Choice Modeling and the Brain: A Study on the Electroencephalogram (EEG) of Preferences

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Abstract

Choice conjures the idea of a directed selection of a desirable action or object, motivated by internal likes and dislikes, or other such preferences. However, such internal processes are simply the domain of our human physiology. Understanding the physiological processes of decision making across a variety of contexts is a central aim in decision science as it has a great potential to further progress decision research. As a pilot study in this field, this paper explores the nature of decision making by examining the associated brain activity, Electroencephalogram (EEG), of people to understand how the brain responds while undertaking choices designed to elicit the subjects' 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, a brain computer interface (BCI) represented by 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 main principal frequency bands, delta (0.5 - 4 Hz), theta (4 - 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. Eighteen 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 while the participants were indicating their preferences. The results show that, when considering the amount of information exchange between the left and right hemispheres, theta bands exhibited minimal redundancy and maximum relevance to the task at hand when extracted from symmetric frontal, parietal, and occipital regions while alpha dominated in the frontal and parietal regions and beta dominating mainly in the occipital and temporal regions.

Keywords: Decision making, Electroencephalogram (EEG), User Preferences.

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1. Introduction

Choice modeling is used to identify the drivers of choice, the relative impact of each of those drivers, and to determine what specifically affects choices (features, attributes, qualities etc) (Chandukala et al. (2008)). Understanding and predicting the behavior of decision makers when choosing among discrete goods has been one of the most fruitful areas of applied research over the last thirty years (Louviere et al. (2000)). Discrete choice experiments are nowadays widely applied in many areas such as marketing, transport, applied economics, and environmental and health economics (Louviere (1981); Fiebig et al. (2010); Street et al. (2008)). In discrete choice experiments, participants are required to make repeated choices amongst alternative product 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 importance weights of the product attributes and the trade-offs made by decision makers among these attributes can be statistically ascertained. Thus, choice models are extremely powerful tools for predicting human choice in many contexts.

Decision research can be further progressed by understanding the human processes underlying decision outcomes that are not easily articulated or controlled (Glimcher et al. (2009); Politser (2008)). A number of nonarticulated factors, including psychological state and emotions, are likely playing substantial roles in some decision making contexts (Aurup (2011)). 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 delta ($0.5-4$ Hz), theta ($4-7$ Hz), alpha ($8-12$ Hz), beta ($13-30$ Hz), and gamma ($30-40$ Hz) (Partala et al. (2000); Takahashi (2004); Bos (2006)). In addition, the literature on psychology reveals that human emotions are related to their preferences (Aurup (2011); Nie et al. (2011)). Since the language of preferences seems intuitive, it is the one typically used in the theory of choice. Several studies attempt to integrate ideas from the fields of psychology, neuroscience, and economics in an effort to specify accurate models of choice. Astoli et al. (2008) 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 Custdio (2010) when he noted that advertisements that received better scores (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 is also promoted in the work of Bourdaud et al. (2008) 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 are the most discriminant. The importance of the left frontal region is also indicated in an experiment relating the smelling of favorite and dislikeable odors to EEG power change suggesting an association between theta wave and alpha wave from the frontal regions and preferences (Yokomatsu et al. (2007)). The importance of theta and alpha bands was also very recently recognized during a preference judgment task when choosing among only two colors simultaneously presented to the right and left hemifields (Kawasaki and Yamaguchi (2012)).

In general, only a limited number of studies gathering both neural (cognitive and emotion) data and preference data 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 (Astoli et al. (2008); Custdio (2010)) and not on the actual preferences. However, it is obvious that the choices people make everyday are affected by unconscious processes in the brain indicating the importance of this field of research. To begin linking these two streams together, the changes in the power spectrum of well-known EEG frequency bands i.e., δ, θ, α, β, and γ needs to be examined with regard to the changes in preferences during decision making. Thus, as a first step toward understanding the role of EEG as a measure of emotional and cognitive response in decision making, we present in this paper a preliminary study on the dynamics of EEG during the elicitation of a persons' preferences.

The structure of this paper is as follows: Section 2 describes the data collection procedure including a description of both the eye-tracker and Emotiv EPOC EEG headset based experiments. Section 3 describes the preprocessing and feature extraction steps, and the use of mutual information to identify associations between preferences and EEG. Section 4 presents the experimental results; and finally, conclusions are provided in Section 5.

2. Data Collection

The data collection process employed two sets of equipment; the first was an eye-tracker system and the second included a brain signals monitoring system as described below.

2.1. 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. 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 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. The complete system is shown in Fig.1 with a participant wearing the Emotiv EEG headset.

