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TOWARDS EEG-BASED SIGNALS CLASSIFICATION OF RGB COLOR-BASED STIMULI

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ABSTRACT: This research looks at the possibility to actuate devices by looking at primary colors, thought to be especially useful for individuals having restricted motor control. Analytic and empirical signal analysis methods for analyzing EEG signals produced by subjects exposed to primary colors (RGB) are presented. Methods used are short time Fourier transform (STFT) and Empirical mode decomposition (EMD). Intrinsic mode functions (IMFs) are obtained using EMD, three of which are used for feature extraction. The features are used as inputs for the machine learning algorithms: random forest (RF), support vector machine (SVM), k-nearest neighbors (kNN), decision tree (DT) and naive Bayes (NB). Using data from 7 subjects, a general model classifies RGB with 0.37 accuracy, while the best subject-specific model achieves an accuracy of 0.58, which is above the chance level of 0.33. The classification accuracy between gray and any one of RGB is 0.98 with NB. Results are encouraging and can be improved by further exploring features and classification techniques.

INTRODUCTION

Electroencephalographic signals (EEG) represent the electrical activity in the brain. By placing electrodes on the scalp, one can record these signals. One electrode records the cumulative electrical activity of neurons. EEG signals are non-stationary, time-dependent, and because of cumulative electrical activity, most likely multicomponent signals [1]. Also, non-invasive EEG signals have a small amplitude and are extremely noisy. These properties are but a few of the reasons raw EEG signals do not provide useful information alone, and dedicated signal analysis is therefore required to extract relevant information contained within the signal. Choosing a suitable signal analysis method is a crucial step when extracting information from EEG data. In general, no particular method will provide the best results. The choice of signal analysis tool depends for instance on the characteristics of the signal and the aim of the experiment.

The goal of certain EEG experiments is to classify signals produced by specific brain activity. A feature is an individual measurable property of the process being observed [2], and any recorded EEG activity includes different features [3]. Researchers, therefore, search for a limited amount of features that can differentiate signals with certainty. The process of selecting only a subset of variables in the input which can efficiently describe the data is called feature selection. Feature selection decreases the effect of noise, irrelevant or redundant variables are reduced, and the predictor performance improved [2][4].

Techniques to predict which color a subject is looking at have been explored using indirect approaches such as analyzing psychological and emotional responses to color [5][6]. Classification of EEG signals produced by random visual exposure to primary colors was presented in [7]. Independent component analysis (ICA) was used to remove artifacts. Event-related spectral perturbations (ERSP) were used as features for a support vector machine (SVM), and the highest classification accuracy was 0.97, more information at [3]. In general, empirical mode decomposition (EMD) for feature extraction from color related EEG signals have proven to be successful in several studies [8]. A neural signature of the unique hues (red, yellow, green, and blue) was discovered 230 ms after stimulus onset at a post-perceptual stage of visual processing [9]. The study used ERPs (activity time-locked to an event) evoked in the response to different hues.

In this paper, analytic and empirical signal analysis methods are investigated to evaluate their ability to reveal color specific patterns in EEG signals produced by exposure to RGB. EMD is used as the basis for feature extraction. Identifying a set of features for color identification in EEG signals would enable less complex machine-learning based models, reducing the computational time for real-time color identification. Reliable real-time classification of EEG signals produced by looking at a color could enable physically disabled people with cognitive functions to control their environment. For instance, a user can open and close doors by looking at colored signs. This research is a step towards discovering a combination of signal analysis method, feature extraction technique, and classification algorithm that can be used to determine which color a subject is looking at using EEG signals.

METHODS AND MATERIALS

Dataset description: The dataset consists of EEG signals from 7 subjects that were watching RGB colors presented on a screen. The distance from the screen to the subject was 3.5m, and the intensity of the colors was constant at $4.5cd/m2$. Each color was presented 60 times to each subject in a randomized order. Gray was used as the base color between RGB exposure. The signals were recorded from channel P1, P2, O1, and O2, according to the 10-20 international system. The acquisition system used was BCI200 with g.tec's MOBIlab portable device and a sampling rate of 256 Hz [7].

