EEG-BASED COLOR CLASSIFICATION SYSTEM USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT

This study aims to investigate the response of the brain when a person is stimulated by unicolor images displayed on a monitor screen using electroencephalograms (EEG). Specifically, a classification system was proposed in order to relegate the EEG signals according to the color shown. The three primary colors: red, green and blue (RGB), and their shades were used as stimuli. The response of the brain was recorded using a 14-channel EEG headset. The data obtained were pre-processed and the pre-identified features were analyzed for significance to ensure proper classification of the EEG response with respect to the color stimuli. The power spectrum vectors of the alpha and beta waves were considered in the study. Alpha asymmetry was explored and results show that the frontal and temporal nodes were left asymmetric and the parietal and occipital nodes were right asymmetric. Artificial neural networks (ANN) were utilized to implement color detection using the features which significantly characterized the color stimuli in the EEG. The maximum accuracy obtained is 86.07% using the alpha band and 88.69% using the beta band.

Keywords: *EEG, Feature Extraction, Alpha Asymmetry, Artificial Neural Networks, Color Classification*

INTRODUCTION

The communication of billions of neurons inside the brain emits minute electrical signals which are usually in the microvolt (µV) range [1]. Triggering a significant change in the EEG response of a person requires stimulus that are intercepted by the different senses of the body. For colors, visual stimulation is the commonly used.

Color perception is one of the fundamental aspect of human vision [2]. Physiologically, colors trigger a change in the activity of the brain [3]. The variation of color stimulation arouses different emotions and is associated to a variety of human activities. All colors have their own place and are correlated to objects. However, the perception of color differ from one person to another [4] [5] [6].

Brainwaves (or EEG) are random signals which contains both noise and information. Pre-processing methods are required in order to prepare them for further processing and analysis. Several features may be extracted from EEG signals in a supervised or unsupervised manner. Feature extraction enables simplification of a large block of data sets [7], making the features the best representation of itself. With this, feature extraction and selection was performed to characterize EEG signals. Moreover, such features were used as basis for training and testing the classification system [8].

In this study, the response of the brain was investigated when it is stimulated by unicolor images displayed on a monitor screen. The signals were characterized with the objective to develop an ANN-based color classification system.

EXPERIMENTAL DATA

A. Color Stimuli

The three primary colors: red (255,0,0), green (0,255,0) and blue (0,0,255) and their shades were considered as the stimuli. The shades were obtained by varying the hues to 100, 150 and 200. Fig. 1 shows the primary colors and their shades. The stimuli were projected using an LED screen monitor.

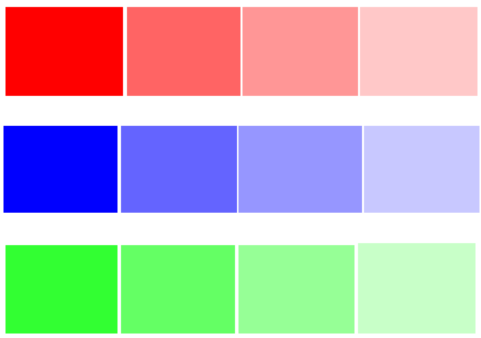


Figure 1. Color Stimuli

These color stimuli were projected in a specific sequence as shown in Table I. It was assured that no colors of similar shade appear next to each other.

Table 1: Color Stimuli Arrangement

	Color Stimulus	Actual Color
Red	R1	C1
	R2	C5
	R3	C7
	R4	C12
Blue	B1	C6
	B2	C9
	B3	C11
	B4	C3
Green	G1	C8
	G2	C2
	G3	C4
	G4	C10

B. EEG Data Set and Data Gathering Procedures

Forty (40) undergraduate students with an age range 17 to 21 volunteered in the experiment. Data gathering was performed inside a dim, acoustically-prepared room at room temperature. A special set up was used to enable the participant to focus only on the stimuli presented using an LED monitor screen. The EEG responses throughout the presentation of the color stimuli were recorded using a 14-channel neuro-headset from Emotiv. The 14 nodes are as follows: AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8 and AF4. The letters F, T, P and O represent the regions or lobes of the brain where the nodes are found, namely, Frontal, Temporal, Parietal and Occipital lobes. The status of the contact quality of each node electrode was monitored in TestBench™ – which presents the real-time display of the neuro-headset data stream. Node electrodes that have good contact are indicated with a green color [9].

The timing diagram of the color stimuli is shown in Fig. 2. The timing diagram indicates the duration of the appearance of the black background as well as the color stimuli.

