Discriminating Different Color from EEG Signals using Interval-Type 2 Fuzzy Space Classifier (A Neuro-Marketing Study on the Effect of Color to Cognitive State)

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Abstract—**Color perception is one of the most important cognitive features of human brain. Different colors lead to different cognitive activities and different mental arousal levels; as revealed by power spectral density obtained from EEG signals. As the color plays an important role in marketing and packaging industry; so neuro-marketing research; based on color stimuli is considered to be an important tool for market researcher. In order to assess the impact of each color; prime focus is to detect different colors from EEG signals. This study employs four color stimuli; e.g. red; green; yellow and blue; that were shown to various subjects and EEG signal corresponding to the mentioned stimulus was acquired. Power spectral density of each color was estimated and different activation areas of brain for each stimulus is illustrated in figures. This paper also employs an Interval-Type-II fuzzy space classifier for distinguishing between different stimuli that are considered for the concerned experiment. It is noted that classification rate is maximum for red color and minimum in case of yellow color. Precision and recall values also have been highlighted here. For detailed analysis; the performance of IT2FS classifier has been compared with other standard classifiers by Friedman Test.**

Keywords—EEG; Neuro-Marketing; Color; PSD; IT2FS; Mental Arousal; Friedman Test; Precision; Recall Value

I. INTRODUCTION

Colour is an impressive feature of any product and can be considered as an important criterion for commercial product development. Aesthetic and cosmetic beauty that leaves an impact on customers' mind mainly depends on the colour of the product [1]. From the work of web designing to branding the business; colour is regarded as prime factor as it defines the mood and emotions and ultimately affects the responses. As now a day; online marketing has increased manifold; so there is ultimate trial by all the business giants for proper use of colour based on psychological response of customers. Neuro-marketing plays a vital role here; according to Lee. *et al.* neuro-marketing is a study discipline that concerns about application of neuroscientific procedure for analysing and understanding human psychology related to marketing [2].In the present context; the paper introduces the colour perception as new tool of neuro-marketing.

Use of physiological signals for judging the colour perception is a more reliable measure than the verbal feedback of subject as they are not able to completely explain the abstract ideas when explicitly asked [3]. Electroencephalogram is a record of physiological signal that measures the electrical activity of the brain.EEG signal has been chosen here as indicator of brain activity because of its non-invasive nature; superior temporal resolution and low cost acquiring facilities [4].

According to some studies; it has been found that colour perception of human brain is mainly caused due to activation of lingual and fusiform gyri situated in occipital lobes and further information about the color is processed in left inferior temporal; left frontal and left posterior parietal cortices. Studies report that different color has different arousal effects which significantly contribute towards emotion [5]. A color based study based on ERP method was carried out to find the role of color in road safety and it was concluded that average response accuracy rate is higher for red cars than blue cars and also energy evoked by red car is higher [6] though another study finds green as most arousing color [7]..A current work shows classification and separation of color responses from EEG signals where SVM was used as classifier [8].In neuro-marketing research also; many studies have already been carried out with an aim to assess consumer psychology [9]–[12].

To use color stimuli as a tool of neuro-marketing research it is at most important to conclude that human brain response in predictive manner to each color stimuli; so this paper mainly focuses on classifying four basic colors (R; Y; G; B) from EEG signals. As EEG signal is stochastic in nature; therefore uncertainty is always associated with it. Fuzzy logic has been applied here to take of the uncertainty. Type 1 Fuzzy space classifier uses a single membership function to represent variation in signal but EEG response evoked for same stimulus for same subject is different for different time; therefore

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Type 2 Fuzzy space classifier employing secondary membership value has been used here. Interval Type 2 Fuzzy classifier uses constant and uniform secondary membership function [13].

In the present context EEG signal has been acquired for four different colour stimuli and Power spectral density has been estimated by Welch method. Extracted features have been classified by IT2FS classifier. The classification result has been compared with other standard classifiers. Activation of different brain region during each stimulus has illustrated by some pictures.

The rest of the paper is organised in the following manner. Section II describes working methodology and Section III describes Experimental setup and results. Finally; Section IV discusses the outcomes of the experiments and also gives concluding remarks.