In the preprocessing stage, the signals were band-pass filtered from $0.1-30$Hz. To reduce the effect of abnormal values, signals crossing $\pm 60\mu V$ were removed. Also, some trails were excluded due to electromyogram-(EMG) and electrooculogram (EOG) artifacts. The final dataset used in this paper consist of 52 trails for each color, in order to obtain a balanced dataset

Next, the data was re-organized in 3 seconds long "epochs" (768 data points). One epoch contains samples from all channels where the subject is looking at gray for one second, followed by two seconds of looking at one of the RGB colors. The colored light switched on at $t = 1s$ in all the following results.

Short time Fourier transform (STFT):

STFT preserves information about the time domain by windowing the signal around a particular instant in time and calculating the local Fourier transform (FT) for each time window. The information obtained from the STFT is presented in a spectrogram. Spectrograms show how the spectral density of a signal varies with time, giving the information about the quantity of the frequency, and at what time this frequency is present.

STFT is limited due to the windowing of the signal, which causes a trade-off between time precision and frequency resolution. Frequency resolution must be sacrificed to detect an event precisely in time, and vice verse. This trade-off between time and frequency resolution makes it essential to choose an appropriate window size to optimize both time and frequency [10].

Empirical mode decomposition (EMD):

EMD is a well-known technique used to analyze non-stationary and non-linear data [11]. EMD does not make assumptions regarding stationary or linearity of data, which motivates its use for analyzing EEG data [8]. In contrast to FT and STFT, EMD is data-driven, based on the assumption that a signal consists of several intrinsic mode functions (IMFs), that must satisfy two basic conditions:

- Number of zero-crossings must equal or differ by one compared with the number of extrema in the signal.
- The mean value of the upper and lower envelope of the signal must be equal to zero at any point.

The EMD algorithm finds all the IMFs trough a process called *Sifting*. The calculation of the IMFs given a signal $x(t)$ are done as follows [11]:

1. Identify all extrema (maxima and minima) in $x(t)$
2. Interpolate between minima and maxima, generating the upper and lower envelope; e_{upper} and e_{lower}
3. Determine the local mean as $a(t) = \frac{e_{upper}+e_{lower}}{2}$
4. Extract the mean from the signal; $h_1(t) = x(t) - a(t)$
5. Decide whether it is an IMF or not based on two basic conditions for IMFs mentioned above
6. Repeat step 1 to 4 until an IMF is obtained.
7. Subtract the IMF from the original signal
8. Repeat steps 1-6 until there are no IMFs left to extract, the last extraction resulting in a residue

The decomposition is complete when the sum of the IMFs and the residue is negligible.

Feature extraction and classification:

The main method used for feature extraction and classification is based on the work presented in [12]. The feature extraction stage for each electrode consists of the computation of energy and fractal features, but additionally, in this paper, a set of statistical values are also computed for each channel. This procedure is illustrated in Fig. 1, and the features are summarized in Tab 1

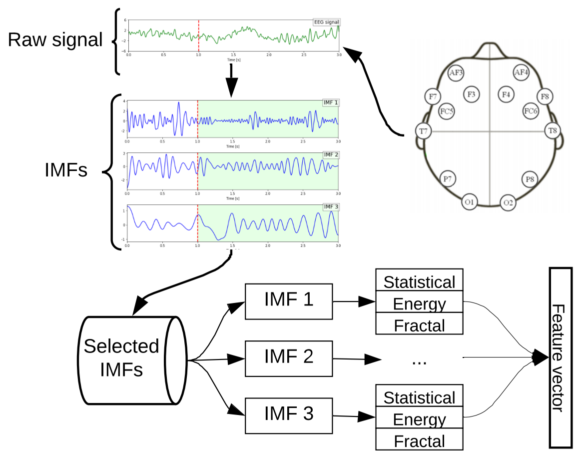

Figure 1: Flowchart illustrating the feature extraction procedure using EMD. The procedure is the same for each channel.

Table 1: Summary of features.