Figure 2. Timing Diagram of the Color Stimuli

For the first three minutes of data gathering, the participants were asked to close their eyes to establish the baseline. After which, a bell will ring, to tell the participants to open their eyes and focus on the screen. A 10-second display of a black background comes next in order to 'relax' the eyes of the participants. The black background will be replaced by the color stimuli with a duration of 2 seconds. The display of a 10-second black background and the 2-second color stimulus continues until all the twelve colors were projected.

Synchronization is an important concern when gathering a continuous data from the neuro-headset. To handle this issue, the physical movement and EEG response of the participants, as well as the display of the colors were video recorded. This made sure that the EEG signals were epoched (segmented) properly, separating the baseline, the black backgrounds and the color stimuli.

FEATURE EXTRACTION

The segmented raw EEG signals were filtered according to the frequency of the alpha (8–13 Hz) and beta (13-30 Hz) bands. The function "eegfilt" was used to accomplish this. The function "eegfilt" is one of the filtering function in EEGLAB, an open-source MATLAB toolbox designed specifically for EEG analysis. The filtered EEG responses were normalized. Thirty out of forty responses were subjected to moving average algorithm for further noise elimination and data smoothening [10].

Twelve features were initially considered in this study. The details of each can be viewed as per citation. The initial features are the following: mean [11], standard deviation [11], skewness [12], kurtosis [12], sample entropy [13], approximate entropy [14], wavelet transform [15], Hjorth Parameters [16], power spectral density [17], cumulative root mean square [18], waveform length [8] and energy spectral density [19]. These features were applied on the power spectrum vector of the EEG data [20]. The power spectrum can be obtained using Equation (1).

$$P_k = \frac{1}{N^2}|X(k)|^2, for\ k = 1, 2, \ldots, N-1 \qquad (1)$$

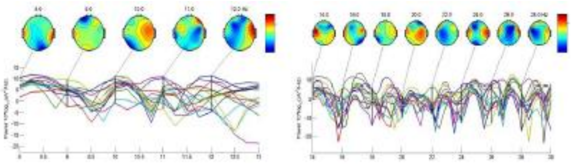
where |X(k)| is the magnitude of the Fourier transform complex coefficients of the time-domain signal and N is the number of samples.

RESULTS

Power Density Distribution

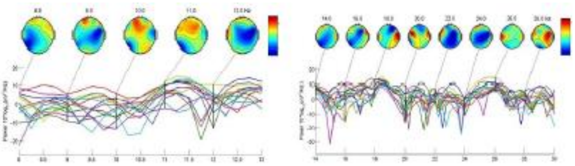
To verify the impact of color stimulation, the power density distribution along the 14 nodes was investigated. By plotting the spectral maps, it was verified that every reaction of the participants to a color stimulus varied in all 14 nodes in terms of power density.

The colors along the spectral maps indicate the intensity of power 'felt' by a node. Red indicates the strongest power while blue indicates the lowest. In Fig. 3 and Fig. 4, notice that no spectral map reacted similarly as compared to another. Moreover, upon comparing the spectral maps of the two color stimuli, almost no similarity was observed indicating that the participants differ in reaction and perception to the two colors.



(a) (b)

Figure 3 (a) Alpha and (b) Beta Power Spectral Maps for Color 1



(a) (b)

Figure 4 (a) Alpha and (b) Beta Power Spectral Maps for Color 2

In determining the power distribution along the 14 nodes, all spectral maps undergone a subjective look wherein the nodes with the highest power distribution (indicated by color red) were tallied. All power density distribution charts, whether along the alpha or beta band, allocate a big chunk to the nodes present along the frontal lobe. Results show that the frontal lobe reacts more than the occipital lobe despite using visual stimuli – the occipital lobe allows a person to process, perceive and discriminate what the eyes can see [21].

Feature Selection

A variance test was performed to determine which among the 12 initial features can significantly describe the EEG data in relation to the color stimuli. The features were extracted from the vectors produced using moving average algorithm forming 29 different feature vectors. The difference between the variances of the feature vectors of the baseline and the color was calculated and the maximum difference was obtained. The maximum difference on the values of the variances was used as an indicator that the reactions of the baseline and color is different from one another.

Kurtosis was found to be the most significant feature for both alpha and beta bands. However, kurtosis was more dispersed along the alpha band as shown in Fig. 5.

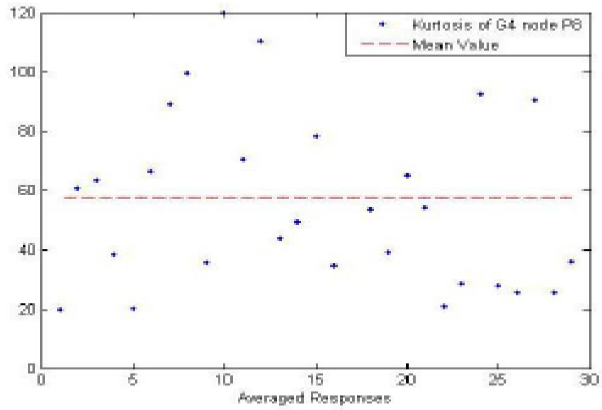


Figure 5 Distribution of Kurtosis that Yielded the Maximum Variance Difference

Furthermore, the fourth shade of green along node P8, kurtosis yielded the highest variance of 938.39. On the other hand, beta yielded a maximum variance of 389.41. Having kurtosis as the most significant feature it indicates that the peakedness of the reaction of the color differed greatly as compared to the baseline or when the participant is relaxed.