II. Theory and Methods

A. Power Spectral Density Estimate

Spectral estimation is done to get the distribution of signal power over the frequency range. For a finite data set *a(n)* and its autocorrelation sequence X_{aa}; the Power Spectral Density (PSD) can be estimated as below,

$$P_{aa}(\omega) = \frac{1}{2\pi} \sum_{l=-\infty}^{+\infty} X_{aa}(l) e^{-j\omega l} \tag{1}$$

If the sampling frequency is denoted as f_s; then ω can be replaced as $\frac{2\pi f}{f_s}$ and above equation can be written as,

$$P_{aa}(f) = \frac{1}{f_s} \sum_{l=-\infty}^{+\infty} X_{aa}(l) e^{-j2\pi fl / f_s} \tag{2}$$

According to Nyquist criteria; the maximum frequency present in the system is half of the sampling frequency (f_s); the average power for entire signal over the entire Nyquist range is described as follows,

$$\int_{-f_s/2}^{f_s/2} P_{aa}(f) df \tag{3}$$

where $P_{aa}(f)$ represents power in an infinitesimal bandwidth; so it is termed as PSD.

1) Welch Method

Welch method [14] belongs to the category of non parametric PSD estimation methods where PSD of a signal is estimated from the signal itself; in other words using Welch method PSD estimate is computed using the Fourier Transform of the signal or the autocorrelation function of the signal.

To compute the complete PSD estimate from a time varying EEG signal; the following steps are followed,

First the signal is split up into overlapping time sequences. Then the segmented signals are passed through a suitably chosen window function; basically a window is applied to each of the segmented signals and further; Discrete Fourier Transform is computed and the result obtained is squared in terms of magnitude to obtain the periodograms and the individual periodograms thus obtained are time averaged to yield a final PSD measure.

Basically; the Welch method comes up with two modifications in the traditional Bertlett'smethod that the subsequences formed are overlapping and instead of time averaging the periodograms; the modified periodograms serve the purpose.

Mathematically; the signal can be split in *L* overlapping sequences of length *M*. The ith signal segment can be expressed as,

$$a_i(n) = a(n + iD) \tag{4}$$

where n=0; 1; 2; ….; M-1 and i=0; 1; 2; ….; L-1.

Next; the signals are required to be windowed before computing the periodograms. Further; after the windowing functions are employed; the periodograms are calculated using,

$$\hat{P}^i_{aa}(f) = \frac{1}{MU} \left| \sum_{n=0}^{M-1} a_i(n) w(n) e^{-j2\Pi fn} \right|^2 \tag{5}$$

where *w(n)* signifies the windowing function and *U* is a normalization factor defined as,

$$U = \frac{1}{M} \sum_{n=0}^{M-1} w^2(n) \tag{6}$$

Finally; Welch PSD estimate is calculated as the time average of the modified periodogram,

$$P^w_{aa} = \frac{1}{L} \sum_{i=0}^{L-1} \hat{P}^i_{aa}(f) \tag{7}$$

B. Interval Type 2 System for Classification

Fuzzy logic [15] has been introduced in order to deal with problems concerned with uncertainties. While Type 1 Fuzzy systems (T1FS) are provided with a search engine with a rule base and the rule corresponding to the maximum membership value gets fired. The membership function generates a value to a particular entity of the fuzzy set in [0; 1] which signifies the extent of belongingness of that entity to that specific fuzzy set. The choice of the membership function lies upon the researcher who is allowed to choose from a wide variety of membership functions used in the literature like Guassian; Trapezoidal; Triangular; Sigmoid etc.In the present context; the signal acquired from the same subject for the same stimulus can also vary while conducting the experiment at different sessions. Not only intra subject variations; but the EEG signals also vary in between different subjects. Hence; in this scenario; the T1FS fails to discriminate between different mental states as a classifier. Although General Type 2 Fuzzy Systems (GT2FS) provides a solution by introducing secondary membership function in order to register the uncertainty observed in primary membership function; but the calculation of the secondary membership function increases the system complexity further; so Interval Type 2 Fuzzy Systems (IT2FS) is chosen as a preferred alternative over the former two because of its uniform and constant secondary membership values and simple solutions.