Feature type	Extracted features
Energy	instantaneous and teager energy
Fractal	Petrosian and Higuchi fractal dimension
Statistical	min, max, mean, median, variance, standard deviation, kurtosis, skew

The feature vectors obtained for each channel are concatenated to obtain a single vector for each instance and later used as input to the classifiers. As will be explained later, some experiments consist of using all the features shown in Tab. 1, while for others, only statistical values were used. For example, using all the 12 features, 3 IMFs and 4 channels, the length of the feature vector for an instance is:

$$\text{Features} * \text{Channels} * \text{IMFs} = 12 * 4 * 3 = 144$$

Using only statistical features the length of the feature vector is only 96 for each instance. Note that the features are computed for each IMF, and all experiments are done with 3 IMFs and 4 channels.

Lastly, supervised machine-learning models were created using 10-folds cross-validation using the accuracy metric. The machine-learning based algorithms used are, random forest (RF), SVM, k-nearest neighbors (kNN), decision tree (DT) and naive Bayes (NB).

To select the best parameters for each classifier, the experiments were repeated using different parameters, thus selecting automatically the classifier with the highest accuracy. The set of parameters for each classifier are listed below:

- Depths for RF: 2, 3, 4, 5, 6, 7, 8
- Neighbors for kNN: 2, 3, 4, 5, 6, 7, 8
- Kernels for SVM: linear (lin.), radial basis function (rbf), sigmoid, polynomial (poly.)

A Gaussian distribution is assumed for the NB classifier, and here the *GaussianNB* from scikit-learn with default parameters are used throughout this work. Unless otherwise stated, default parameters of scikit-learn classifiers are used [13].

RESULTS

Signal analysis:

Fig. 2 shows the grand average for each color. The gray background illustrates the duration for which the subject was looking at gray, while the red vertical line indicates the moment of color exposure ($t = 1$).

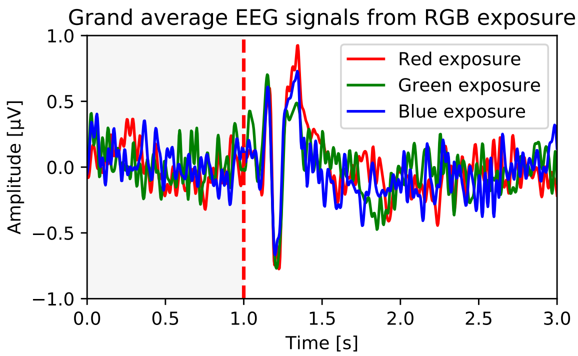

Figure 2: Grand average of all epochs. The colored light is switched on at $t = 1s$

STFT was applied to investigate possible changes of frequencies over the given time period. An STFT with a "Hanning" window size of 200 samples ($\approx 781ms$) overlap off 190 samples ($\approx 742ms$) and sampling frequency of 256 Hz was used to produce the spectrogram in Fig. 3 The spectrogram represents the grand average for RGB respectively. Despite apparent prevalence of noise, there is an amplitude increase in $2 - 12Hz$ for all colors, and for green there is an amplitude increase for $0 - 5Hz$ in the time frame $1 - 2s$. Hence, averaging data reveals a

