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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, which is thought to be especially useful for impaired individuals having restricted motor control. Such a brain-computer interface (BCI) requires reliable detection of color related features captured in electroencephalograph (EEG) data. This paper presents analytic and empirical signal analysis methods for analyzing EEG signals, motivated by the search for features directly related to the color perception in the human brain. Methods used are Fourier transform (FT) and short time Fourier transform (STFT). Empirical mode decomposition (EMD) is used to extract information used for feature extraction. Classification accuracies are tested using 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, while the best subject specific model achieves an accuracy of 0.58. The classification accuracy between gray and any one of the RGB colors is 0.98 with NB. These 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 in the process of finding useful information in EEG data. In general, no particular method will provide the best results. Choice of signal analysis tool depends for instance on the characteristics of the signal and the aim of the experiment.

The goal of most EEG experiments is to classify signals produced by specific brain activity correctly. A feature is an individual measurable property of the process being observed [2], and any recorded EEG activity includes many 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].

Researchers have explored techniques to predict which color a subject is looking at using different indirect approaches such as analyzing psychological and emotional response to color [5][6]

Recently, 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 has proven to be successful in several studies [8].

A neural signature of the unique hues (red, yellow, green, and blue) were discovered 230 ms after stimulus onset at a post-perceptual stage of visual processing [9]. This interesting study uses ERPs (recorded neural activity time-locked to an event) evoked in the response to different hues.

In this paper, analytic and empirical signal analysis methods are investigated in order to evaluate their ability to reveal color specific patterns in EEG signals produced by exposure to primary colors. EMD is used as 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. A 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.

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METHODS AND MATERIALS

Fast fourier transform (FFT):
Information is often contained in the frequencies of a signal. A signal is transformed from the time domain to the frequency domain with the Fourier transform (FT). The discrete Fourier transform (DFT) [10] is defined as

$$F_n = \sum_{k=0}^{N-1} f_k \cdot e^{\left(-\frac{2\pi i n k}{N}\right)}$$

For faster computation, FFT is often used. FFT computes the DFT of a signal. For a signal of length N, DFT needs $2N^2$ computations, while the FFT uses only $2N \cdot log(N)$. A significant drawback of the FT is the loss of time characteristics and is therefore not suitable for interpreting time-dependent signals. Methods based on the time-frequency domain have been developed for feature extraction in non-stationary signals.

Short time Fourier transform (STFT):
STFT preserves information about time domain by windowing the signal around a particular instant in time and calculating the local 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 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 [11].

Empirical mode decomposition (EMD):
EMD is a well-known technique used to analyze non-stationary and non-linear data [12]. EMD does not make assumptions regarding stationary or linearity of data, which motivates it's use for analyzing EEG data [8]. In contrast to FFT 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 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 [12]:

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 [13]. The feature extraction stage for each electrode consists on the computation of energy (instantaneous and teager energy) and fractal (Petrosian and Higuchi fractal dimension) features, but additionally, in this paper, a set of statistical values (min, max, mean, median, variance, standard deviation, kurtosis, skew) are computed for each channel. This procedure is illustrated in Fig. 1. Lastly, supervised machine-learning based models were created using 10-folds cross validation using the accuracy metric. The machine-learning based algorithms used are, random forest(RF), support vector machine (SVM), k-nearest neighbors (kNN), decision tree (DT) and naive Bayes (NB).

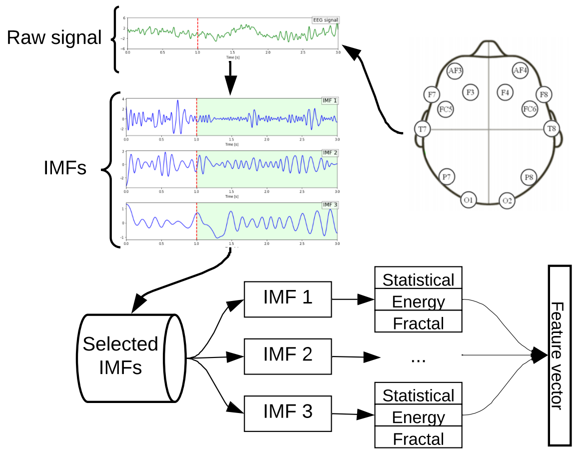

Figure 1: Flowchart illustrating the feature extraction procedure using EMD. The procedure is the same for each channel