Alpha-wave Asymmetry

Since the left and right hemispheres of the brain perform different functions [14], the pair of nodes from both hemispheres must have a distinct reaction with respect to each other. Figure 6 shows how nodes AF3 and AF4 reacted differently using Color 1 (C1) as stimulus. The asymmetrical response of these nodes were evident along both alpha and beta bands.

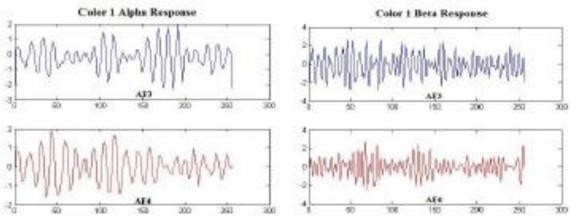


Figure 6 Node Asymmetry on pair AF3-AF4

Using the difference score method (DSM) [22], the pairs of nodes that showed left or right asymmetry were tallied, showing that the frontal and temporal nodes were left asymmetric while the parietal and occipital nodes were right asymmetric. This is evident for all the 12 color stimuli.

Participant Responses

For both alpha and beta bands, it was observed that all participants react similarly to all color stimulus. The significant difference of these responses was observed using Analysis of Variance (ANOVA) with a confidence level of 95%. All resulting *p*-values obtained from all 40 participants, for all 14 nodes, showed no significant differences between the responses of all participants despite differences between their age, gender and handwriting orientation.

Color Detection System

A color detection system using ANN was designed and implemented to predict the color seen by the 10 test participants. The features with highest significance served as the inputs for the network. The attributes used in training the neural network used all the 14 nodes, the RGB colors and three different sets of features: Set1 - 9 features, Set2 - 5 features and Set3 - 3 features. Waveform Length was removed due to its high dependence on data length. In addition, sample and approximate entropy were not considered since they were found to be least significant based on the variance test.

The training was done using a single-layer network wherein the number of neurons was varied from 50, 100, 500, 1000 and 2000. Using feedforward network, the training was re-iterated until the mean square error was less than 0.1. The desired output would only be the primary colors: red, blue and green. The accuracy of the performance of the color detection system was done using sensitivity and specificity. A sample confusion matrix is shown in Table II.

Table 2: Color Detection System Decision Chart (Test for Red)

	Red	Not Red
Predicted: Red	True Positive	False Positive
Predicted: Not Red	False Negative	True Negative

To obtain the actual result for every color, all the nodes that showed the True Positive, True Negative, False Positive and False Negative responses were counted. The summations per category were treated as the result for the color.

Using 9 features as part of the attributes, it resulted to a higher accuracy as compared to the networks that used the top 5 or top 3 features. The maximum accuracy in the alpha band is 86.07% while in the beta band, a maximum accuracy of 88.69% is obtained. Both maximum accuracies were obtained from a 1000-neuron ANN. Accuracy results are shown in Tables III, IV and V.

Lesser number of neurons entailed lower sensitivity for color groups red and green. As the number of neurons increases, the sensitivity of the two color groups increases. The sensitivity of red and green showed a direct proportional relationship with the number of neurons only until 1000 neurons. Results at 2000 neurons is lesser as compared to that of 1000 neurons.

Table 3: Accuracy Results for the Alpha and Beta Bands with 9 Features

Neurons	TEST FOR RED		TEST FOR BLUE		TEST FOR GREEN		ACCURACY
	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	
50	10.89%	98.92%	95.54%	11.52%	11.25%	98.39%	59.48%
100	13.04%	98.57%	95.54%	15%	14.82%	98.13%	60.75%
500	23.57%	97.5%	89.46%	24.59%	23.93%	96.70%	63.77%
1000	74.29%	97.32%	89.82%	73.93%	73.21%	97.41%	86.07%
2000	71.61%	97.23%	89.29%	71.70%	71.43%	97.23%	84.96%