A sequence of choice sets were developed. These were made of a combination of three objects that varied in both color and pattern. The objects were possible screen backgrounds that the user could set for their personal computer. Three colors (blue, green and yellow) and three patterns (bamboo, messy and none) were used to create the objects as shown in Fig.2. The colors and patterns were varied using a full factorial design producing nine unique objects. A full factorial design was then used to vary the combinations of objects producing the choice sets. This design yielded 72 possible choice sets of three objects when order effect was compensated for. Each of the 72 choice sets was shown on the screen one at a time. The sets consisted of a black screen with the 3 objects (or background options) aligned on the left, middle, and right positions as per the example shown in Fig.3. The specific task asked the participant to click the image he/she felt that they liked the most for their personal computers' background. Throughout the task, Tobii eye tracker system monitored their eye gaze.

In addition to recording eye gaze data, the Tobii eye tracker also made 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, conditional upon the physical dimensions of each of the choice ob-

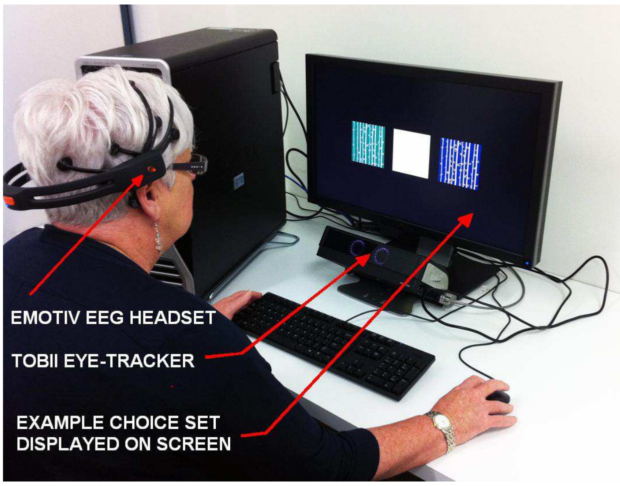


Figure 1: The experimental setup utilized in this paper

jects. Additionally, the available timestamps were utilized to align the eye tracker data with the EEG data.

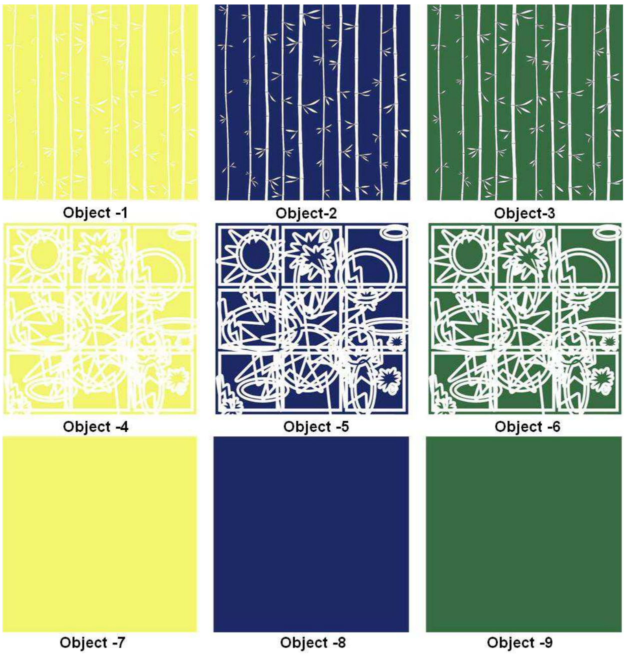


Figure 2: Illustration of the developed choice set objects/images which vary color and pattern

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

2.2. 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 measure for 2 dimensional control (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 $10-20$ system as shown in Fig.4 (Campbell et al. (2010)) and Fig.5. Two electrodes located just above the participants ears (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 a 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 moistened 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 display to ensure quality of measurements (Bobrov et al. (2011); Anderson et al. (2011)). The effectiveness of the EPOC headset as a real-time brain EEG scanner was demonstrated in a number of recent publications[1], including a demonstration at the well-known neural information processing conference [2].

Both of the EPOC and eye tracker were made to start at the same time by means of 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.

2.3. Subjects

Eighteen participants, including both males and females, were recruited for this study. All participants were aged between 25 and 65 years. Participants were a combination of right-and-left-handed with only two subjects employing medical glasses. The experimental procedure was approved by the human research ethics committee in the University. 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 choice set of three objects for the full sequence of 72 sets.

[1] A list of recent publications on Emotiv EPOC is available at http://www.emotiv.com/researchers/