In case of T1FS; the membership value assigned to a variable is calculated from the membership function parameters (mean and standard deviation in case of Gaussian membership functions) of respective classes and depending on the maximum value an entity is assigned to a particular class. T1FS system fails to capture the variation of the primary membership over time; for example if the mean and standard deviation of Gaussian membership curve varies in between different sessions conducted on different days. To get rid of these issues; a secondary membership curve $\tilde{m}(x, m(x))$ is introduced which takes care of the uncertainty of the primary membership curve *m(x)*.The union operation of the primary membership curves yield a region termed as Footprint of Uncertainty (FOU) bounded by the secondary membership curve and the minimum and maximum values of the primary membership curve denotes the Upper Membership Curve (UMF) and Lower Membership Curve (LMF); as shown in Fig. 1. For IT2FS systems; the secondary membership function assumes a constant value of 1 if the value of *m(x)* falls in between UMF and LMF and 0 otherwise.

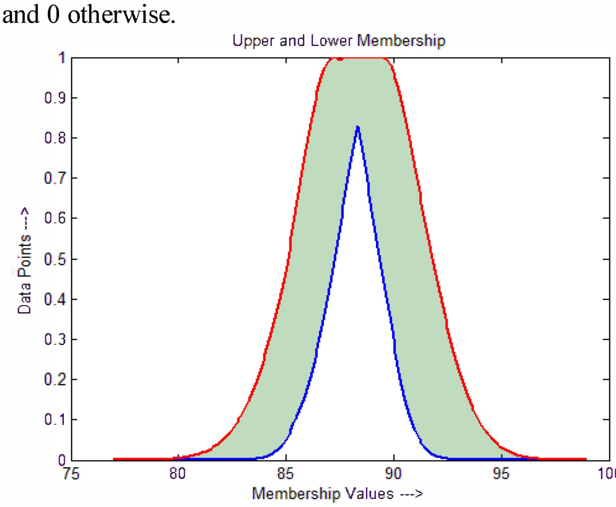

Fig. 1: Upper and Lower Membership Function

To illustrate further; let us consider Q number of likely observations for each of the C number of classes considered for the experiment. Each such signal is expressed in the form of an $M \times N$ matrix that constructs a feature space consisting of M observations and N features corresponding to each observation. Now; as discussed earlier; LMF; UMF and FOU are constructed depending upon the primary membership value over Q sets; for each feature $F_i (1 \le i \le N)$; with an aim to classify an unknown test feature vector f.

Firstly; it is checked if any component of the feature vector $f$falls outside the region of F_i and if it is found to be existing beyond the range; extrapolation is used. Now all the components f_i $(1 \le i \le N)$; are projected to the FOU to determine the intersection of the respective components with LMF and UMF and thus find LMF_iandUMF_i. In the next step; for a particular class c fuzzy t-norm of all LMF_iandUMF_i is carried out which yields $LMF_{T,c}$and$UMF_{T,c}$. Finally; strength of class cR_c is calculated as,

$$R_c = (LMF_{T,c} + UMF_{T,c}) / 2 \qquad (8)$$

where $1 \le c \le C$. After calculating the strengths of all the classes the test vector is assigned to the class having maximum strength R_c.

III. EXPERIMENTAL SETUP

Following steps have been used for EEG signal processing.

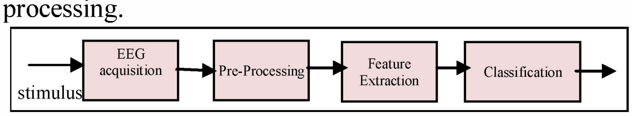

Fig. 2: Steps of Data Processing

A. EEG Data Acquisition

EEG data has been acquired from 7 healthy subjects who have not gone through any serious disease in recent past; out of them 4 were male and 3 were female and everyone was within the age group of 22-30. The purpose of the study was made clear to them before the experiment and a consent form was also signed them stating their willingness to take part in the experiment. All other safety and ethical issues were maintained according to the declaration of Helsinki of the year 1972 revised in 2000 [16].

