). The event-related potential (ERP) is a signal that arises from the nervous system at the cerebral cortex when a visual or auditory stimulus occurs. Well-known frequency ranges have been observed due to its distribution over the scalp or its biological significance (Nicolas-Alonso & Gomez-Gil, 2012). Rhythms are specified as Delta, Theta, Alpha, Mu, SMR, Beta and Gamma from the lowest to the highest frequency respectively (Bashashati et al., 2007). Each of these rhythms can be produced by a specific stimulus. For example, the Mu rhythm is produced by motor imagery.

The use of colors has always been a source of information for humans to interpret and decide on what actions to take. Such stimulus produces more efficient BCI systems due to its high information transfer rate, while the brain responds to colors faster than any other stimulus and it is expected to reduce the learning time by users in the case of real color detection because users do not need to prepare themselves like they do in performing motor movements or imagination of movements.

Recently, research has studied colors' impact on the brain signals and tried to figure out which of the EEG's components is responsible for color recognition in order to classify it by using some classification modules. The ultimate intention is to decode the information used to recognize colors, i.e., that information which is carried in EEG signals. The results were that the theta, alpha and beta rhythms are the main components which respond to different color stimuli (Münch et al., 2014; Yoto et al., 2007, Zhang & Tang, 2011).

The future direction of using colors in BCI development is directed at evaluating the possibility of applying different color stimuli in real-time BCI control, using the online classification, which is one of the main challenges in BCI systems (Gao & Gao, 2014). Online classification means the real-time capability to perform the classification task and respond with appropriate output within a short (i.e., in the order of milliseconds) time period with minimal variation (i.e., latency jitter).

The purpose of this research is to perform a single trial classification of EEG signals that are evoked by RGB color stimulus. Such classification has not been done earlier to the best of our knowledge. In this study we used EMD analysis method due to its signal dependency, and sub-band flexibility. In addition, different feature extraction algorithms were investigated in order to find the best features, which can be used in the classification issue. A new feature selection method is created by taking into account the response time of the brain while presenting the stimulus. In the classification stage we are going to focus on Support Vector Machine (SVM) classifier because most of BCI systems have used it as the classification module, while it gives the highest accuracy and the best results (Bashashati et al., 2007; Tan & Nijholt, 2010; Major & Conrad, 2014).

The remaining of this paper is organized as follows: section II includes literature review, section III introduces the methods and techniques for our proposed system, section IV represents results and discussions, and the conclusion with future work is placed in section V.

2. Review of Related Literatures

The complexity of EEG signals' representation makes it difficult to define the circle that encloses most data points of the total data points. EMD allows a flexible sub-band signal decomposition, while preserving the nonlinear and nonstationary features of the signals, which is crucial for brain activity analysis.

Novel and interesting results were presented (Shen et al., 2007) on human mental and cognitive states estimation in which the subject was asked to control the selection of intelligent computing applications. The recorded channels were decomposed into intrinsic mode functions (IMF) which are a result of empirical mode decomposition (EMD). IMF components were transformed into the Hilbert domain and compared within amplitude and phase domains, using the clustering technique in order to identify only those carrying responses which presented stimuli to the subjects. The strength of the proposed technique is based on adaptive filtering design in the completely data driven approach. This is a step forward in EEG signal processing applications, which could be useful primarily for creating user friendly BCI that would be flexible, adaptive, and response automatic detection focused resulting in fast estimation of user attention to the stimuli. Moreover, the author introduced a comparison between the blind source separation (BSS), independent component analysis (ICA) and empirical mode decomposition (EMD) methods. BSS and ICA methods were not able to separate strong ocular muscle interference from neurophysiological signals, while the proposed method which is based on EMD was able to separate ocular artifacts without additional scaling problems, unlike other approaches.