[2] http://milab.imm.dtu.dk/nips2011demo

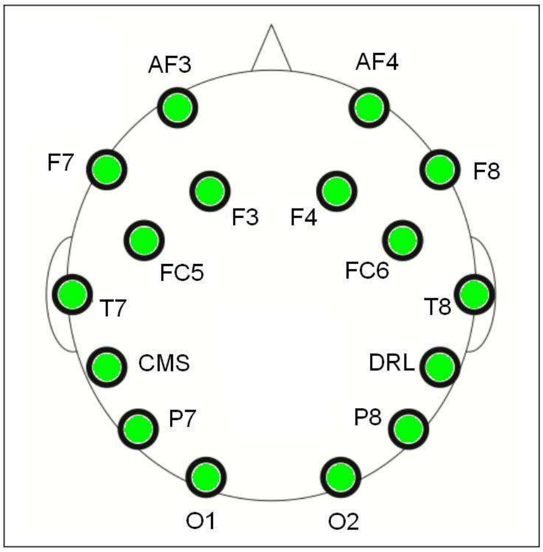


Figure 4: Emotiv EPOCs electrode positioning

Figure 5: Emotiv EPOCs headset on a subject

3. DATA ANALYSIS

The data analysis procedure for measuring the correlations between different brain activities at different channel locations with the choice task is shown in Fig.6. The processing starts with a baseline removal section due to the included DC offset in the EPOC EEG readings since the data is transmitted as an unsigned integer. The analytical procedures are detailed below.

3.1. Principal Component Analysis (PCA)

Principal component analysis (PCA) is a classical technique in statistical analysis the purpose of which is to, given a set of multivariate measurements,

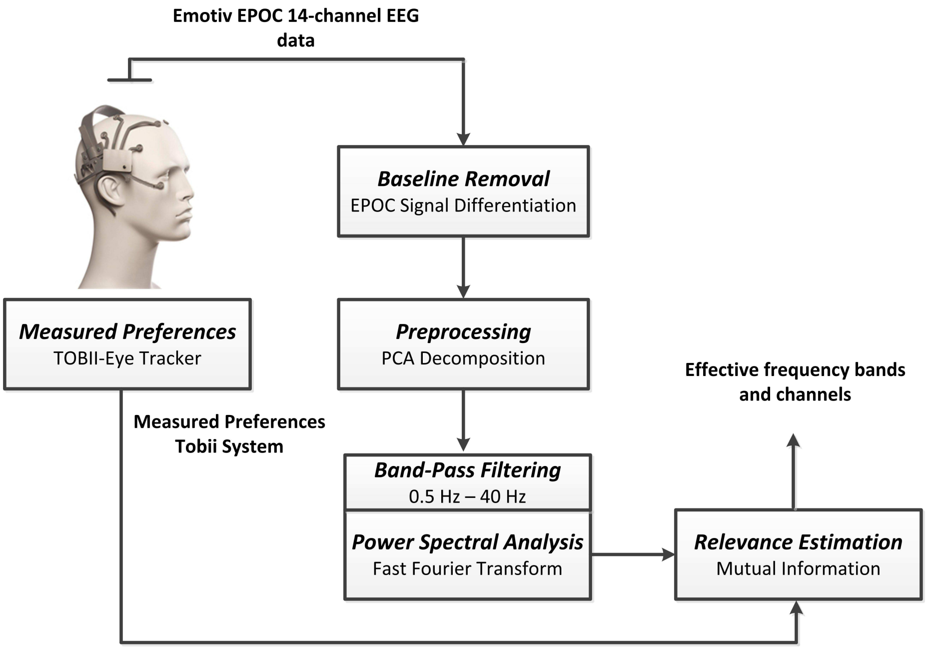


Figure 6: Flowchart of data processing procedures of the proposed system

find a smaller set of variables with less redundancy that would give as good a representation as the original variable list (Hyvarinen et al. (2001)). PCA is related to independent 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 $\overline{\mathbf{v}}$, the PCA transform starts first by subtracting the mean from the vector (Hyvarinen et al. (2001); Jackson (1991))

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

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

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

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 ($\overline{\mathbf{e}}_1 ... \overline{\mathbf{e}}_N$) (Hargrove et al. (2009)). In the proposed system, only the eigenvectors corresponding to $\geq 98\%$ of the total variance are kept while all other eigenvectors removed. In such a case, the common noise components are removed and only the important signal parts are kept along all of the channels.

3.2. Power Spectral Analysis

Analysis of changes in spectral power and phase can characterize the perturbations in the oscillatory dynamics of ongoing EEG (Lin et al. (2006)). After cleaning the EEG data from the noise components by the PCA step and retrieving the clean EEG signals, the collected EEG records were band-pass filtered between 0.5 Hz-to-40Hz to eliminate artifacts related to higher frequencies. The Fast Fourier Transform (FFT) was used to calculate the spectral power in the well-known EEG rhythms of δ, θ, α, β, and γ. It should be noted here that each participant spent different amount of time looking at each of the 72 sets of objects with the participants showing a decreasing linear trend in terms of the time spend on looking at each of the 72 choice sets as the participants became familiar with the choice objects toward the end of the experiment. The time spent by each participant was calculated from the data provided by the eye-tracker and the the total time across all participants was acquired by averaging the individuals time as shown in Fig.7.

