A neuroscientific approach to choice modeling: Electroencephalogram (EEG) and user preferences

Conference Paper · June 2012

DOI: 10.1109/IJCNN.2012.6252561

6 authors, including:

Rami N. Khushaba
The University of Sydney
83 PUBLICATIONS **2,210** CITATIONS

Sarath Kodagoda
University of Technology Sydney
171 PUBLICATIONS **2,814** CITATIONS

Luke Greenacre
Monash University (Australia)
38 PUBLICATIONS **357** CITATIONS

Jordan Louviere
University of South Australia
278 PUBLICATIONS **30,747** CITATIONS

A Neuroscientific Approach to Choice Modeling: Electroencephalogram (EEG) and User Preferences

Rami N. Khushaba
and Sarath Kodagoda
Centre of Intelligent Mechatronic Systems (CIMS)
Faculty of Engineering and Information Technology
University of Technology, Sydney (UTS)
Email: Rami.khushaba, sarath.kodagoda@uts.edu.au

Luke Greenacre, Sandra Burke
and Jordan Louviere
Centre of Study of Choice (CenSoC)
University of Technology, Sydney (UTS)
Email: luke.greenacre@gmail.com
Sandra.Burke, Jordan.Louviere@uts.edu.au

***Abstract*—Discrete choice experiments have traditionally focused on improving the prediction of static choices that are measured through external reflection and surveys. It is argued that considering the underlying processes of decision making across a variety of contexts may further progress decision research. As a pilot study in this field, this paper explores the dynamic nature of decision-making by examining the associated brain activity, Electroencephalogram (EEG), of people while undertaking choices designed to elicit their preferences. To facilitate such a study, the Tobii-Studio eye tracker system was utilized to capture the participants' choice based preferences when they were observing seventy two sets of objects. These choice sets were composed of three images offering potential personal computer backgrounds. Choice based preferences were identified by having the respondent click on their preferred one. In addition, the commercial Emotiv EPOC wireless EEG headset with 14 channels was utilized to capture the associated brain activity during the period of the experiments. Principal Component Analysis (PCA) was utilized to preprocess the EEG data before analyzing it with the Fast Fourier Transform (FFT) to observe the changes in the four principal frequency bands, theta (3 ? 7 Hz), alpha (8 - 12 Hz), beta (13 ? 30 Hz), and gamma (30 ? 40 Hz). A mutual information (MI) measure was then used to study left-to-right hemisphere differences as well as front-to-back difference. Six participants were recruited to perform the experiments with the average results showing clear and significant change in the spectral activity in the frontal (F3 and F4), parietal (P7 and P8) and occipital (O1 and O2) areas when while the participants were indicating their preferences. The results show that the highest rate of information exchange between the left and right hemispheres in the theta bands occurred in the frontal regions with alpha dominating in the frontal and occipital regions while beta dominating mainly in the occipital and temporal regions.**

I. Introduction

Choice models are sophisticated research techniques that involve constructing models that replicate how consumers actually behave [1], [2]. Discrete choice experiments are used to collect aggregate choice frequencies to model choices and to infer the relative impact of each attribute on choice [3], [4]. Thus, choice modeling is used to identify the drivers of choice and the relative impact of each of those drivers; and to determine what specifically affects choices (features, attributes, qualities etc). Choice modeling has been shown to be highly predictive in terms of choice outcomes and far more predictive than other survey/intention based methods. While choice modeling techniques have expanded and continue to expand the frontiers of our understanding of human choice, the techniques are by design outcome based. They focus on revealed preferences and determine the statistical models behind choice by analyzing repeated observed choices [5]. In discrete choice experiments, participants are required to make repeated choices amongst alternative profiles in which the attribute levels have been systematically varied. For example, participants may make choices among alternative milk products with the attributes of price and fat content varied over the respective levels of 1 and 1.50, and skim and regular. Based on the choices made across the experimentally varied alternatives, the attribute importance weights and trade-offs made by decision makers can be statistically ascertained. Thus, choice models are extremely powerful tools for predicting human choice in given contexts.

It is recognized that decision research can be further progressed by understanding the human processes underlying decision outcomes that are not easily articulated or controlled [5], [6]. It can be argued that a number of non-articulated factors, including such things as psychological state and emotions, are likely playing substantial roles in some decision making contexts [7]. The literature on emotion recognition reveals that emotions can be extracted from physiological signals like heart rate, skin conductance, and brain signals i.e., the Electroencephalogram (EEG) along the well-known EEG frequency bands such as theta ($3-7$ Hz), alpha ($8-12$ Hz), beta ($13-30$ Hz), and gamma ($30-40$ Hz) [8], [9], [10]. On the other hand, the literature on psychology reveals that human emotions are related to their preferences [7], [11]. Since the language of preferences seems intuitive, it is the one typically used in decision theory. As a consequence of this gap in the literature, several studies attempted to integrate ideas from the fields of psychology, neuroscience, and economics in an effort to specify more accurate models of choice. Astoli *et al.* [12] demonstrated that the cortical brain activity elicited in the frontal and parietal areas when viewing TV commercials that were remembered by subjects were markedly different from the brain activity in the same areas elicited during the observation of TV commercials that had been viewed but since forgotten. A similar finding was also reported by Custodio [13] when he noted that advertisements that received better score (on the survey instrument employed) had more emotional processing neural circuits activated than the advertisements that received worse scores; and that Alpha band activity was observed in the occipital regions and theta activity in the midline and frontal cortical regions for the better scoring advertisement. The use of EEG technology was also promoted in the work of Bourdaud *et al.* [14] for the study of the correlates of the brain electrical activity, particularly those related to the exploratory behavior. It was shown that the bilateral frontal and parietal areas were the most discriminant.