Any recorded EEG activity includes many features, which can be selected as the base of the classification process. Traditional methods such as the Fourier transform are not very suitable because they depend on the use of frequency information only without considering the time domain information. The researches show that the combination of frequency information and time domain information can provide more completed features that improve the classification performance of EEG signals. One of the methods which are based on this principle is the Wavelet Packet Decomposition (WPD) (Ting et al., 2008). It uses the coefficients mean of wavelet transform (information in time-domain) and power at special subsets as the initial features (information in frequency-domain), the selection rule is based on the Fisher distance criterion, in which the features that had a higher separability were considered effective and used to form the final feature vector. Compared with other approaches of feature extraction, WPD supplied more information and put forward a selection rule of Fisher distance criterion. The wavelet transform (WT) is designed to address the problem of non-stationary signals. It involves representing a time function in terms of simple, fixed building blocks and termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations.

In Rasheed & Marini (2015) an investigation was presented to classify EEG signals produced by the random visual exposure of primary colors i.e. red, green and blue to the subject. Seven healthy subjects went through the experiment. Each color was randomly presented for three seconds. Independent Component Analysis decomposition (ICA) was used to remove artifacts with a frequency over 60 Hz. Event-related spectral perturbations (ERSP) are used as features for support vector machine (SVM). ERSP shows significant power variations in the delta, theta and alpha bands. After the onset of the stimuli, the highest increase in power was seen in red, and the lowest in green during an interval from 100 to 400ms within the delta and theta bands. Moreover, a discriminative decrease in power among all the colors is seen in alpha band within 1000ms after the onset of stimulus. EEG signals were successfully classified as Red, Green and Blue classes' with accuracy of 84%, 89% and 98% with linear, polynomial and radial basis function (RBF) kernels respectively. The highest classification accuracy was 97% with RBF kernel while it converts the data space to higher dimensional feature space making separation much more likely for nonlinear cases.

In Yang & Leung (2013) a BCI arithmetic game was developed, where the answers were determined through decoding the user's attention to red and blue color stimuli. The idea of this game is very simple, the users were asked questions that involved simple addition and subtraction of two numbers and the answers were placed as choices in red and blue rectangles. To ensure that the color options were clearly seen, the text was relatively small and the space between two rectangles were considered in order to minimize their impact in the classification stage where the acquired signal should consider the color itself, not the text. Fast Fourier transform used to extract features at theta, alpha and beta power bands. LIBSVM toolbox was used for the classification process. The accuracy of the proposed system was calculated by conducting 3 rounds for each user, then taking the mean of the percentages of the correct classification among three rounds. The accuracy ranged between 70%-80%. The classification accuracy needs to be higher than the achieved percentage for a more accurate application.

3. Methods and Techniques

In this section, we will introduce an exhaustive detail for all techniques and methods which are used in this study, starting with the signal acquisition stage until the classification process.

a. Signal Acquisition Stage

The data used in this study is taken from Rasheed & Marini (2015). Seven subjects have undergone that experiment, age ranging from 20 to 36 years. All subjects were free of neurological and psychiatric disorders and have normal color vision. The experiment was performed in a dark room in front of a large curved screen on which the color was presented as a square with the size of a 10 degree angle on a much wider gray background. The subjects were seated on a comfortable chair. The distance between the subjects and the screen was of 3.5 meters and 1.5 meters high from the ground. The luminosity of each color was kept constant at approximately 4.5 cd/m2, and it was measured using the device Minolta SPOTMETER F. Screw-able gold EEG electrodes were used on the subject’s scalp at P3, P4, O1 and O2 sites and referenced to the right ear lobe and grounded at site AFz. The experiment protocol is shown in Figure 1, which depicts the duration of one sequence. In this protocol, each color was presented for three seconds, twice in one sequence. There are five events in one sequence. Only one color is presented in one sequence. After all the events occurred in a sequence, the next sequence is started and another color is presented. When all the 3 colors are presented at random, the subjects were allowed to rest for 9 seconds after every 3 sequences while keeping their eyes closed. A uniform gray background color was displayed before and after every color to reduce and balance the possible after-effects of the RGB stimuli. EEG signals were recorded using BCI2000[10] with g.tec’s g.MOBIlab+[11] portable device sampled at 256 Hz.

b. Signal Analysis Stage

Various methods exist to enhance and pre-process EEG signals by removing different artifacts like eye movement and blinking, Electrooculography (EOG) or Electromyography (EMG). The complexity of EEG signal's representation makes it difficult to define the circle that encloses most of the data points of their total. The problem with these methods is that they work at frequency domain or time domain, but not both, which causes a loss of important data during the processing stage. The researches show that the combination of frequency and time domain information can provide more completed features that improve the classification performance of EEG signals. Empirical Mode Decomposition (EMD) has recently been developed by N. (Huang Huang et al., 1998) as an adaptive time-frequency data analysis method. It has proven to be quite versatile in a broad range of applications for extracting signals from data generated in noisy nonlinear and non-stationary processes. Wavelet Transform (WT) is also an analysis method that uses the time-frequency domain. However, EMD acts essentially as a filter bank, resembling those involved in wavelet decompositions.