Only the records of EEG data that corresponded to the periods of decision making for each of the 72 choice sets were analyzed. Information from the eye-tracker enabled us to remove the EEG time sections relating to the periods when the users were just clicking to indicate their preferences as both the eye-tracker and the Emotive EEG headset were synchronized to start together. The windowed EEG portions were always longer than 0.5 sec as the participants went through cognitive processing of the visual information to decide on their preferences. For each participant, the shortest EEG record length was observed and all other records were divided into equal portions of this length and then FFT was applied and the results were averaged for long records, i.e., functioning as the short-time Fourier transform. This in turn allowed accurate estimation of the power spectrum.

The EEG trace within a certain epoch is expressed as a function of frequency $X[k]$. Denoting $P[k]$ as the phase-excluded power spectrum (the

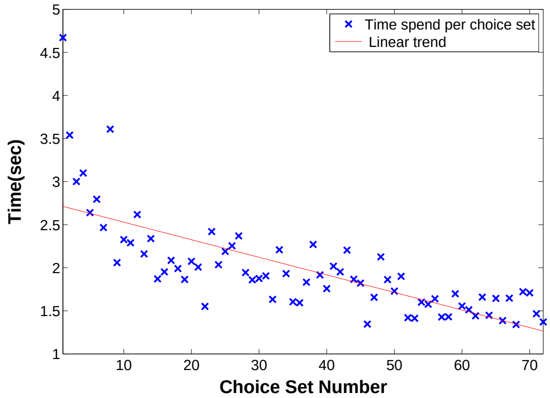


Figure 7: Average time spent by the participants to elicit their preferences on each of the utilized 72 choice sets.

result of a multiplication of $X[k]$ by its conjugate $X^*[k]$), and denoting W as the bandwidth of the spectrum, we define our features in terms of the power spectral moments. Spectral moments appear to be one of the promising approaches for EEG characterization and has been utilized in several EEG studies (Hjorth (1970); Saltzberga et al. (1985)). The m'th order spectral moment is given as

$$M_m = \sum_{k=0}^{W} k^m P[k] \tag{4}$$

According to Flusser et al. (2009), a robust implementation of spectral moments is achieved through proper normalization by low-order moments as they are more stable to noise and easier to calculate than higher order moments. On the other hand, higher order moments, like the second moment, was pointed out by Hjorth (1970) to be an important measure to describe the EEG activity. Thus, we employ in this paper the ratio of the second moment to the zero moment of each of the EEG frames and use these as the extracted features for each of the EEG bands of δ, θ, α, β, and γ and the total spectrum. These features are given as shown below.

$$Delta = \left| \frac{\sum_{k=0.5}^{4} k^2 P[k]}{\sum_{k=0.5}^{4} P[k]} \right| \tag{5}$$

$$Theta = \left| \frac{\sum_{k=4}^{7} k^2 P[k]}{\sum_{k=4}^{7} P[k]} \right| \tag{6}$$

$$Alpha = \left| \frac{\sum_{k=8}^{12} k^2 P[k]}{\sum_{k=8}^{12} P[k]} \right| \tag{7}$$

$$Beta = \left| \frac{\sum_{k=13}^{30} k^2 P[k]}{\sum_{k=13}^{30} P[k]} \right| \tag{8}$$

$$Gamma = \left| \frac{\sum_{k=30}^{40} k^2 P[k]}{\sum_{k=30}^{40} P[k]} \right| \tag{9}$$

$$Moment = \left| \frac{\sum_{k=0.5}^{40} k^2 P[k]}{\sum_{k=0.5}^{40} P[k]} \right| \tag{10}$$

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 (Lin et al. (2006)).

3.3. 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 the combined 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 based upon the colors and patterns that the participants selected. An example of one participant's preferences are shown in Table.1, where this data is obtained by counting the repeated choices for each subject. 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. After capturing the preferences of the participants, the next task was to investigate the different brain activities and channel locations to infer the areas of the brain that showed a significant change in terms of the EEG power spectrum while the subjects were indicating their preferences. A class label for each participant's 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.

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 and accurately identify the areas of the brain being activated.

Table 1: 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

3.4. 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 through the knowledge of another random variable (Klir (2006); Cover and Thomas (2006)). 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

$$I(X;Y) = \sum_{y \in Y} \sum_{x \in X} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \tag{11}$$

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

$$\begin{aligned} I(X;Y) &= H(X) - H(X|Y) \\ &= H(Y) - H(Y|X) \\ &= H(X) + H(Y) - H(X,Y) \end{aligned} \tag{12}$$

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. In addition, when studying the difference between the activities of the frontal vs occipital regions (which are particularly relevant for this type of choice task), a subset of EEG features was created combining the features from each two symmetric channels and computing their mutual information as a proposed symmetric measure of importance; this is given as

$$SMI = a_1 \times I(C; \{f_1, f_2\}) - a_2 \times \frac{I(f_1; f_2)}{H(f_1) + H(f_2)} \quad (13)$$