As our objective is to understand the colour perception ability of human mind; therefore EEG data was acquired from Frontal; Temporal; Occipital and Parietal area of the brain. 10 electrodes that were placed over the scalp is given as follows;

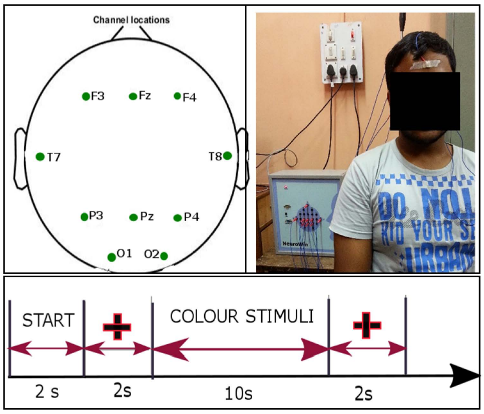

Fig. 3: Electrode Placement and Stimuli Timing Diagram

F3; F4; Fz; P3,Pz; P4; O1; O2; T7; T8. All the subjects were shown visual stimuli which consists of four different colours (Red; Yellow; Green; Blue) which appears randomly on the screen and stays for screen for10 seconds. A blank screen of 2 second appears between two successive colour stimuli. In each session each colour appears 20 times in the screen and 5 such sessions per subject were recorded for this experiment. 19 channel EEG amplifier ‘Neurowin’ made by NASAN was used for EEG data acquisition. Sampling rate of the amplifier is 256 Hz. Fig. 3 depicts the electrode placement and timing diagram of visual stimulus.

B. EEG Preprocessing

1) Spectral Filtering

Generally; EEG signal ranges from 0.1-70 Hz but here the power spectral density estimate of the raw EEG signal reveals that band power is dominant within the frequency range of 0.5-40 Hz. Fig. 4 illustrates the same. Acquired raw EEG signal is also contaminated with various artifacts like eye blink; muscular artifacts and artifacts due to moving of head. An elliptical band pass filter of order 10 which gives the sufficient roll off; has been employed to filter the signal between desired frequency range.

2) Spatial Filtering

Spatial filters are used to get a more localized signal corresponding to a single source. Common average referencing is a useful spatial filter which has been used here to eliminate the interference effect of signals of neighbour channels. Mean of all equally weighted channels is subtracted from each individual channel which eliminates the commonality but its temporal features are preserved.

3) Feature Extraction and Classification

Welch method has been used here for one sided power spectral density estimate. A hamming window of length 50 has been used and half of the window length is used as overlap section. The signal is divided into section of length of window. Current algorithm calculates 256 point discrete Fourier transform. Extracted features correspond to each electrode has been normalised in such way that it has zero mean and unity variance.

Feature space also has been cross validated before it is fed to train the classifier.

Interval type 2 fuzzy classifier is used to discriminate between different colours. Along with the IT2FS; results obtained from T1FS; SVM with RBF kernel and backpropagation through time neural network have been compared here. T1FS and IT2FS in both the cases Gaussian membership function has been used for simplicity. Classification accuracy; sensitivity and specificity are the three metrics used here for comparison of classifiers. In all the above cases OVA or one Vs all approach was undertaken to classify the data.