[10] http://www.schalklab.org/research/bci2000
[11] http://www.gtec.at/Products/Hardware-and-Accessories/g.MOBIlab-Specs-Features

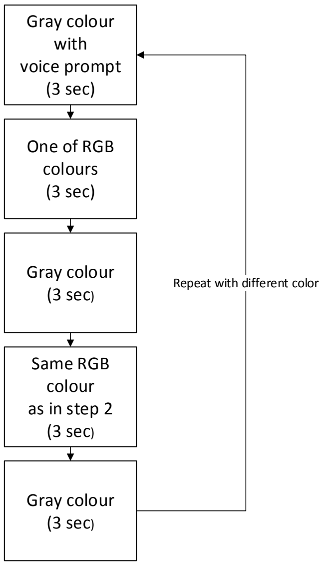


Figure 1. Experimental protocol

On the other hand, in wavelet analysis this sub-band filtering is pre-determined and, on the contrary, in EMD this sub-band filtering is signal dependent. EMD-wavelet differences details are described in Huang et al. (1998). Hence, EMD is proposed as a tool for processing and extracting features of EEG signals. It has been used to analyze P300 evoked potentials [19], steady-state evoked potential (Rutkowski, Zdunek, & Cichocki, 2007). It was used also with motor imagery BCI systems to study the active frequency range extract features (Trad et al., 2011). Moreover, EMD used to classify seizure and seizure-free brain signals (Bajaj & Pachori, 2012) and mental tasks BCI (Rutkowski et al., 2010).

i. Empirical Mode Decomposition rule

EMD allows a flexible sub-band signal decomposition while preserving the nonlinear and nonstationary features of the signals which is very crucial for brain activity analysis. It is an adaptive method; that is, the decomposition it produces is specific to the analyzed signal. It decomposes the signal into a sum of components, each with varying amplitude and phase, and should separate phenomena occurring on different time scales. Each component of the EMD is called an Intrinsic Mode Function (IMF). An IMF is defined as a function that satisfies the following two conditions (Huang et al., 1998):

a) In the entire signal, the number of extremes and the number of zero-crossings must be either equal or differ at most by one.
b) At any point, the mean value of the envelope defined by the local maxima and the envelope defined by the local minima must be zero (or close to zero).

The computation of IMFs which satisfy the two criteria and sum to create the signal goes as follows:

1) A candidate for the highest-frequency IMF is determined by first fitting a cubic spline through all local maxima to create an upper envelope. A lower envelope is constructed in the same manner.
2) The envelopes form a candidate for the time-varying amplitude of the IMF. However, we want to ensure that the component function will have negligible local mean.
3) If the average of the two envelopes does not fall uniformly within the threshold value of zero, we subtract the mean from the envelopes.
4) The construction is repeated until the second criterion is satisfied. The result of this inner loop produces the first IMF.
5) Subtract the IMF from the original signal; the difference is the residue for the outer loop of the process.

The construction of an IMF is now repeated for the residual signal. This EMD procedure is repeated until the residue is either constant or monotone. This final residue should reveal any trend that exists in the data.

c. Feature Extraction Stage

We investigate various feature extraction methods in this thesis in order to find out the features which properly represent the signal and give the best classification accuracy. The features investigated here are: Event-related spectral perturbations (ERSP), Target Means with Fast Fourier Transform (FFT), Wavelet Packet Decomposition (WPD), Auto Regressive coefficient and EMD residual. The extracted features from each of these methods are used in the classification stage and a comparison for their accuracy is introduced in the result section. EMD residual was found to be the best method which gives the proper features that have the highest accuracy value.

i. Event-related spectral perturbations (ERSP)