Only a limited number of studies gathering the two streams of emotions and preferences have been conducted as this is a newly emerging area. As seen, many of the available studies focus on the brain activities elicited during the observation of TV commercials [12], [13] and not on an actual preferences. To begin linking these two streams together, the changes in the power spectrum of well-known EEG frequency bands i.e., θ, α, β, and γ needs to be examined with regard to the changes in preferences during decision making process. Thus, as a first step in our pilot study toward understanding the role of EEG and emotions in decision making, we present in this paper a preliminary study on the dynamics of EEG during the elicitation of a persons' preferences for a product.

The structure of this paper is as follows: Section II describes the data collection procedure including both of the eye-tracker and the Emotiv EPOC EEG headset based brain activity experiments. Section III describes the preprocessing and feature extraction steps, and the use of mutual information to identify associations between preferences and EEG. Section IV presents the experimental results and finally, conclusions are provided in Section V.

II. Data Collection

In the data collection process two sets of equipment were utilized, the first was an eye-tracker system and the second included a brain signals monitoring system as described below.

A. Extracting and analyzing Eye-tracking Data

The experiments were conducted using the Tobii X60 eye tracker (www.tobii.com); a stand-alone eye tracking unit designed for eye tracking studies of real-world flat surfaces or scenes such as physical objects, projections and video screens. This eye tracker has an accuracy of 0.5 degrees which averages to 15 pixels of error with a drift factor of less than 0.3 degrees and has a sampling rate of 60 Hz. Tobii Studio 1.3 was employed as it offers an easy-to-use solution to extract and analyze eye tracking data. The package facilitates efficient multi-person and multi-trial studies in the fields of experimental psychology, commercial usability, advertising, low-vision studies and more. To facilitate meaningful studies, the software combines the collection and analysis of eye gaze data with numerous other data sources, including keystrokes, external devices, video recordings and web browser activities. The complete eye tracker system is shown in Fig.1. The X60 monitor mount accessory provided fixed geometry for the eye tracker and screen, allowing the setup to be adjusted for each subject without impacting data quality. Thus, the eye tracking system was calibrated on each subject to provide the best results.

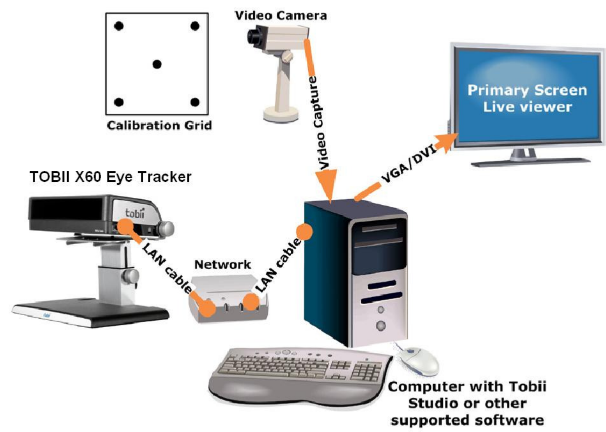


Fig. 1. The eye tracker system utilized in this paper

A sequence of choice sets were developed. these were made of a combination of three objects that varied in both color and pattern. Three colors (blue, green and yellow) and three patterns (bamboo, messy and none) were used to create the objects as shown in Fig.2. This yielded 72 possible choice set combinations of three objects when order was controlled for. The 72 choice sets were shown on the screen, one set at a time. Each of the sets consisted of a black screen with the 3 objects (or images) aligned on the left, middle, and right positions as per the example shown in Fig.3. Each of these alternative images represented one possible candidate background image for a desktop computer that the user was asked to select. The specific task asked the participant to click the image the he/she felt that they liked the most for their personal computers' background, while the Tobii eye tracker system monitored their eye gaze.

In addition to recording eye gaze data, the Tobii eye tracker also makes an audio/video recording of the study session. The eye gaze data included timestamps, gaze positions, eye positions, pupil size, and validity codes. In this study, we use gaze positions to determine where the participants were looking, given the physical dimensions of each of the choice objects. Additionally, the available timestamps were utilized to align the eye tracker data with the EEG data.