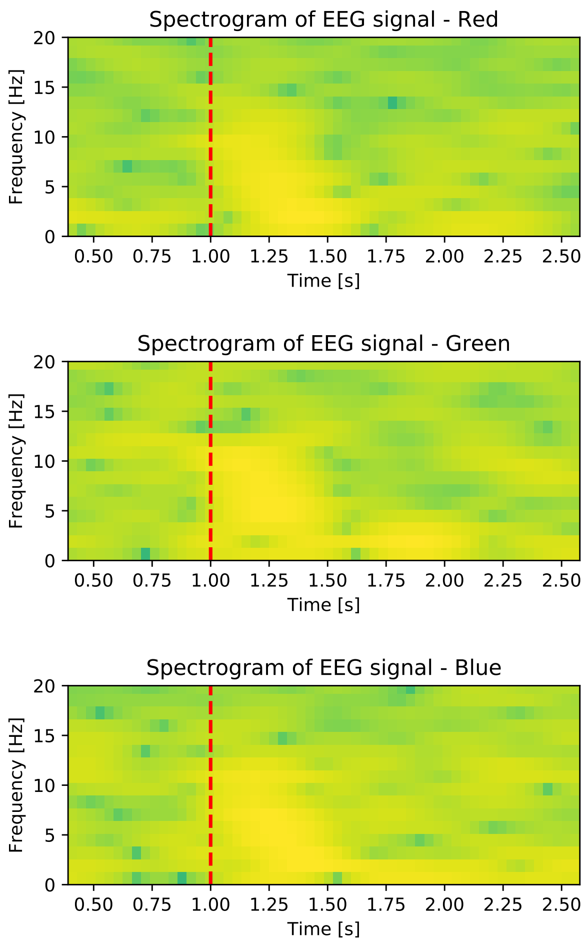

Figure 3: Spectrogram of grand average EEG signal for RGB

change caused by visual stimuli from gray to RGB colors $200 - 300$ms after exposure. However, is clear from their overlap that frequency alone is not sufficient to separate three colors. In addition, there is no lasting change in frequency, even though all subjects are continuously looking at color from from $t = 1s$ to $t = 3s$. Information gain from STFT is limited, and doubtfully sufficient to reveal a signal feature specific for each of the colors.

For this reason, the EMD algorithm was applied on each raw signal, and after 10 siftings, the residual fulfills IMF requirements discussed in the methodology section. Fig. 4 shows an example of the 5 IMFs and the residual for color green. Note, however, that in the feature extraction stage, this procedure is repeated for all the colors and not only green, as in this example.

EMD does not use windows. Using windows in the analysis of the signal would force the ends to zero, and therefore mask end effects. The end effect problem has not been taken into account in this paper. In Fig. 5 a spectrogram of each of the IMF is plotted. EMD successfully extracts the highest frequency components in the first IMFs. IMF1 reveals slight increase in magnitude for all frequencies at $t \approx 1.5$. This might be related to color exposure or change of mental state for the person in the experiment. Extracted IMFs can be representing the physical prop-

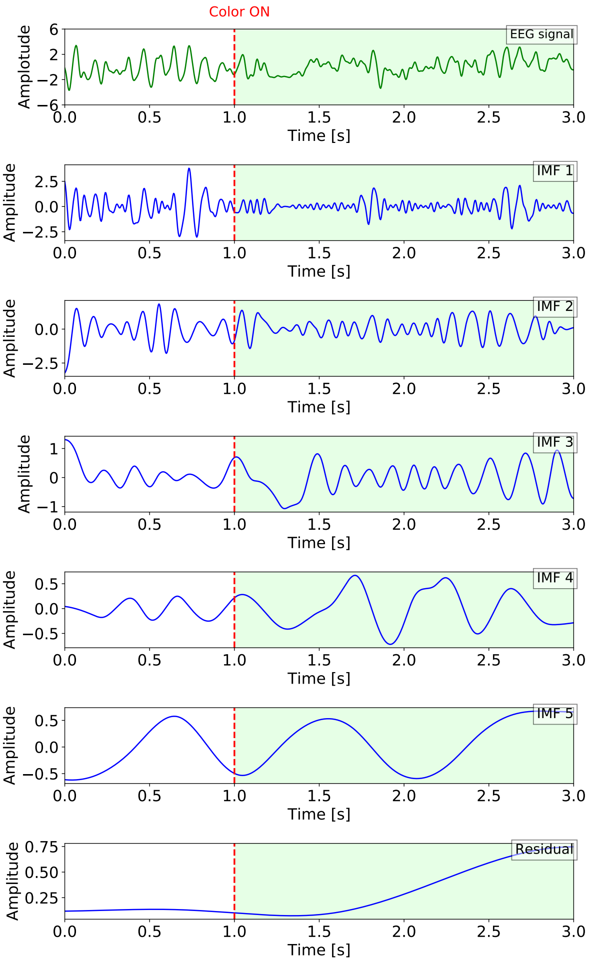

Figure 4: Original EEG signal, extracted IMFs and the residual. Green background represents green light is continuously on

erties of the process from which the signal is obtained. However, the problem of mode mixing in EMD caused by the presence of adjacent frequencies will cause loss of meaningful information in the IMFs. A new method for separating closely spaced spectral tones using EMD is presented in [14][15], and could be implemented to improve results.

Neither spectrograms nor IMFs reveal distinct color dependent frequency or amplitude related characteristic by visual inspection.