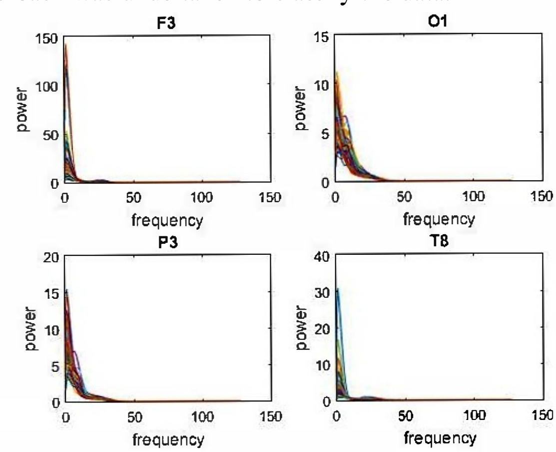

Fig. 4: Power Spectral Density of Raw EEG Signal

4) Performance Analysis

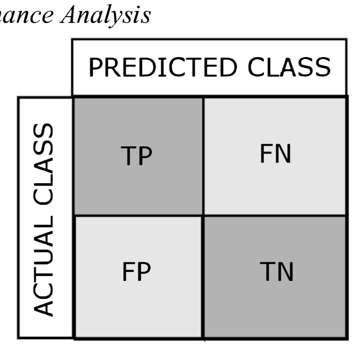

Fig. 5: Confusion Matrix

Performance of each classifier has been evaluated in terms of three metrics given as Classification accuracy (*CA*); Specificity (*SP*) and Sensitivity (*SN*). The above three terms have been calculated from confusion matrix. Confusion matrix is a 2x2 matrix with following fields; True positive (TP); True Negative (TN); False Positive (FP) and False Negative (FN). Following matrix illustrates the field of a typical confusion matrix,

TABLE 1: CLASSIFICATION RESULT

Color \ **Classifier**		**IT2FS**	**T1FS**	**SVM (RBF)**	**BPTT**
Red	CA%	85.26	78.49	83.2	75.26
	SP%	82.18	77.56	83.29	74.92
	SN%	76.24	74.66	79.21	70.98
Yellow	CA%	76.4	74.52	76.1	69.25
	SP%	74.24	72.89	77.23	66.58
	SN%	74.66	69.96	74.91	65.47
Green	CA%	78.32	75.93	76.26	72.66
	SP%	77.95	72.62	76.10	69.63
	SN%	76.85	69.59	75.98	66.52
Blue	CA%	80.2	74.42	79.68	72.16
	SP%	79.65	72.11	78.44	68.21
	SN%	77.32	69.24	78.26	67.39

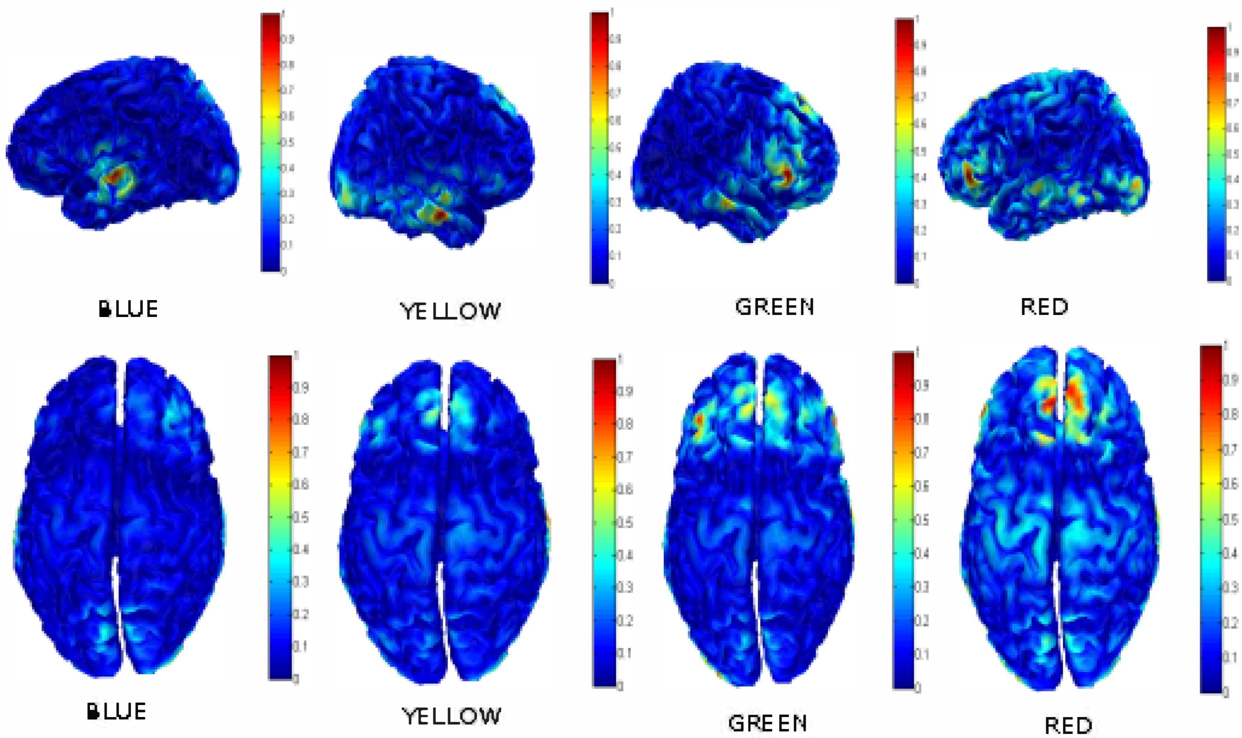

Fig. 6: Brain Activation Map

The above metrics can be computed from given formulae;