B. Emotiv EPOC-based EEG Data Collection

The EPOC is a low cost Human-Computer Interface (HCI) comprised of 14 channels of EEG data and a gyroscope measures for 2 dimensional controls (www.emotiv.com). The electrodes are located at the positions AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4 according to the International 1020 system as shown in Fig.4 and Fig.5 [15]. Two electrodes located just above the subjects ears

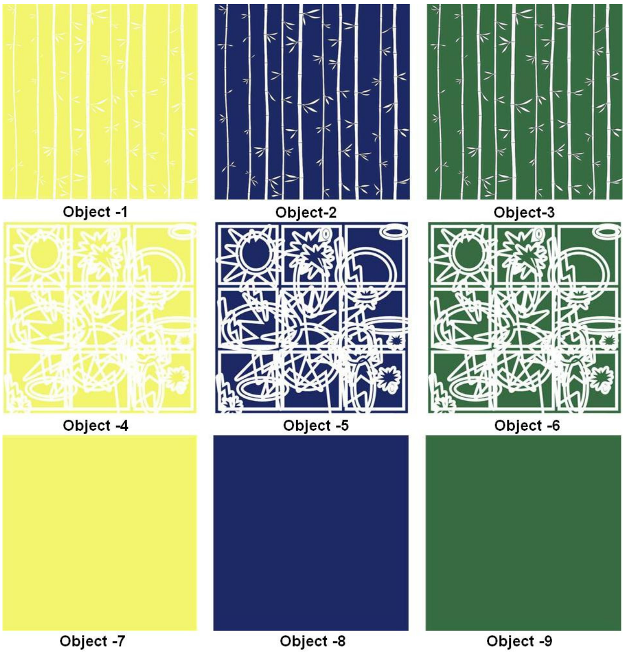


Fig. 2. Illustration of the developed choice set objects/images which vary color and pattern

Fig. 3. An example of choice one set with three images composed of different color and pattern combinations.

(CMS/DRL) are used as references (one for the left and the other for the right hemisphere of the head). The EPOC internally samples at a frequency of 2048 Hz which then gets down-sampled to 128 Hz sampling frequency per channel, with the data then sent to the computer via Bluetooth. It utilizes a proprietary USB dongle to communicate using the 2.4GHz band. Prior to use, all felt pads on top of the sensors have to be moisturized with a saline solution. The Emotiv Software Development Kit (SDK) provides a packet count functionality to ensure no data is lost, a writable marker trace to ease single trial segmentation tasks, and real-time sensor contact to ensure quality measurements [16].

Both of the EPOC and eye tracker were made to start at the same time by means of a synchronization software written in Visual Basic to start both of these modules together. After the data collection step, all of the collected data was transferred to Matlab for further processing as will be described in the next sections.

C. Subjects

Six participants, three females and three males, aged between 23 - 36 were recruited for this study. All participants

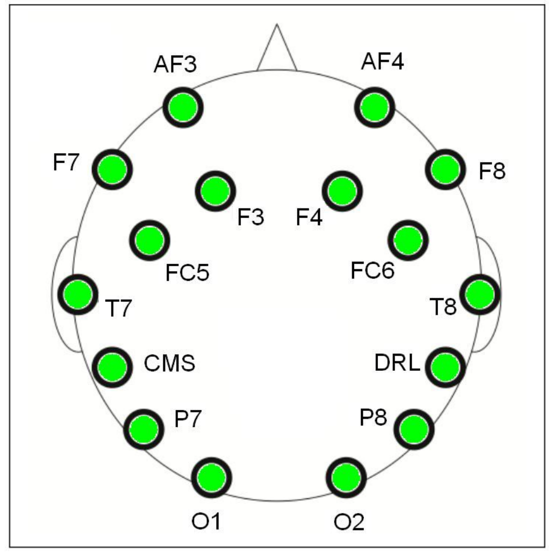


Fig. 4. Emotiv EPOCs electrode positioning

Fig. 5. Emotiv EPOCs headset on a subject

were right-handed with only two subjects employing medical glasses. The experimental procedure was approved by the human research ethics committee in the University. All experiments involved non-invasive EEG monitoring using the EPOC headset while the subjects were seated in front of a personal computer on which the eye tracker was running. The eye tracker was re-calibrated on each subject to provide accurate measurements for the participant's gaze during the experiments. The whole experiment lasted for less than 5 mins for each participant as they only had to click their preferred image from each set of three objects/images for the full sequence of 72 sets.

III. DATA ANALYSIS

The proposed data analysis procedure for measuring the correlations between different brain activities at different channel locations is shown in Fig.6. Analytical modules are detailed below.

A. Principal Component Analysis (PCA)

Principal component analysis (PCA) is classical technique in statistical analysis the purpose of which is to, given a set of multivariate measurements, find a smaller set of variables with less redundancy that would give as good a representation as the original variable list. [18]. PCA is related to independent

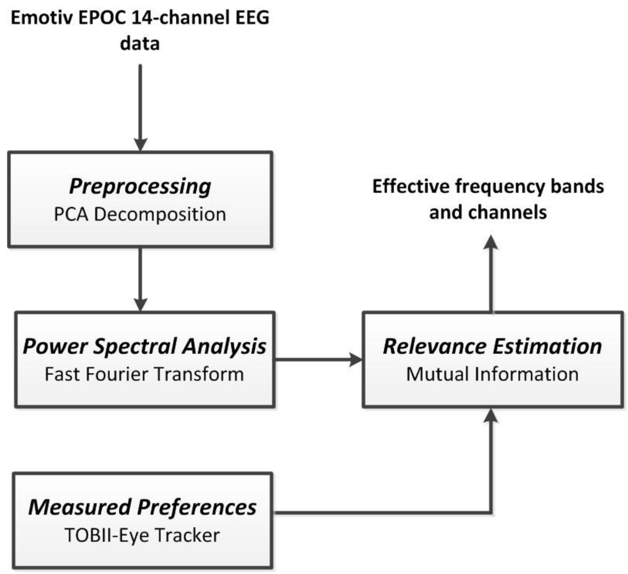


Fig. 6. Flowchart of data processing procedures of the proposed system

component analysis (ICA). In PCA the redundancy is measured by correlations between data elements, while in ICA the concept of independence is used; further, in ICA the reduction of the number of variables is given less emphasis. In this case PCA was used due to compatibility with the literature in the decision making field. Given M observations of an N length random vector $\overline{\mathbf{x}}$, the PCA transform starts first by subtracting the mean from the vector [18], [19]