Event-related Spectral Perturbation (ERSP) [24] is a measure to study the event-related brain dynamics. It reflects the information about variation in power at different frequencies at a certain point in time. ERSP is computed by calculating baseline spectra from the EEG immediately preceding each event. This is done by computing the power spectrum over a sliding latency window then averaging across data trials. Narrow band event-related desynchronization and synchronization is generalized by the ERSP measures. Overlapping data windows are created by splitting the epoch to create the moving average of the amplitude spectra. Normalization is performed on individual response epochs for each spectral transforms by dividing their respective mean baseline spectra. An ERSP is produced by taking average of normalized response for many trials. For n trials, if $F_k(f,t)$ is the spectral estimate of trial k at frequency f and time t, then ERSP is computed using the following formula (1):

$$ERSP(f,t) = \frac{\sum_{k=1}^{n} |F_k(f,t)|^2}{n} \quad (1)$$

Here $F_k(f,t)$ is computed using sinusoidal wavelet transform in which the number of cycles is increased slowly with frequency and provides better frequency resolution at higher frequencies than a conventional wavelet approach that uses constant cycle length.

EEGLAB comes with a function that is used to calculate ERSP for single or multiple trails. By running EEGLAB, we can use the function directly through Matlab interface by the following line of equation (2):

$$[ersp, \mathrm{itc}] = newtimef(X, frame, [epochtime], r, c) \quad (2)$$

Where X is the ERP trail/s, frame is the number of time points in the trail, epoch time is the starting-ending time of an epoch, r is the signal sampled rate and c indicates the number of cycles for the time-frequency decomposition. This function returns multiple variables, but the most important ones are ERPS and inter-trial coherencies (ITC) features. In this study we used ERSP as a feature set.

ii. Target Means with Fast Fourier Transform (FFT)

The Fast Fourier Transform (FFT) [25] is simply a fast way to calculate the Discrete Fourier Transform (DFT) which reduces the number of computations needed for N points from $2N^2$ to $2NlgN$, where lg is the base-2 logarithm. FFT is a computationally efficient method which affects the time of finding out the desired features.

First, we passed the ith IMF of the jth event to FFT function, and then the output was averaged as the formula in equation (3). This method was introduced by Feature Finder toolbox [26] which was used here to reach the desired features.

$$Avg_{ij} = \frac{\sum_{j=1}^{n} fft(imf_{(j,i)})}{n} \quad (3)$$

iii. Wavelet Packet Decomposition (WPD)

It used the coefficients mean of wavelet transform (information in time-domain) and power at special subsets as the initial features (information in frequency-domain), the selection rule is based on the Fisher distance criterion, in which the features that had a higher separability were considered effective and used to form the final feature vector. Compared to other approaches of feature extraction, WPD supplied more information and put forward a selection rule of the Fisher distance criterion. The wavelet transform (WT) is designed to address the problem of non-stationary signals. It involves representing a time function in terms of simple, fixed building blocks and termed wavelets. These building blocks are actually a family of functions which are derived from a single generating function called the mother wavelet by translation and dilation operations.

Matlab includes a ready to use WPD function which can be used directly by passing each IMF separately to return the features vector, and then we concatenate all features together. The format of Matlab function is written in equation (4).

$$F_i = wpdec(imf_i, N, 'wname', E) \qquad (4)$$

Where N is the depth of WT, wname is the type of the used WT and E is the entropy. We use depth of 3 with type db1 in Shannon entropy.