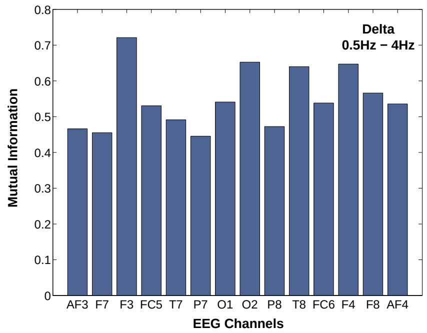
where a_1 and a_2 are factors controlling the importance of the two terms and were chosen empirically as 1.25 and 0.75 respectively; $I(C; \{f_1, f_2\})$ is the mutual information between the two features f_1, f_2 and the class label C; and $I(f_1; f_2)$ is the mutual information between the two features. Finally, the self-contained, cross-platform, package for computing the mutual information provided by Peng et al. (2005) was utilized as it has proved very suitable for feature selection problems[3].

4. EXPERIMENT RESULTS

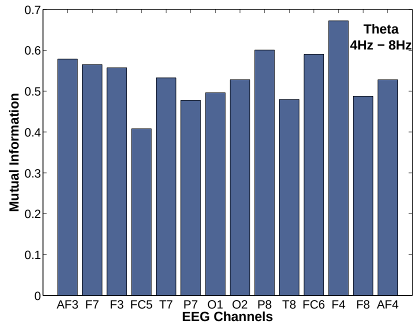
Given the extracted features from each participant's EEG data, the analysis attempted to identify which of the δ, θ, α, β, and γ components of the EEG exhibited the highest mutual information with the class label that reflected the individual participant's preferences. In order to accomplish this task, each of the δ, θ, α, β, and γ features were extracted from each of the channels and then the normalized mutual information, i.e., $\frac{I(C;f_1)}{H(f_1)}$, was calculated for each of the features across each of the participants. It should be noted here that the mutual information values across each of the bands were further normalized so that the channel that achieved the highest mutual information across a specific band will have a value of '1', while all other channels will have a value of mutual information that is less than '1'. This was done in order to find the most promising channels along each of the aforementioned EEG bands regardless of the exact value for the mutual information. The average mutual information, across all participants and between each of the EEG bands' power and the corresponding class label (representing the elicited preferences), was then plotted as shown in Fig.8.

These results indicate several important points; the first is that, across each of the EEG bands, there is a clear difference between the mutual information value achieved by symmetric channels on the left and the right hemispheres. This difference indicates asymmetric activities in terms of the EEG bands power while the participants were making their decisions regarding their preferred colors, patterns, and the combination of both. From these

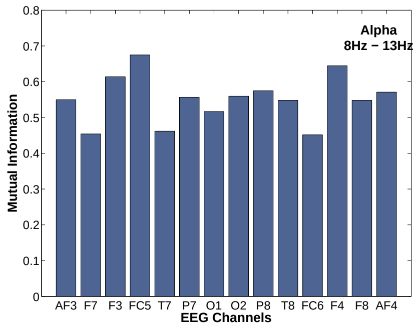
[3]available at http://penglab.janelia.org/proj/mRMR/



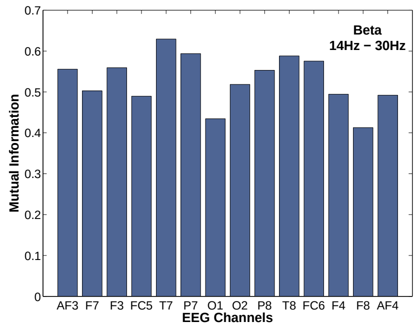
(a) Delta (δ)



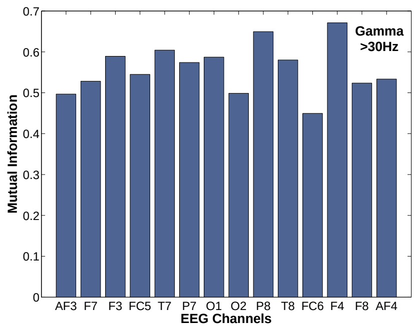
(b) Theta (θ)



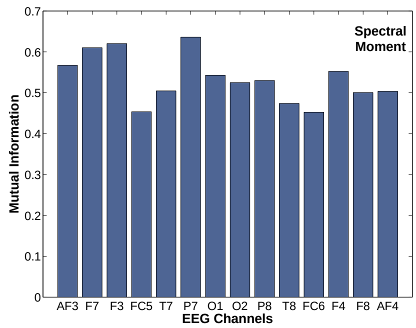
(c) Alpha (α)



(d) Beta (β)



(e) Gamma (γ)



(f) Spectral Moment

Figure 8: 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, averaged across all subjects.