Dataset description:
The dataset consist of EEG signals that were recorded from P1, P2, O1 and O2 channels according to the 10-20 international system using the BCI200 with g.tec's MOBIlab portable device with a sample rate of 256 Hz [7].
The dataset consist of EEG signals from 7 Subjects while watching RGB colors, each color was presented randomly 60 times to each subject. 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. In addition, 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.

RESULTS

Signal analysis:
Fig. 2 shows a single EEG signal, where the red vertical line indicates the moment of color exposure, and green background illustrates when green light is continuously on.

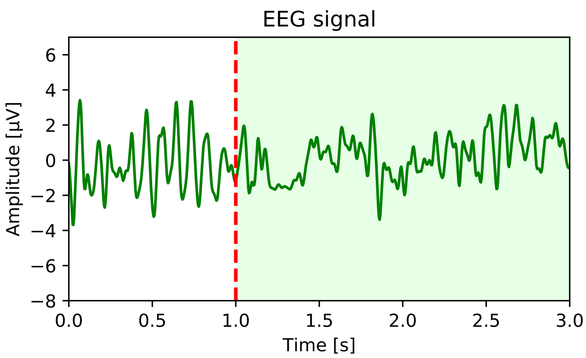

Figure 2: Example of one EEG signal where green light is switched on at $t = 1$, from channel P1

As an example of FFT from the above EEG signal is presented in Fig. 3. A larger magnitude at lower frequencies $0-10$Hz than $10-33$Hz is observed. Presence of higher magnitudes in $0-12$Hz is expected. These frequency bands corresponds to Delta, Theta and Alpha rhythms in the brain [14]. It is reasonable to believe that the person in the experiment was in a day dreaming / relaxed / wide awake state during data collection, and FFT satisfies the expectation. There are no frequencies above 33Hz, confirming successful prepossessing. As frequencies with lower magnitude are by eye inspection uniformly spread, it is difficult to draw further conclusions about frequencies in the EEG signal based on FFT.

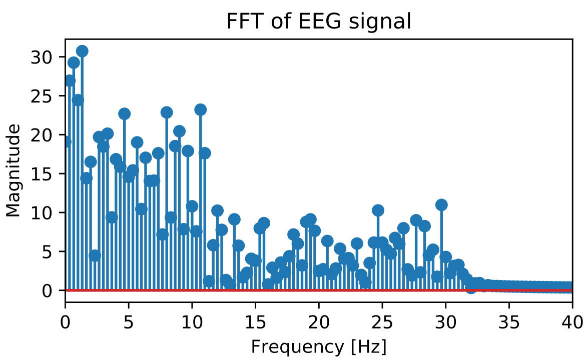

Figure 3: FFT of grand average EEG signal (green)

Since the aspect of time is lost in FFT, STFT was applied to investigate possible changes of frequencies over the given time period. A STFT with a "Hanning" window size of 200 samples, overlap off $200-10$ samples and sampling frequency of 256 Hz was used to produce the spectrogram in Fig.4