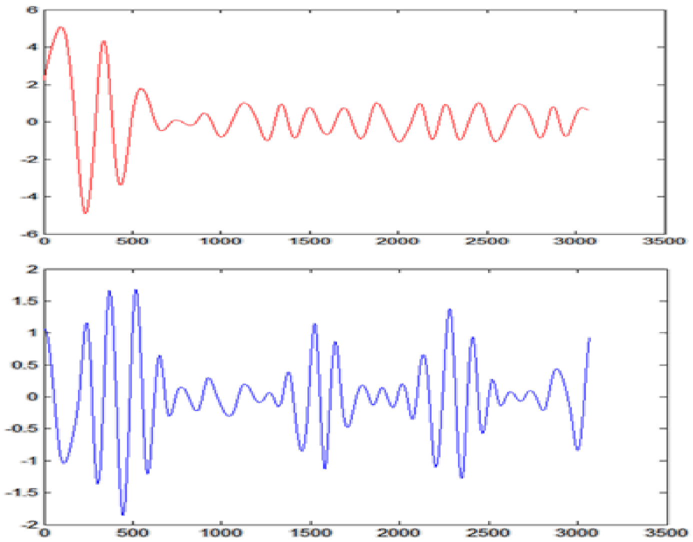
3.3.4. Auto Regressive coefficient

The auto regressive (AR) model has high ability to represent the EEG signal characteristics and form reliable feature sets (Hatamikia, Maghooli, & Nasrabadi, 2014). The AR function computes the coefficients of an AR model of order p on each channel individually. Each sample is obtained from the summation of previous weighted samples. The model order is determined by the number of weights, which are called AR coefficients. The AR model of order p for a zero-mean time series $x(t)$ can be written as shown in equation (5).

$$x(t) = \sum_{i=1}^{p} a_i x(t-i) \qquad (5)$$

Where p denotes the number of previous time points used to model the current time point, and x_t denotes a zero-mean process with variance σ2. We compute the AR coefficients αi, i = 1, …,p for each channel separately, and concatenate the results to form a feature vector for a window. Because each channel is treated individually, the spatio-temporal information that exists in the time series cannot be directly estimated, which is considered a limitation of this function. There is a built in function in Matlab that can be used directly by passing each IMF separately with the order of the AR model as shown in equation (6).

$$F_{i=ar(imf_i\ ,n)} \qquad (6)$$



3.3.5. EMD Residual

EMD decomposes the signal into a set of high frequency mode called Intrinsic Mode Functions (IMFs) and low frequency component called the residual. The starting point of EMD is to locally estimate a signal as a sum of a local trend i.e. the low frequency part and a local detail i.e. the high frequency part. When this is done for all the oscillations composing a signal, the procedure is then applied again to the residual, considered as a new times series, extracting a new IMF and a new residual. The process continues until IMF satisfies the two criteria which are specified earlier in this chapter. At the end of the decomposition process, the EMD method provides a signal as the sum of a finite number of IMFs and a final residual.

Since the residue is the lowest frequency component left after decomposition, it provides the frequency representation of the delta, alpha and beta rhythms. As seen in section II, these rhythms are the main components of ERP which respond to different color stimuli. From signal residual, the principal components were extracted as features set (Sarma & Sarma, 2013) and used to train the SVM classifier. The features set of the j^{th} IMF of the i^{th} signal are computed as shown in equation (7).

$$F_{(i,j)} = \sum_{1}^{j} imf_j * imf_j$$

3.4. Feature Selection

In order to reduce the dimensionality of the feature vector, we applied a selection criterion to add a feature into the training set. This criterion is based on the EEG peak's time which is generated due to the stimulated color. The response time for the red color was found to be concentrated at 200ms to 400ms, and it is clearly found a high peak at 300ms. So, the residuals of red stimuli EEG signals that have high peak concentrated in this time interval were taken into account, and the others were ignored. For the blue color, the highest peak is concentrated around 450ms, so the residual of blue stimuli which have high peaks after this time were ignored.

Each IMF component represents the local characteristics corresponding to the distribution of ERP within a certain frequency band. These distributions differ in different IMFs, and undoubtedly contain some inherent properties related to the presented stimulus. Before starting the feature selection process, the features are scaled to [0,1] in order to get better results. As we discussed in section III, different feature extraction (FE) methods are investigated in this study.

We apply 2 conditions at the feature selection stage to minimize the number of features that can be trained in order to reduce the complexity of the construction process. These conditions depend on the time of the highest peak which is related to each color. While the concentration of the red color exposure is around 300ms, 450ms for the blue color, we select the energies of the red and blue stimuli which are falling in this time band and eliminate the energies which have higher values than that. The green color had the least frequency, so we depend in the selection process on red and blue only. Figure 2 displays the time of frequency concentration for the red and blue color.