results, it can be seen that the frontal, parietal and occipital regions were the most active indicating a significant change in the underlying EEG spectral activity during the decision making process. As an example, δ band exhibited its highest mutual information with the class label when extracted from F3, O2, F4, and T8. Delta oscillations are present in the EEG activity not just in sleep, but in awake state and are thought to be generated by neocortical and thalamocortical networks. Knyazev (2007) noted in his review of the functional roles of different EEG oscillations that a number of observations support the idea that the delta rhythm is a signature of reward processing and salience detection, a finding which was further confirmed by Wacker et al. (2009). It has also been recently shown that task performance correlates with prestimulus δ oscillatory phase and that reaction times correlate with the phase of the δ band oscillation at target onset (Stefanics et al. (2010)). These findings support the importance of the δ band during the elicitation of preferences, and this is very clear of the frontal regions, especially on F3. An analysis of variance (ANOVA) test was performed to identify if there were any significant differences between actual δ band feature values from different EEG channels (significant level is reported at $p < 0.05$). The results indicated significant differences between δ band features from each of the channels in the set made of F3, O2, F4, and T8 channels and the rest of the channels from the same set with $p < 0.001$.

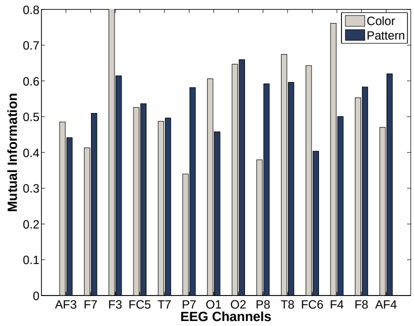
Theta θ band exhibited very high mutual information with the elicited preference especially in the frontal regions (F4, FC6, AF3, F7, and F3) and in the parietal regions (P8). Theta waves have long been associated with emotional processes, and it is believed to be correlated with emotions and limbic regions with some studies indicating higher θ activity when a preference is being made on advertisements (especially F3 and F4) (Custdio (2010); Yokomatsu et al. (2007); Ohmea et al. (2010)). 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. Various studies report that either F3 or F4 could be interchangeably more active across different participants (Aurup (2011)). ANOVA test results also indicate clear significant differences between θ band features at F3 and F4 with $p < 0.001$. α band also agreed with θ on the importance of F3, FC5, and F4 with some α activity on the occipital and parietal regions as well. Both θ and α were very recently studied to observe the subjective preference of colors on the visual attention-related brain activities with results revealing that θ synchronizations and α desynchronizations were modulated by subjective preferences

(Kawasaki and Yamaguchi (2012)).

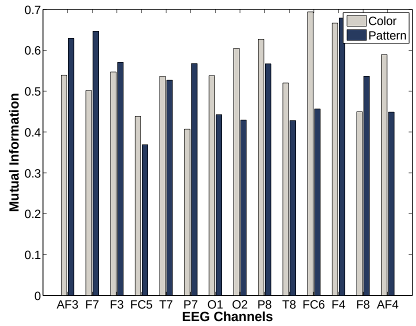
In terms of β, the highest mutual information values were exhibited in the temporal and occipital regions with more important β spectral changes at the left frontal regions than that on the right frontal regions. However, no evidence exists in the literature regarding the significance of β in choice modeling due to the limited number of EEG channels and EEG bands utilized in previous studies (Aurup (2011)). Additionally, it is not clear from the current analysis if the occipital regions were activated by the visualization of different colors or if they are actually related to the users preference changing, as the results here are averaged across all subjects regardless of their preferences. It is generally known that colors stimulate the occipital regions and this might be a reason for the high scores on β bands on the occipital regions. Thus, a more appropriate approach to understanding the importance of these bands would be to observe their effects on two individual groups of subjects according to their preferences. Gamma band also showed its highest spectral changes on both F4 and P8 supporting the importance of the frontal and parietal regions with γ also shown in the literature to correlate well with preferences (Aurup (2011)). Finally, the spectral moment of the whole spectrum also suggests the importance of the frontal and parietal regions.

In the next part of the experiments the sample was split to separate those participants with a strong preference for a color (and not a pattern), forming 10 subjects, from those who prefer a pattern (and not a color), forming the remaining 8 subjects. The mutual information values were averaged as shown in Fig.9.

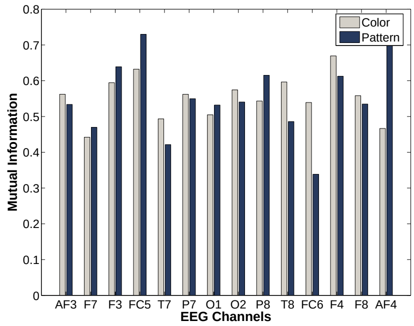
These results clearly indicate that δ, θ, α, β, and γ bands tend to exhibit different scores on mutual information values for the different brain regions between the two participant groups. As an illustration, when the preference is for a certain color the most important channels in terms of δ are shown to be F3 and F4, while F3, O2, and AF4 exhibit highest mutual information when the preference is for a certain pattern (regardless of color). Both β and γ clearly exhibit the effect of the different preferences between the groups on the mutual information scores. Across the subjects with color preferences, β exhibited its highest mutual information value at FC6 and AF3 while the same band exhibited its highest mutual information with the decision making process on temporal, frontal, and parietal regions when the preference was a pattern. γ also showed its highest score on P7 with colors preferences and on F4 with patterns preferences. An important finding from these results is that