$$\overline{\mathbf{x}} \leftarrow \overline{\mathbf{x}} - E[\overline{\mathbf{x}}] \tag{1}$$

The $N \times N$ covariance matrix C_x is computed

$$C_x = E[\overline{\mathbf{x}}\overline{\mathbf{x}}'] \tag{2}$$

The principal components $\overline{\mathbf{z}}$ of $\overline{\mathbf{x}}$ are given in terms of the unit-length eigenvectors ($\overline{\mathbf{e}}_1 ... \overline{\mathbf{e}}_N$), of C_x

$$\overline{\mathbf{z}} = W\overline{\mathbf{x}} \tag{3}$$

Where the projection matrix W contains the eigenvectors ($\overline{\mathbf{e}}_1 ... \overline{\mathbf{e}}_N$) [20]. In the proposed system, only the eigenvectors corresponding to almost $\geq 98\%$ of the total variance are kept while all other eigenvectors are simply removed. In such a case, the common noise components are removed and only the important signal parts are kept along all of the channels.

B. Power Spectral Analysis

Analysis of changes in spectral power and phase can characterize the perturbations in the oscillatory dynamics of ongoing EEG [21]. After cleaning the EEG data from the noise components and retrieving the clean EEG signals the Fast Fourier Transform (FFT) was then used to calculate the spectral power in the well-known EEG rhythms of θ, α, β, and γ with a maximum frequency of 64 Hz as the signals were sampled at 128 Hz. It should be noted here that each participant spent different amount of time looking at each of the 72 sets of objects. In such a case, one can analyze the records of EEG that corresponds to the periods of decision making for each of the 72 choice sets. However, the windowed EEG portions were almost always longer than 0.5 sec which in turn allowed accurate estimation of the power spectrum after padding with extra zeros resulting in power-spectrum density estimation with a frequency resolution near 1 Hz. Denoting $P[k]$ as the phase-excluded power spectrum, the extracted features from the θ, α, β, and γ bands are given as shown below

$$P[\theta] = \left| \frac{\sum_{k=3}^{7} P[k]^2 - \sum_{k=1}^{64} P[k]^2}{\sum_{k=1}^{64} P[k]^2} \right| \tag{4}$$

$$P[\alpha] = \left| \frac{\sum_{k=8}^{12} P[k]^2 - \sum_{k=1}^{64} P[k]^2}{\sum_{k=1}^{64} P[k]^2} \right| \tag{5}$$

$$P[\beta] = \left| \frac{\sum_{k=13}^{30} P[k]^2 - \sum_{k=1}^{64} P[k]^2}{\sum_{k=1}^{64} P[k]^2} \right| \tag{6}$$

$$P[\gamma] = \left| \frac{\sum_{k=31}^{40} P[k]^2 - \sum_{k=1}^{64} P[k]^2}{\sum_{k=1}^{64} P[k]^2} \right| \tag{7}$$

After extracting the aforementioned features a logarithmic transformation was applied since the power of the EEG rhythms tend to change more linearly in the logarithmic scale than in the normal scale [21].

C. Preference Estimation

Given the huge amount of information provided by the Tobii studio 1.3 software, one can analyze a large set of parameters describing the underlying choice experiment. In this paper, we analyzed the decision made regarding each of the colors and patterns individually and combined into a color/pattern interaction. Thus the specific choice objects are not the focus of this analysis, as they are interesting only in that they provide us access to the underlying features of participants' preferences. Generally, all participants showed a tendency to prefer either a certain color or pattern more than the possible combinations of colors and patterns. Thus, the decisions were built upon the colors and patterns that the participants selected the most desirable. An example of one participant's preferences are shown in Table.I, where this data is obtained by counting the repeated choices. It can be seen that in total there were 72 choices observed in the frequencies (23+19+12+12+6 =72) reflecting the 72 choice sets in the experiment design, with a clear tendency for this subject to select anything associated with a blue color. . This can be seen in that the blue color choice frequency is 23+19+12 =54 out of 72 sets. Green is chosen only 18 times, and yellow was not chosen at all. This participant also demonstrates the low preferences for a specific pattern with bamboo selected 23 times, messy 31 times, and none 18 times. Having capture the preferences of the participants, the next task was to look at the different brain activities and channel locations and infer where the areas of the brain were that showed a significant change in terms of the EEG power spectrum while making their choices. A class label for each participants preferences was constructed for each of the colors and patterns as follows: for a blue class label, the class variable is filled with 1's upon selecting either object 2, or 5, or 8 (See Figure 2) while populating the class label with 0's upon selecting all other objects. The yellow class label is populated with 1's upon selecting either object 3, or 6, or 9 while populating the class label with 0's upon selecting all other objects, and so on for the rest of the colors and patterns.