$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN) \quad (9)$$

$$\text{Sensiivity}=TP/(TP+FN) \quad (10)$$

$$\text{Specificity}=TN/(FP+TN) \quad (11)$$

IV. RESULTS AND DISCUSSION

This section provides a detailed interpretation of the results obtained from different experiments conducted for the present work.

The result section discusses the performance of different classifier and it also finds out the activation areas of different brain lobes subjected to different color stimuli; it enlightens the impact of different color to the marketing product and also to the neuro-marketing strategy. Here all computation has been carried out using Intel i7 processor and with the aid of MATLAB software.

It is evident from result that red color has been identified most accurately from rest of the colors. It has got 85.26% classification accuracy. Blue and Green has got average classification accuracy of 80.2% and 78.32% respectively. The yellow color has got the lowest average accuracy of 76.4%. It is also found that in each case IT2FS classifier performed better than all other classifiers used here; such as T1FS; SVM with "radial basis function" kernel and BPTT neural network. Table I is given for results.

As discussed earlier different colors are associated with different emotion and mental arousal state. A comparative figure of brain activation area has been shown in Fig. 6.

C. Statistical Validation and Friedman Test

Friedman Test [17] is a non-parametric test which has been carried out here to compare the classifier performance and to statistically validate them. The test has been carried out for 7 subjects; i.e. N=7 and 4 algorithms are considered for comparison; therefore k=4.

TABLE 2: STATISTICAL ANALYSIS OF FRIEDMAN TEST

Friedman Test Result	Algorithms			
	IT2FS	T1FS	SVM(RBF)	BPTT NN
Mean Accuracy	80.04	75.84	78.81	72.33
Rank	1	3	2	4

Number of degrees of freedom F is calculated as k-1; which becomes 3 in this case. The governing equation for Friedman test is given bellow,

$$\chi_F^2 = \frac{12N}{k(k+1)}\left[\sum_{j=1}^{k} R_j^2 - \frac{k(k+1)^2}{4}\right] \qquad (12)$$

Friedman statistics is distributed by χ_F^2 having (k-1) or F degrees of freedom. Algorithm employs null hypothesis and assumes the rank R_j is equal for all the classifiers and the null hypothesis is rejected if the computed value of χ_F^2 is greater than $\chi_{3,0.95}^2$. Now the computed value of χ_F^2 is 21 which is greater than the listed value of 7.81; clearly $\chi_F^2 > \chi_{3,0.95}^2$; therefore the null hypothesis is rejected and all the classifier do not act same. They can be ranked according to the mean classification accuracy obtained in Table I. The Table II determines the rank of the applied classifiers.

V. CONCLUSION

Neuro-marketing strategy uses the cognitive bias of consumers' mind to influence their decision making process. There are several factors which could influence the cognitive bias and visual perception of color is one of them. From product development to web design; color plays an important role to increase the conversion rate and to increase consumer number.

A paper published by Hedwig VonRestorff suggests that color also plays vital role in recalling any particular item.Now to judge the cognitive state of human brain influenced by any color; this paper employs non-invasive EEG and power spectral density estimate of different brain regions have been carried out; brain activation maps show that red color is the most responsible for mental arousal and cognitive activity followed by green; blue and yellow color.

To discriminate visual perception of different colors; an Interval Type 2 fuzzy space classifier has been proposed; which takes care of the stochastic nature of EEG. Proposed classifier also outperforms the contender classifiers by a large margin. It has got highest accuracy of 85.26% in case of red.