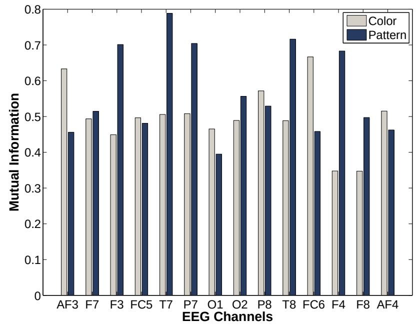
(a) Delta (δ)



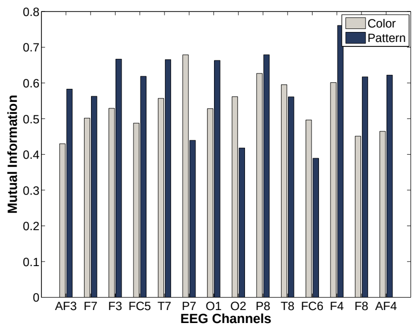
(b) Theta (θ)



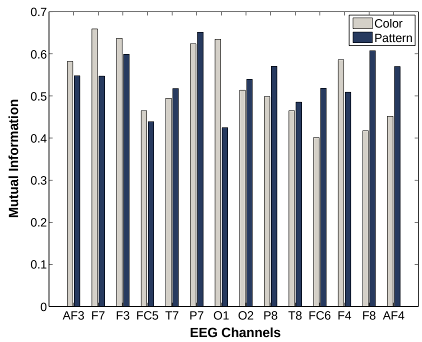
(c) Alpha (α)



(d) Beta (β)



(e) Gamma (γ)



(f) Spectral Moment

Figure 9: 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, averaged across all subjects.

both θ and α showed the least amount of discrepancy among their achieved mutual information values with both color and pattern preferences. In order to validate this finding, the absolute value of the cumulative differences among the mutual information values with color and pattern preference for each band and across each channel was computed and plotted as shown in Fig.10. The results indicate that both θ and α bands are more related to the process of decision making than to what was actually selected as a preference. The same finding also applies for the mutual information results across the total spectral moment, as shown through the low discrepancy between the bars.

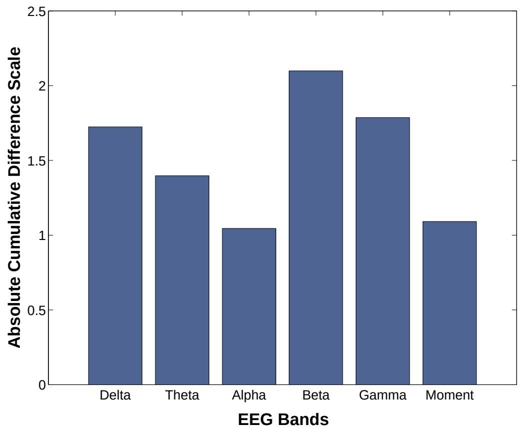


Figure 10: Absolute cumulative difference between the mutual information values achieved along each band and across each channel with colors and patterns preferences showing alpha with least discrepancy.

In the next part of the analysis we focused on 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. 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.11 for one participant.

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.13 while considering each of the δ, θ, α, β, γ bands, and the total spectrum separately.

To illustrate the results from these analysis, Fig.12 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 feature from F3 and α feature from F4, i.e., $I(f_1; f_2)$, and the two features together with the class label, i.e., $I(C; \{f_1, f_2\})$. In such a case and in terms of information exchange between symmetric channels, δ band seems to exhibit its maximum relevance to the problem when extracted from temporal (T7-T8) and frontal (F3-F4 and AF3-AF4) regions. The relevance of θ was also very clear on occipital (O1-O2), parietal (P7-P8), and frontal regions (F3-F4). Alpha again seemed to reflect consistent results with the previous findings showing more relevance to the problem when extracted from frontal (F3-F4) and parietal (P7-P8) regions, while β achieved its maximum at the occipital (O1-O2) regions followed by temporal (T7-T8) and parietal regions (P7-P8). In terms of γ, temporal (T7-T8), parietal (P7-P8), and