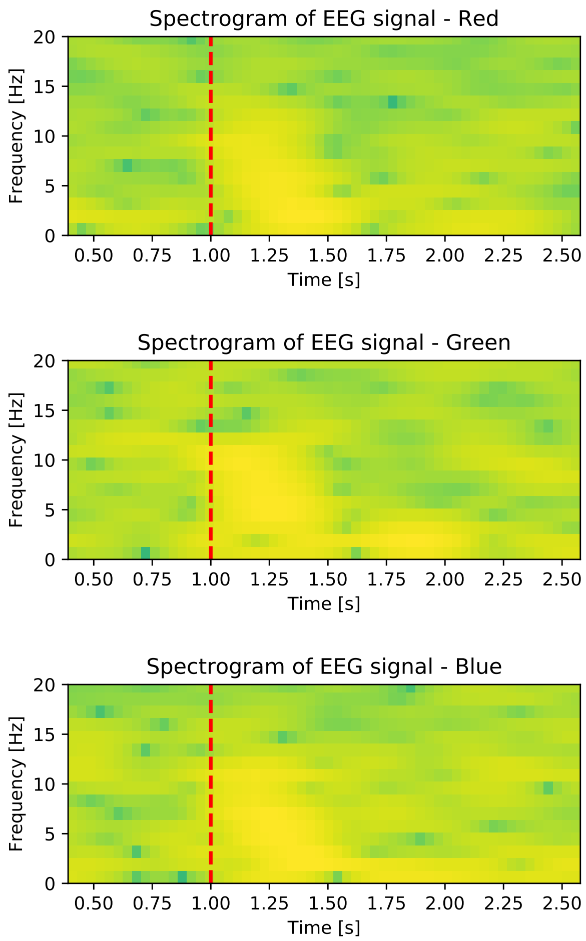

Figure 4: Spectrogram of grand average EEG signal for RGB

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 also a notable amplitude increase for $0-5Hz$ in the time frame $1-2s$. Hence, averaging data reveals a 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, EMD algorithm was applied on the signal, and after 10 siftings, the residual fulfills IMF requirements discussed in the methodology section. Fig. 5 shows an example of the 5 IMFs and the residual for color green.

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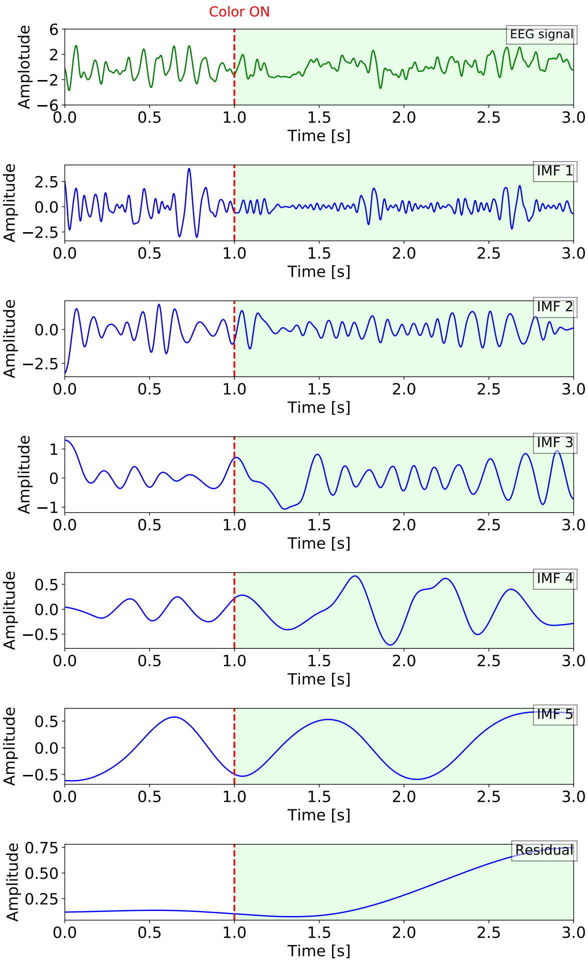

Figure 5: Original EEG signal, extracted IMFs and the residual. Green background represents green light is continuously on

EMD does not use windows. Using windows in 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. 6 a spectrogram of each of the IMFs are 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 physical properties of the process from which the signal is obtained. However, the problem of mode mixing in EMD caused by 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 [15][16], 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 colors for each subject
3. Classification of red, green and blue considering the EEG signals from all the subjects

The aim of the first experiment is to provide experimental information about the performance of the method and to check if there are feature that can separate these two classes (gray or RGB colors).
In the second experiment mentioned, the classifier consist of three classes (red, green and blue) with the aim 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 a 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 consist of the same experiment but considering the EEG signals from all the Subject 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, number of neighbours or deph depending of each one and the best parameters are automatically selected. Unless otherwise stated, default parameters of scikit-learn classifiers are used [17]. 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 an RGB color. An event-related potential (ERP) (P300) is expected approximately $300ms$ after 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, and referred to as "data excluded". Results for gray vs color classification are presented in Tab. 1.