3.5. Classification Stage

The Support Vector Machine (SVM) classifier is considered the best model among all classifiers. Most of BCI systems (Tan & Nijholt, 2010; Bashashati et al., 2007; Major & Conrad, 2014) used SVM in their classification stage, while it gives the highest accuracy and the best results. In this thesis we will use the SVM classifier to classify the signal into three classes: red, blue and green. LIBSVM toolbox (Chih-Chung & Chih-Jen, 2011) is used under Matlab r2013a version.

The selected features are scaled to [0, 1] in order to use them with the SVM classifier. Then, the scaled features with their labels are used as a training set. A grid search and cross validation of the size 10 are used for selecting good parameters, mainly -c and -g. After finding them, we re-train the whole data without the -v option to build the model which can be used directly with any new signal.

The selected features are divided into 2 sets: training and testing. While there is no specific rule for splitting data set into training and testing sets, we used two percentage splitting for the data to be trained and tested. The first percentage was 60% for the training set and 40% for the testing set. The second percentage was 80% for the training set and 20% for the testing set. LIBSVM parameters used are:
-s 1 representing nu-SVC svm_type for multi-classes, -t 2 is the polynomial kernel function, -c is the cost value, and –g is gamma value which is used in kernel function. Grid search is used to obtain the best values for c and g parameters.

4. Results and Descussion

We used EEGLAB toolbox to read the recorded signals. Epochs extracted with the time limits between -1 second before stimulus, and 2 seconds after the presented stimulus. The baseline was subtracted before starting EMD processing.

Each data set is recorded with 60 trails for each color from four channels, each trail contains 768 frames per channel. In order to train all the data from all channels, the trail contained 3072 frames as one vector. Then, trail by trail passed to EMD to reduce the data into a collection of intrinsic mode functions (IMF) from which the features can be extracted. Each data set represents 9 IMFs, each IMF contains lower frequency components than the previous one. In this paper, we investigate some of feature extraction methods to find out which one can give us the most reliable features. In order to know that, we trained these features with the SVM classifier and the accurate results are placed in the below tables. The classification's accurate results of the investigated feature extraction methods are shown in Figure 3.

According to the accuracy of the results, we found that the best method to extract features is through the EMD residual, where the average accuracy was of 88.5% within 14 seconds. This is due to the nature of the residue as it provides the frequency representation of the delta, alpha and beta rhythms, which are the main components of ERP that respond to different color stimuli. A flow chart is inserted in Figure 4 as a summary for the used methods in this study.

Table 1. ERSP features classification accuracy

Subject	**Svm Parameters**	**Training/ Test Size**	**Accuracy**	**Training/ Test Size**	**Accuracy**
1	-c 128 -g 0.0313	60/40	49.33%	80/20	54.50%
2			47.60%		52.80%
3			38.46%		50.89%
4			44.49%		53.40%
5			48.80%		51.33%
6			46.70%		52.33%
7			48.90%		54.90%

Table 2. Target means with FFT features classification accuracy

Subject	**SVM Parameters**	**Training/ Test Size**	**Accuracy**	**Training/ Test Size**	**Accuracy**
1	-c 128 -g 2	60/40	67.21%	80/20	69.41%
2			62.45%		63.41%
3			60.69%		65.90%
4			65.58%		68.50%
5			64.56%		66.66%
6			64.22%		67.42%
7			69.44%		68.23%

Table 3. WPD features classification accuracy

Subject	Svm Parameters	Training/ Test Size	Accuracy	Training/ Test Size	Accuracy
1	-c 8 -g 2	60/40	59.08%	80/20	65.88%
2			55..89%		65.88%
3			57.90%		65.88%
4			58.78%		65.88%
5			60.49%		65.88%
6			58.80%		65.88%
7			60.08%		65.88%

Table 4. AR features classification accuracy

Subject	Svm Parameters	Training/ Test Size	Accuracy	Training/ Test Size	Accuracy
1	-c 512 -g 0.5	60/40	64.46%	80/20	66.66%
2			64.46%		66.66%
3			64.46%		66.66%
4			64.46%		66.66%
5			64.46%		66.66%
6			64.46%		66.66%
7			64.46%		66.66%