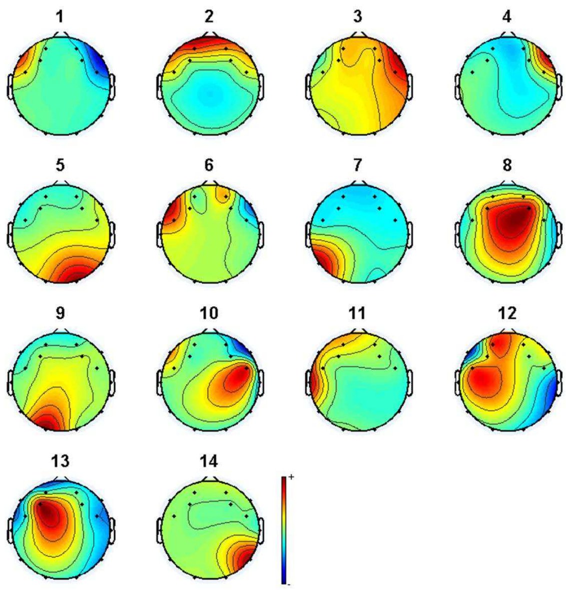


Figure 11: 2D Component map of the 14 channels EEG data from Emotiv EPOC, plotted using the EEGLAB software.

occipital (O1-O2) regions are shown to be more active in terms of information exchange between these symmetric channels. The same regions were again the most active in terms of the moment of the total spectrum which also shows clear activity on F3-F4. All of these results were again supported by an ANOVA test showing significant differences ($p < 0.001$) between the features extracted from symmetric channels.

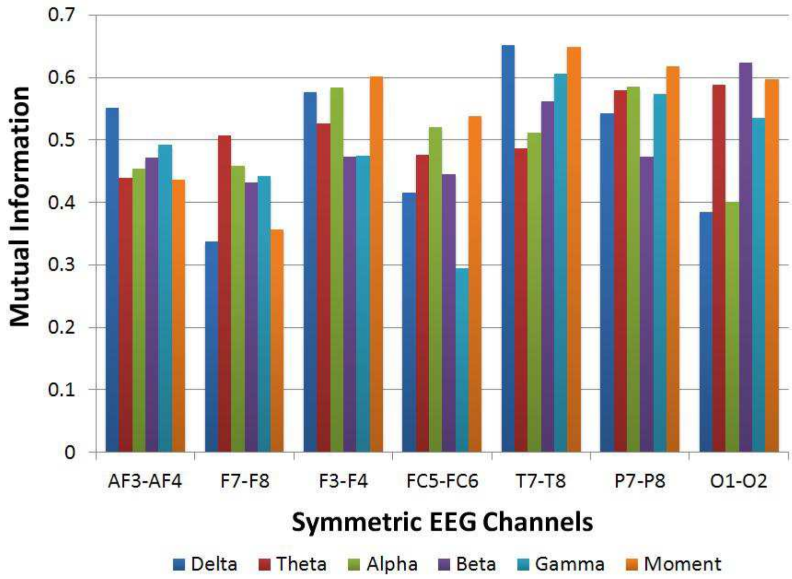


Figure 12: Mutual information between symmetric EEG channels along each of the δ, θ, α, β, γ and total spectral moment bands and the class label.

The results have thus far demonstrated the dominance of the frontal, parietal, and occipital regions. It was also shown that the different bands of the EEG play a significant role in different regions in the brain. In the third stage of the analysis, the extracted features, represented by the power of the δ, θ, α, β, and γ bands, from all of the participants were grouped into one large data matrix to perform a subject independent analysis of mutual information. The resultant data matrix was then normalized to have zero mean and unit standard deviation to remove the effect of different data distributions from each subjects' dataset. The purpose of this was to investigate the regions of the brain that best interact together along each of the EEG bands to produce the highest mutual information with the class label. Unlike the previous analysis, the class label was the original label of choice objects as shown in Table.1, i.e., a nine classes problem. This step ensures the importance of the ranked features, as basis for mutual information, is not tied to the existence of a specific class, such as the color blue, but will in turn describe the general differences between the EEG features extracted from different regions throughout choice behavior. The mutual information between each of the extracted features from each channel and the rest of the channels with the choice object based class label, i.e., $I(C; f_1, f_2)$ was computed along each of the δ, θ, α, β, and γ bands. An ANOVA test was used to confirm the statistical significant differences among the well interacted features. The results showed that θ power features best interact together when extracted from F3 and O1 ($p < 0.0001$). Alpha power features, on the other hand, best interact together when extracted from channels O1 and F4 ($p < 0.0001$), while β features best interact together when extracted from AF3 and O2 ($p < 0.0026$), and finally γ from AF3 and T7 ($p < 0.0309$).

5. Conclusion

In this paper, we employed a commercially available wireless EEG headset to investigate the brain activities taking place during decision making. A set of choice objects were shown to participants with them asked to select their preferred object by clicking on it. The frequencies of their choices were recorded by eye tracker software from a 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, high mutual information values between preferences and the different EEG bands were found in F3 and F4 (regardless of colors and patterns preferences). In order to investigate the reported relevance of other bands, further analysis were conducted to study the amount of information exchanged between symmetric EEG channels. This showed a dominance of the δ band in the temporal regions, θ in the frontal, parietal and occipital regions, α in frontal and parietal regions, and β and γ 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, that is 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 generalizability. We are also 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 when preferences are elicited through choice behavior.

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