Classification:

To test if machine-learning models can classify RGB colors from EEG signals using features based on EMD, the following experiments are proposed:

(1) Classify RGB colors from gray color

(2) Classification of red, green and blue considering the EEG signals from all the subjects

(3) Classification of red, green and blue colors for each subject

The first experiment aims to provide experimental information about the performance of the method and to check if there is a feature that can separate these two classes (gray or RGB colors).

In the second experiment mentioned, the classifier consists of three classes (red, green, and blue) intending to check if using the proposed method is possible to differentiate between them. It can be the second step for a real implementation of a BCI based on RGB colors. Since the first step can identify when an RGB color is presented and then recognize the specific color. Following this aim is important to check the feasibility of a general model for the second experiment, that is why the last experiment consists of the same experiment but considering the EEG signals from all the subjects to create the classifier.

For all experiments, the procedure described for *Feature extraction and classification* is used. Accuracy metric after 10-fold cross-validation is presented. All the classifiers are tested with different kernels, the number of neighbors or depth depending on each one, and the best parameters are automatically selected. Note that the chance level for the first experiment is 0.5 of accuracy, and for experiment 2 and 3 it is 0.33

Experiment (1); gray vs RGB:

For a possible real-time application, it will be important to clearly distinguish if the subject is looking at nothing in particular, or decisively looking at a color. To simulate "nothing in particular", gray color is used. The complexity of such differentiation was investigated by first classifying if subjects were looking at gray or RGB color. An event-related potential (ERP) (P300) is expected approximately 300*ms* after the presentation of an infrequent stimulus. The part of the signal where the subject is exposed to the color will, therefore, contain the P300 component, and it can easily be distinguished from a signal not containing an ERP. Therefore, classification removing data points between $t = 1 - 2$ was investigated. Results for gray vs. color classification are presented in Tab. 2.

Table 2: Accuracies (Acc) obtained for the first experiment using all features (all), the statistical features (stat.) and only one statistical feature, the mean (mean).

Data	**Feat.**	**Classifier**							
		RF		kNN		SVM		DT	NB
		Acc.	depth	Acc.	k	Acc.	ker.	Acc.	Acc.
Full	all	**0.99**	5	0.72	6	**0.99**	lin.	0.98	0.98
	stat.	0.88	4	0.72	6	**0.92**	lin.	0.83	0.87
	mean	0.89	6	**0.91**	8	0.84	rbf	0.87	0.89
Limited*	all	**0.87**	5	0.62	4	0.85	lin.	0.86	0.85
	stat.	**0.89**	6	0.62	4	0.73	poly	0.86	0.85
	mean	0.90	6	**0.92**	4	0.87	rbf	0.88	0.87

*Accuracy obtained when removing data points

Surprisingly, when excluding the data samples between $t = 1 - 2$, the accuracy only decreases with 0.12 using all features. An interesting finding is a 0.92 accuracy when using data without ERP (Limited*), and only one feature; the mean. In this experiment, the lowest accuracy obtained is well above than the chance level, which in two class classification is 0.5. These results yield a promising first step towards a less complex real-time application for separating between gray and RGB colors.