Thus, the analysis now simplifies to computing the mutual information between the estimated EEG power spectrum from all of the channels with the estimated class label which in turn represents the problem as a binary classification problem. In such a case, one can monitor the changes in EEG more accurately with each of the selected colors and patterns individually or combined and accurately identify the areas of the brain being activated.

TABLE I
AN EXAMPLE OF THE ESTIMATED CHOICE FREQUENCIES FROM TOBII EYE TRACKER SOFTWARE FOR ONE SUBJECT.

Object	Choice Frequencies	Color	Pattern
1	0	yellow	bamboo
2	23	blue	bamboo
3	0	green	bamboo
4	0	yellow	messy
5	19	blue	messy
6	12	green	messy
7	0	yellow	none
8	12	blue	none
9	6	green	none

D. Mutual Information-based Relevance Estimation

In information theory, the concept of mutual information (MI) is defined as the reduction of uncertainty about a random variable due to the knowledge of another random variable [22], [23]. The MI between two random variables X and Y, denoted as $I(X;Y)$, measures the amount of information in X that can be predicted when Y is known and is given as

$$I(X;Y) = \sum_{y\in Y}\sum_{x\in X} p(x,y)\log\frac{p(x,y)}{p(x)p(y)} \tag{8}$$

where $p(x,y)$ is the joint probability distribution function of X and Y, and $p(x)$ and $p(y)$ are the marginal probability distribution functions of X and Y respectively. Shannon entropy, which is a measure of uncertainty of random variables, is usually used to represent mutual information according to the following formula

$$\begin{aligned} I(X;Y) &= H(X) - H(X|Y) \\ &= H(Y) - H(Y|X) \\ &= H(X) + H(Y) - H(X,Y) \end{aligned} \tag{9}$$

where $H(X)$ and $H(Y)$ are the entropy of X and Y respectively, $H(X,Y)$ their joint entropy, and $H(X|Y)$ and $H(Y|X)$ the conditional entropies of X given Y and of Y given X, respectively. In a learning task, X and Y can be any two features, i.e., f_1 and f_2, and $I(f_1;f_2)$ is used to reflect the amount of information *Redundancy* between the two features. When two features highly depend on each other, the respective class-discriminative power would not change much if one of them was removed. Alternatively, either f_1 or f_2 could be replaced by the class label C and $I(C;f_1)$ or $I(C;f_2)$ is used as a measure of *Relevance*, i.e., how relevant f_1 or f_2 is to the problem at hand that is characterized by the decisions in the class label. In this paper, the concept of normalized mutual information, given as $\frac{I(C;f_1)}{H(f_1)}$, between the extracted EEG power spectrum features in the well-known rhythms and the constructed class labels is utilized when studying the left-to-right hemisphere activities. In such a case, one can identify the most active portions or areas on the brain and then to identify the EEG bands that have the highest normalized mutual information with the choice frequencies. On the other hand, when studying the difference between the activities of the frontal vs occipital regions a subset of features was created combining the features from each two symmetric channels and computing their mutual information as a proposed symmetric measure of importance that is given as

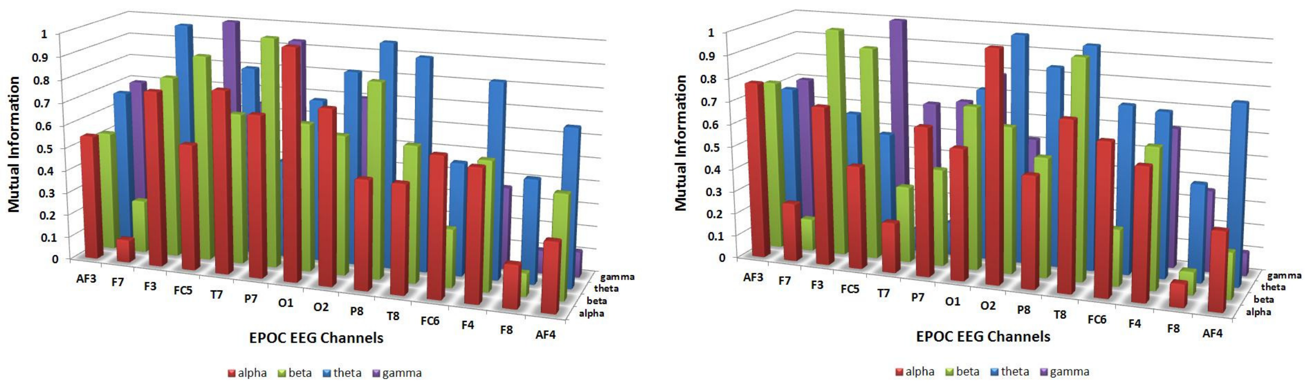
$$SMI = a_1 \times I(C;\{f_1,f_2\}) - a_2 \times \frac{I(f_1;f_2)}{H(f_1)+H(f_2)} \tag{10}$$

where a_1 and a_2 are factors controlling the importance of the two terms and were chosen empirically as 1.25 and 0.75 respectively; $I(C;\{f_1,f_2\})$ is the mutual information between the two features f_1, f_2 and the class label C; and $I(f_1;f_2)$ is the mutual information between the two features.