Table 1: Accuracy (Acc) obtained for the first experiment using all the features (feats.), the statistical features (S.) and only one statistical feature (the mean).

	Acc		Acc, data excluded	
All feat.	0.99	RF depth 5	0.87	RF depth 5
S. feat.	0.92	linear SVM	0.89	RF depth 6
Mean	0.91	8-NN	0.92	4-NN

Surprisingly, when excluding data from $t = 1-2$, the accuracy only decreases accuracy by 0.12 using all features. An interesting finding is a 0.92 accuracy when using data

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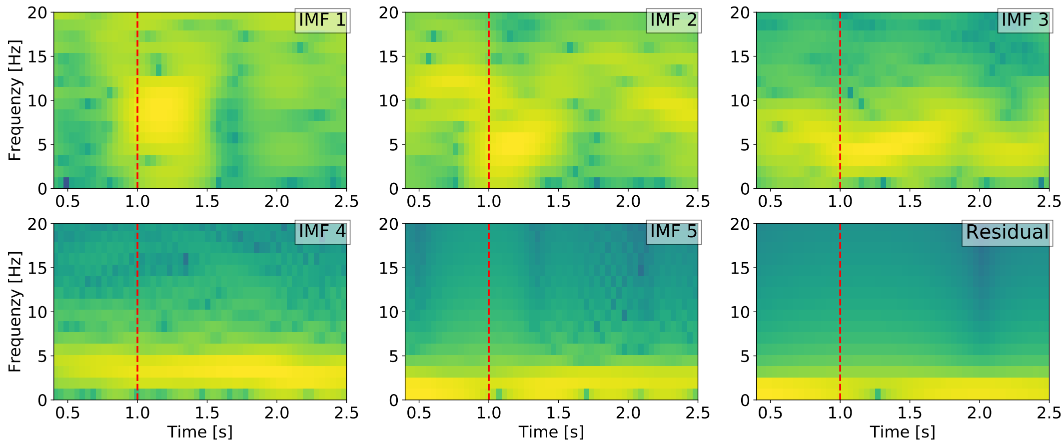

Figure 6: Spectrogram of original EEG signal, each IMF and residual

without ERP, and only one feature; the mean. These results yields a promising first step towards a less complex real-time application for separating between gray and RGB colors.

Second experiment; classification of red, green and blue color:
Firstly, a model including data from all seven subjects were developed, reaching an accuracy of 0.37 using a Gaussian distributed NB. Limited amount of data and individual differences are believed to impair the result, and hence subject specific models were developed. No classifier alone performed better for all subjects; but rather different classified yield better result 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. 2 summarizes accuracies of the RGB models considering each subject separately.

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

	Accuracy	Classifier
Average	0.42	Depends on the subject
Max	0.58	NB

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 is the highest individual accuracy obtained for one subject.
Interestingly, the accuracy increase when including only one feature - the mean. A possible explanation can be that redundant features forms the model, due to very limited source data.

CONCLUSIONS AND DISCUSSION

In this paper, 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, FFT, STFT and EMD were investigated.
The FFT indicates that the subject was in relaxed and/or in an awake state during the data collection, which indicates a realistic dataset. The STFT successfully identify the P300 when averaging all the data for each color.
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 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 poor 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 individual subject level was obtained using NB with and accuracy of 0.58. It can be concluded that color classification suffers from subject dependencies. Though NB yields highest accuracy in the classifications, it should not be concluded as a general preference for RGB classification algorithm.
These results indicate the feasibility of using the method for feature extraction and experimental evidence of differences between RGB colors EEG-based. Considering the results obtained in this paper and the experiments

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proposed, it is reasonable to assume that improving the feature extraction stage with a subject tailored system, the accuracy can improve, which will be tested in future works.

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