This paper mainly addresses two major issues; first one is the effect of color in neuro-marketing strategy and second is cognitive bias of human mind. These two ideas are vast and encompass many more things than what is discussed over here; in future a huge opportunity lies in this domain of research.

REFERENCES

[1] A. F. Da Rocha; F. T. Rocha and L. H. Arruda; "A Neuromarketing Study of Consumer Satisfaction," Available SSRN 2321787; 2013.

[2] N. Lee; A. J. Broderick and L. Chamberlain; "What is 'neuromarketing'? A discussion and agenda for future research," Int. J. Psychophysiol.; vol. 63; no. 2; pp. 199–204; 2007.

[3] G. Vecchiato; L. Astolfi; F. De Vico Fallani; J. Toppi; F. Aloise; F. Bez; D. Wei; W. Kong; J. Dai and F. Cincotti; "On the use of EEG or MEG brain imaging tools in neuromarketing research," Comput. Intell. Neurosci.; vol. 2011; p. 3; 2011.

[4] A. Mazumder; A. Rakshit and D. N. Tibarewala; "A back-propagation through time based recurrent neural network approach for classification of cognitive EEG states," in Engineering and Technology (ICETECH); 2015 IEEE International Conference on; 2015; pp. 1–5.

[5] L. L. Chao and A. Martin; "Cortical regions associated with perceiving; naming and knowing about colors," Cogn. Neurosci. J.; vol. 11; no. 1; pp. 25–35; 1999.

[6] H. Wang and N. Zhang; "The analysis on vehicle color evoked eeg based on ERP method," in Bioinformatics and Biomedical Engineering (iCBBE); 2010 4th International Conference on; 2010; pp. 1–3.

[7] M. M. Rana; M. Islam; D. Nath; S. Wahed; P. C. Biswas and M. Ahmad; "Inherent features extraction for different colors stimulation of EEG signal," in Electrical Engineering and Information Communication Technology (ICEEICT); 2015 International Conference on; 2015; pp. 1–6.

[8] K. Phillips; O. Fosu and I. Jouny; "Separation and classification of EEG responses to color stimuli," in Biomedical Engineering Conference (NEBEC); 2015 41st Annual Northeast; 2015; pp. 1–2.

[9] D. Zakzewski; I. Jouny and Y. C. Yu; "Statistical features of EEG responses to color stimuli," in 2014 40th Annual Northeast Bioengineering Conference (NEBEC); 2014.

[10] H. Zhang and Z. Tang; "To judge what color the subject watched by color effect on brain activity," IJCSNS Int. J. Comput. Sci. Netw. Secur.; vol. 11; no. 2; pp. 80–83; 2011.

[11] S. M. McClure; J. Li; D. Tomlin; K. S. Cypert; L. M. Montague and P. R. Montague; "Neural correlates of behavioral preference for culturally familiar drinks," Neuron; vol. 44; no. 2; pp. 379–387; 2004.

[12] S. Hanslmayr; B. Pastötter; K.-H. Bäuml; S. Gruber; M. Wimber and W. Klimesch; "The electrophysiological dynamics of interference during the Stroop task," Cogn. Neurosci. J.; vol. 20; no. 2; pp. 215–225; 2008.

[13] A. Konar; Computational intelligence: principles; techniques and applications. Springer Science & Business Media; 2006.

[14] P. D. Welch; "The use of fast Fourier transform for the estimation of power spectra: A method based on time averaging over short; modified periodograms," IEEE Trans. audio Electroacoust.; vol. 15; no. 2; pp. 70–73; 1967.

[15] S. Datta; A. Khasnobish; A. Konar and D. N. Tibarewala; "Cognitive Activity Classification from EEG Signals with an Interval Type-2 Fuzzy System," in Advancements of Medical Electronics; Springer; 2015; pp. 235–247.

[16] J. Mellin-Olsen; S. Staender; D. K. Whitaker and A. F. Smith; "The Helsinki declaration on patient safety in anaesthesiology," Eur. J. Anaesthesiol.; vol. 27; no. 7; pp. 592–597; 2010.

[17] E. B. Page; "Ordered hypotheses for multiple treatments: a significance test for linear ranks," J. Am. Stat. Assoc.; vol. 58; no. 301; pp. 216–230; 1963.