IV. EXPERIMENT RESULTS

Given the extracted features from each participant's EEG data, the analysis attempted to identify which of the θ, α, β, and γ components of the EEG exhibited the highest mutual information with the class label that reflected the preferences. In order to accomplish this task, each of the θ, α, β, and γ features were extracted separately from each of the channels and then the normalized mutual information $\frac{I(C;f_1)}{H(f_1)}$ was calculated for each of the features across each of the participants. The sample was then split so that those participants who have a strong preference for a color (and not a pattern) are separate from those who prefer a pattern (and not a color). The total mutual information was then plotted as shown in Fig.7.a across participants preferring certain colors only (regardless of patterns) and in Fig.7.b across participants preferring certain patterns only (regardless of colors).

These results indicate several important points; the first is that there is a clear asymmetry between the left and the right hemispheric activities in terms of the EEG bands power while the participants were making their decisions on their preferred objects (colors, patterns, and their combinations).



(a) Results for subjects preferring certain colors (regardless of patterns)

(b) Results for subjects preferring certain patterns (regardless of colors)

Fig. 7. A plot of the normalized mutual information between each of the four main EEG-bands power with the class label along each of the different EEG channels, accumulated across all subjects.

From the results in Fig.7.a one can clearly infer that across the participants who preferred certain colors only, regardless of patterns, all of the α, β, and γ had higher mutual information with the decisions made when extracted from the EEG activity collected from channel F3 (left hemisphere) than that in F4 (right hemisphere). At the same time, both α and β showed similar levels of mutual information values with the decision across F3 with higher θ activity than both α and β activities. In contrast, participants who tend to prefer a certain pattern (regardless of colors) exhibited higher discrepancy between α and β in terms of their mutual information and across F3 with θ showing less mutual information than both of the aforementioned activities. According to the literature, the frontal regions were reported as being very important for indicating preferences [13], [25]. However, there is no clear agreement on which channel, F3 or F4, and which bands from these channels, should be more related to the decision making process than the other, with some studies reporting that either F3 or F4 could be interchangeably more active across different participants [7].

The second important point inferred from these results is that across the total number of participants, the α band achieved its highest mutual information values with the decisions in the occipital regions (O1 when selecting colors and O2 when selecting patterns) as the participants were visually stimulated by the different colors and patterns and also in the frontal regions, which is also in line with findings from the literature [7], [13], [25]. On the other hand, and across all participants, β activity showed higher mutual information on the left hemisphere (F3, FC5 and P7) than that in the right hemisphere when selecting colors and in the left hemisphere (T8 $\gg$ T7) when selecting patterns. It is also very obvious that θ activity exhibited higher mutual information with the decision label in the left hemisphere (when colors were the preferences) as apposed to that exhibited by the same bands in the right hemisphere (when patterns were the preferences). Theta waves have long been associated with emotional processes, and it is believed to be correlated with emotions and limbic regions with some studies indicating higher θ activity when a preference is being made [13]. In contrast, γ activity appears to be more correlated with decisions across FC5 than all other channels, with γ also shown in the literature to correlate well with preferences [7]. All of the above results were also supported by running a two way analysis-of-variance test (ANOVA with significance level set to 0.05) with an achieved p value of $p \leq 0.01$ which indicated significant differences between the values of the EEG bands features from the left and right hemispheres.

In the next part of the analysis we focused on studying the front to back brain activations in order to identify which areas of the brain highly correlate with decision making regardless of the left and right hemisphere activities, as these might be correlated. In simple words, Fig.7 shows some very high activity along many of the EEG channels on the right or left hemisphere while in reality only F3, F4, O1, O2 and some other channels might be the most promising ones for this task according to the literature. In order to observe the active regions in the brain a 2-dimensional component map was generated using the well-known EEGLAB toolbox (using ICA to preprocess the data and then plotting the 2D component map), with an example given in Fig.8 for one participant.

It is clear that there is high activity on both F3 (component 13) and F4 (component 8) which in turn confirms the importance of the EEG data collected from these two channels. However, in order to validate the importance of the features extracted from these channels we employed the proposed SMI measure from Eq.10 while considering each of the θ, α, β, and γ bands separately.

To illustrate the results from this analysis, Fig.9 shows the importance of each pair of symmetric channels (for example F3 and F4 or AF3 and AF4 and so on), computing the mutual information between each two features extracted from the

EEG bands; Say, for example, the mutual information between α from F3 and α from F4, and the class label. In such a case, it can be seen that of all of the EEG bands features, channels F7-F8 always had the lowest mutual information with the class label. It is theorized that both of these channels are contaminated by the eyes blink activity, and subtracting $I(f_1; f_2)$ from the mutual information with the class label $I(C; \{f_1, f_2\})$ clearly reduced the mutual information with the decision making process. This is likely due to the high redundancy among these two channels (infected by blinks from both left and right eyes).