Experiment (2) and (3); classification of red, green and

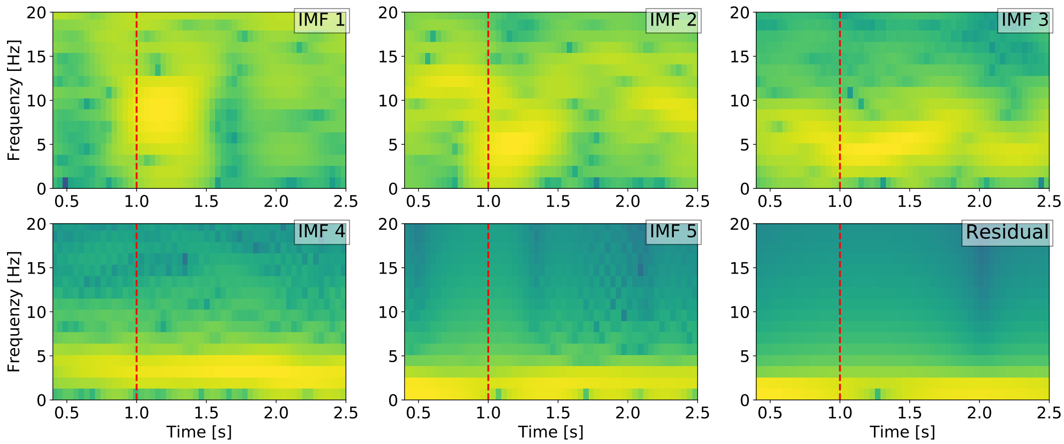

Figure 5: Spectrograms of each of the 5 IMFs and the residual obtained from 10 siftings.

blue color:
First, a model including data from all seven subjects was developed (2), reaching a maximum accuracy of 0.37 using both RF with depth 2 and Gaussian NB. A limited amount of data and individual differences are believed to impair the result, and hence, subject-specific models were developed (2). No classifier alone performed better for all subjects, but rather different classifiers yield better results dependent on the subject. There were, in particular, one subject that consistently obtained higher accuracy, when testing with all classifiers: 0.58 of accuracy using NB, 0.51 using linear SVM, 0.47 with 6-NN, 0.53 using DT, and finally 0.57 using RF with depth 4. On the other hand, another subject model classified at chance level. Tab. 3 summarizes accuracies of the RGB models for both a general model and considering each subject separately.

Table 3: Accuracy (Acc) reached for the second and third experiment, classifying red, green and blue colors considering a general model (2) and each subject separately (3)

Description	Classifier accuracy							
	RF		kNN		SVM		DT	NB
	Acc.	depth	Acc.	k	Acc.	kernel	Acc.	Acc.
all subjects	**0.37**	2	0.34	6	0.33	rbf	0.35	**0.37**
individual average	**0.41**	**	0.37	**	0.39	**	0.39	0.38
best individual	0.57	4	0.47	6	0.51	lin.	0.53	**0.58**

** Average of all individual models. Parameters differs for each subject, hence none of them are listed in particular

The mean accuracy for the subject model is found by finding the maximum accuracy for each subject individually and then performing the mean of these. The best performing classification algorithm differs dependent on the subject, and hence no algorithm, in particular, can be preferred. The maximum accuracy, being 0.58 is the highest individual accuracy obtained for one subject using NB. It should be noted that the chance level for this experiment is 0.33, and the lowest accuracy obtained is still above that value.
The accuracy increase when including only one feature - the mean. A possible explanation can be that redundant features forms the model, due to limited source data.

DISCUSSION

Several methods have been explored in order to check if there exist features that can be useful to describe the EEG data while the subject is looking at gray or RGB colors, and also considering RGB separately. In the signal analysis step, STFT and EMD were investigated.
The EMD method decomposed the original signals from each channel into several IMFs. Since the IMFs alone do not provide any information, they are analyzed further with STFT for visual inspection, and later used as the basis for feature extraction.
None of the methods yields a lasting unique frequency marker sought after for RGB; however, there where clear frequency modulations detected in the spectrogram of each IMF. The frequency modulation after color exposure is confirmed with a successful classification of gray and RGB color with 0.99 of accuracy.
Accuracies from the second experiment, classifying RGB considering all subjects together yields incomplete or inadequate results, considering the chance level of 0.33 for the 3 classes, and with the best accuracy of 0.37 using NB. The highest classification of RGB on an individual subject level was obtained using NB with an accuracy of 0.58. It can be concluded that color classification suffers from subject dependencies. Though NB yields the highest accuracy in the classifications, it should not be concluded as a general preference for RGB classification algorithm.

CONCLUSIONS

These results indicate the feasibility of using the method for feature extraction. Experimental evidence of differences between RGB colors preserved in EEG-data was presented. Further investigation of which features are best suited to describe the primary colors is suggested as part of the next step towards a less complex classification model.

For a real implementation and future work, ensemble learning should be considered as the best results in this paper were obtained using different classifiers depending on the subject.

Considering the results obtained in this paper and the experiments proposed, it is reasonable to assume that improving the feature extraction stage with a subject tailored system could improve accuracy, which will be tested in future works.

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