(a) Alpha Band

Neurons	TEST FOR RED		TEST FOR BLUE		TEST FOR GREEN		ACCURACY
	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	
50	8.39%	98.39%	95.54%	7.86%	6.79%	99.11%	57.94%
100	17.14%	97.59%	93.57%	17.14%	15.54%	98.39%	61.39%
500	21.43%	97.59%	91.61%	21.70%	20.89%	97.68%	63.10%
1000	78.57%	97.95%	92.32%	78.57%	78.21%	98.04%	88.69%
2000	75.36%	97.77%	91.79%	76.88%	77.86%	97.86%	87.78%

(b) Beta Band

Table 4: Accuracy Results for the Alpha and Beta Bands with 5 Features

Neurons	TEST FOR RED		TEST FOR BLUE		TEST FOR GREEN		ACCURACY
	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	
50	0.89%	99.82%	99.11%	1.69%	2.32%	99.64%	56.07%
100	2.14%	99.64%	98.75%	4.11%	5.54%	99.46%	56.98%
500	8.04%	98.84%	95.89%	11.43%	13.75%	98.57%	59.48%
1000	69.29%	96.79%	90.18%	71.79%	73.75%	98.04%	85.16%
2000	66.07%	96.70%	89.82%	67.14%	67.5%	97.86%	82.98%

(a) Alpha Band

Neurons	TEST FOR RED		TEST FOR BLUE		TEST FOR GREEN		ACCURACY
	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	
50	2.14%	99.82%	99.29%	2.23%	2.31%	99.82%	56.39%
100	3.39%	99.46%	98.39%	4.38%	5%	99.55%	57.06%
500	8.03%	99.02%	96.61%	8.39%	8.04%	98.93%	58.37%
1000	66.96%	97.05%	88.93%	68.30%	68.57%	96.88%	83.21%
2000	61.25%	97.77%	90.71%	60.98%	60.17%	97.32%	80.48%

(b) Beta Band

Table 5: Accuracy Results for the Alpha and Beta Bands with 3 Features

Neurons	TEST FOR RED		TEST FOR BLUE		TEST FOR GREEN		ACCURACY
	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	
50	0.71%	99.82%	98.93%	1.96%	3.04%	99.55%	56.15%
100	5.36%	99.73%	98.93%	5.98%	6.07%	99.46%	57.86%
500	13.03%	98.57%	94.29%	15.8%	16.07%	97.95%	60.75%
1000	17.68%	98.13%	92.14%	20.54%	21.96%	97.23%	62.62%
2000	62.14%	96.25%	86.07%	63.04%	63.75%	96.70%	80.44%

(a) Alpha Band

Neurons	TEST FOR RED		TEST FOR BLUE		TEST FOR GREEN		ACCURACY
	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	Ave. Sensitivity	Ave. Specificity	
50	3.39%	99.73%	98.57%	3.13%	2.32%	99.29%	56.51%
100	2.85%	99.73%	98.57%	3.39%	3.57%	99.38%	56.67%
500	10.36%	99.10%	96.25%	10%	9.11%	98.75%	59.05%
1000	12.14%	98.66%	95.71%	12.32%	11.43%	98.66%	59.84%
2000	40.71%	97.23%	8929%	39.46%	36.25%	96.43%	70.28%

(b) Beta Band

On the other hand, the specificity was found to have an inverse proportional relationship with the increasing number of neurons. This was observed for color groups red and green. Similar to sensitivity, specificity increases as the number of neurons increases except when the number of neurons reached 2000.

The color group blue had an opposite result to that of red and green, having an inverse directional relationship with sensitivity but with a direct proportional relationship with specificity. Yet still, their trend changed with 2000 neurons.

The network with 50, 100 and 500 neurons showed very low sensitivity but relatively high specificity. It shows that with these settings, the accuracy of the ANN purely depends on its specificity - allowing a reasonably good detection indicating that a certain color is being differentiated from another color group. The low sensitivity indicates that the nodes 'see' wrong colors.

Networks with 1000 and 2000 neurons had higher sensitivity. This indicates that the nodes could predict the right color better with more neurons. Despite slightly lower specificity, the accuracy of the network was higher because it was now affected by both sensitivity and specificity.

CONCLUSION

In this study, an EEG-based color detection system was developed by using the brainwave signals stimulated by the using 12 different color stimuli. The EEG responses were segmented such that the signals for the baseline and the color stimuli were obtained. Out of the 12 features identified, kurtosis was found to be the most significant feature for both alpha and beta bands. Alpha wave asymmetry results confirm the assumption of the functions of the two hemispheres of the brain [21] showing that both frontal and temporal nodes left asymmetric while the parietal and occipital nodes being right asymmetric. The responses of the participants showed no difference with one another despite demographical differences. The color detection system using ANN was developed to identify the color seen by a person using EEG responses. The performance of the color detection system yielded to maximum accuracies of 86.07% and 88.69% for the alpha and beta band, respectively with 9 significant features and running at 1000-neuron ANN.

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