Another very important finding is that the highest exchange of information between symmetric channels across θ band occurred in the frontal regions (AF3-AF4, F7-F8, F3-F4, and FC5-FC6) with θ having higher mutual information with the preference than all other bands. In contrast, the mutual information of the same band was lower than that achieved by all other bands in all of the T7-T8, P7-P8 and O1-O2 channels. In contrast, the highest α was observed on O1-O2 followed by P7-P8 and then F3-F4 while the highest mutual information for β was achieved along T7-T8, O1-O2, P7-P8, and F3-F4. The γ band showed a lower information exchange rate with the decision making process across almost all symmetric channels except T7-T8 and O1-O2. Additionally, it can be noted here that the differences between α and β activities tend to get smaller on F3-F4, P7-P8 and O1-O2, another factor indicating the importance of the different EEG bands during the decision making process.

V. Conclusion

In this paper, we employed a commercially available wireless EEG headset to investigate the brain activities taking a

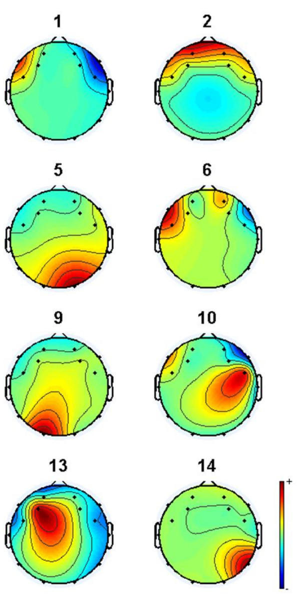


Fig. 8. 2D Component map of the 14 channels EEG data from Emotiv EPOC, plotted using the EEGLAB software.

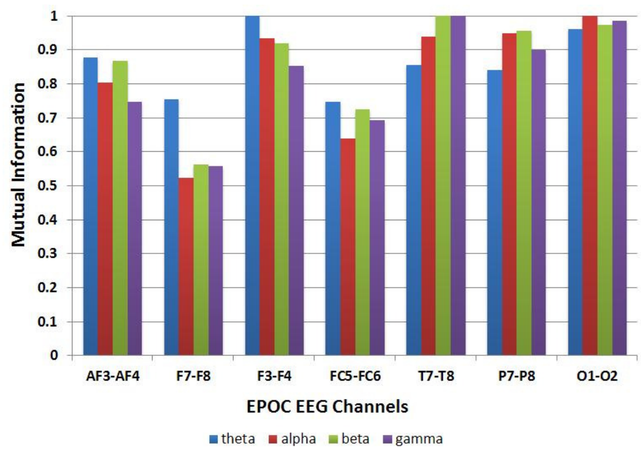


Fig. 9. Mutual information between symmetric EEG channels along each of the θ, α, β, and γ bands showing higher importance for α and β.

place during decision making. A set of images were shown to participants with them asked to select their preferred image by clicking on them. The frequencies of their choices were recorded by eye tracker software from Tobii X60 eye-tracker system. The eye tracker system was used in this case solely to map the transition between the choice sets and the actual choice of object. The actual eye tracking component of the data was captured but will be analyzed at a later time. When studying the EEG activities related to the choices made by participants several important points emerged. The first is that there is a clear asymmetry between the activities taking a place in the right and left hemispheres. Secondly, when considering individual relevance, the highest mutual information rates in the α band were shown in the occipital regions (O1 when selecting colors and O2 when selecting patterns). In addition, higher mutual information between preferences and α was found in F3 than in F4 (regardless of colors and patterns). Additionally, when selecting colors θ dominated in F3 while also dominating O2 when selecting patterns. In order to investigate the reported relevance of other bands further analysis was conducted to study the amount of information exchanged between symmetric EEG channels. This clearly showed a domination by θ in the frontal regions, α in frontal and occipital regions, and β in the temporal, parietal and occipital regions. Finally, more important than individual relevance of the EEG bands along individual channels was the observation that the variations of the choice objects played a significant role in electing different regions on the brain, i.e., what was selected (colors, patterns, or their combinations) had a contributing role in defining the most active regions on the brain during the decision making process. Our experiments continue as we are currently developing more complicated choice tasks to offer greater external validity and recruiting more participants for the greater generalization. Also, we are examining ways to incorporate the data from the eye tracking system regarding what the participant is looking at to provide further insight into how the visual cues in the experiment may play a part in neural responses.

REFERENCES

[1] J. Louviere, "'On the Identification of the Functional Form of the Utility Expression and its Relationship to Discrete Choice"', in *Applied Discrete-Choice Modelling*, D. A. Hensher and L. W. Johnson Eds. pp. 385-416, 1981.

[2] S. R. Chandukala, J. Kim, and T. Otter, "'Choice Models in Marketing: Economic Assumptions, Challenges and Trends"'. Now Publishers Inc. Hanover, MA, USA, 2008.

[3] D. G. Fiebig, M. Keane, J. Louviere, and N. Wasi, "'The generalised multinomial logit model: Accounting for scale and coefficient heterogeneity"', *Marketing Science*, vol. 29, no. 3, pp. 393-421, 2010.

[4] D. J. Street, L. Burgess, R. Viney and J. Louviere, "'Designing Discrete Choice Experiments for Health Care"', in *The Economics of Non-Market Goods and Resources*, Ian J. Bateman Eds., vol. 11, no. 1, pp. 47-72, 2008.