Table 5. EMD residual features classification accuracy

Subject	Svm Parameters	Training/ Test Size	Accuracy	Training/ Test Size	Accuracy
1	-c 32 -g 0.5	60/40	92.45%	80/20	97.56%
2			76.74%		78.94%
3			83.33%		84.00%
4			89.58%		89.58%
5			77.58%		83.50%
6			83.00%		88.88%
7			91.66%		97.05%

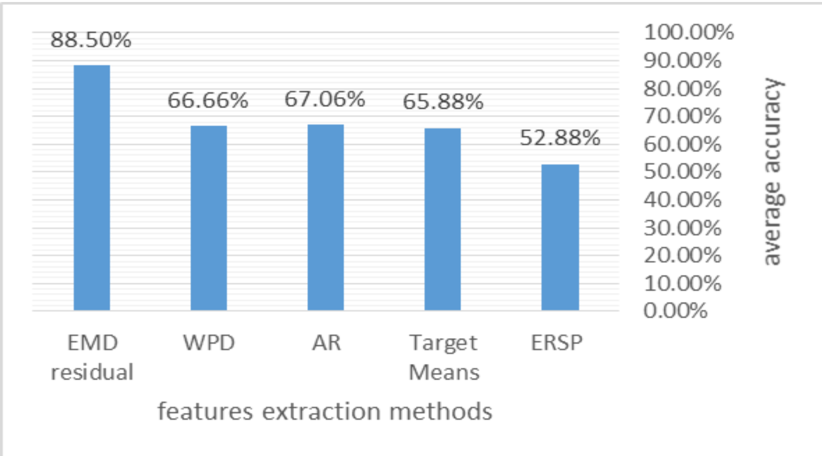


Figure.3.Average accuracy of investigated FE methods

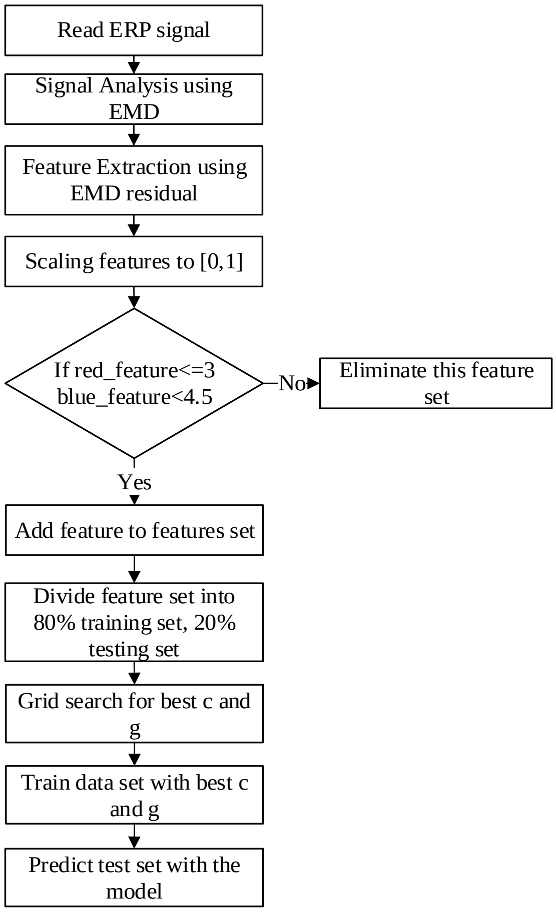


Figure.4. Proposed system's flow chart

5. Conclusion and Future Work

In this paper we proved the possibility to perform a single trial classification the EEG signals which are evoked by the RGB color stimulus. The required time to do this process is much shorter than the time which is required by any other stimulus, such as imagery and spelling words, which is presented in the previous researches. This result proves the main idea behind using colors in the next generation of BCI systems, which is based on introducing more efficient and faster systems that are able to give a quicker response than any other time.

As a future work, we are going to conduct a BCI application that controls a cursor movement on PC by using those signals. This is unlike earlier BCI systems where cursor controlled movement application is controlled by the imagination of foot and hand movement, but no one has controlled it with colored stimuli before. Such study would be used to simulate an environment where a disabled person would be expected to drive a vehicle in a virtual environment with a possible uniform background, in which the vehicle will either start and/or stop moving on appearance of Green and Red lights respectively.

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