[5] P. W. Glimcher, C. F. Camerer, E. Fehr, and R. A. Poldrack, "Introduction: A Brief History of Neuroeconomics", In *Neuroeconomics: Decision Making and the Brain*, P. W. Glimcher, C. F. Camerer, E. Fehr, and R. A. Poldrack Eds., Academic Press, pp. 1-12, 2009.

[6] P. Politser, "'Neuroeconomics: A Guide to the New Science of Making Choices"', Oxford University Press, Inc., 2008.

[7] G. M. M. Aurup, "'User Preference Extraction from Bio-Signals: An Experimental Study"', Master Thesis, Department of Mechanical and Industrial Engineering, Concordia University, Montreal, Quebec, Canada, 2011.

[8] T. Partala, M. Jokiniemi, and V. Surakka, "'Pupillary Responses to Emotionally Provocative Stimuli"', In Proceedings of the 2000 Symposium on Eye Tracking Research and Applications, New York, NY, USA, ACM Press, pp. 123129, 2000.

[9] K. Takahashi, "'Remarks on Emotion Recognition from Bio-potential Signals"', In Proceedings of the 2nd International Conference on Autonomous Robots and Agents, pp. 186191, 2004.

[10] D. O. Bos, "'EEG-based Emotion Recognition, The Influence of Visual and Auditory Stimuli"', Internal Report, Department of Computer Science, University of Twente, 2006.

[11] D. Nie, X. W. Wang, L. C. Shi, and B. L. Lu, "'EEG-based Emotion Recognition during Watching Movies"', In Proceedings of the 5th International IEEE EMBS Conference on Neural Engineering Cancun, Mexico, April 27 - May 1, 2011.

[12] L. Astoli, F. D. V. Fallani, F. Cincotti, D. Mattia, L. Bianchi, M. G. Marciani, S. Salinari, A. Colosimo, A. Tocci, R. Soranzo, and F. Babiloni, "'Neural basis for brain responses to TV commercials: A high-resolution EEG study"', *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 6, pp. 522-531, 2008.

[13] P. F. Custdio, "'Use of EEG as a Neuroscientific Approach to Advertising Research"', Master Thesis, Instituto Superior Tcnico, Universidade Tecnica De Lisboa, 2010.

[14] N. Bourdaud, R. Chavarriaga, R. Galan, and J. Millan, Characterizing the EEG correlates of exploratory behavior, *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, vol. 27, no. 6, pp. 549-556, 2008.

[15] A. T. Campbell, T. Choudhury, S. Hu, H. Lu, M. K. Mukerjee, M. Rabbi, and R. D. S. Raizada, "'Neurophone: Brain-mobile phone interface using a wireless eeg headset"'. In Proceedings of The Second ACM SIGCOMM Workshop on Networking, Systems, and Applications on Mobile Handhelds (MobiHeld10). ACM New York, NY, USA, 2010.

[16] P. Bobrov, A. Frolov, C. Cantor, I. Fedulova, M. Bakhnyan, and A. Zhavoronkov, "'Brain-Computer Interface Based on Generation of Visual Images"', PLoS ONE, vol. 6, no. 6, e20674, pp. 1-12, 2011.

[17] E. W. Anderson, K. C. Potter, L. E. Matzen, J. F. Shepherd, G. A. Preston, and C. T. Silva, "'A User Study of Visualization Effectiveness Using EEG and Cognitive Load"', *Computer Graphics Forum*, vol. 30, no. 3, pp. 791-800, 2011.

[18] A. Hyvarinen, J. Karhunen, and E. Oja, "'Independent Component Analysis"', John Wiley and Sons Inc., 2001.

[19] J. E. Jackson, "'A User's Guide To Principal Components"', John-Wiley and Sons Inc., 1991.

[20] L. J. Hargrove, G. Li, K. B. Englehart, and B. S. Hudgins, "'Principal Components Analysis Preprocessing for Improved Classi?cation Accuracies in Pattern-Recognition-Based Myoelectric Control"', *IEEE Transactions on Biomedical Engineering*, vol. 56, no. 5, pp. 1407-1414, 2009.

[21] C. T. Lin, L. W. Ko, I. F. Chung, T. Y. Huang, Y. C. Chen, T. P. Jung, and S. F. Liang, "Adaptive EEG-based Alertness estimation system by using ICA-Based Fuzzy Neural Networks", *IEEE Transactions on Circuits and Systems-I*, vol. 53, no. 11, pp. 2469-2476, 2006.

[22] G. J. Klir, "Uncertainty and Information: Foundations of Generalized Information Theory", John Wiley and Sons, Inc, New Jersey, USA, 2006.

[23] T. M. Cover and J. A. Thomas, "Elements of information theory, second edition", John Wiley and Sons, Inc., New Jersey, USA, 2006.

[24] L. I. Aftanas and S. V. Pavlov, "Trait anxiety impact on posterior activation asymmetries at rest and during evoked negative emotions: EEG investigation.", *International Journal of Psychophysiology*, vol. 55, no. 1, pp. 85-94, 2005.

[25] R. Ohmea, D. Reykowska, D. Wiener, and A. Choromanska, "'Application of frontal EEG asymmetry to advertising research"', *Journal of Economic Psychology*, vol. 31, pp. 785793, 2010.