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Integrating Eye-Tracking and Wireless Electroencephalogram (EEG) in Consumer Neuroscience

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Abstract— **Consumer neuroscience addresses marketing relevant problems through the integration and application of neuroscientific theories, concepts, findings and methods to the research discipline of consumer behavior. The key contribution of this paper is to complement the advancement of traditional consumer research through the investigation of the patterns of interdependency between the Electroencephalogram (EEG) signals from the different brain regions while participants undertook a choice task designed to elicit preferences for a marketing product (crackers). Specifically, the task required participants to choose their preferred crackers described by shape (square, triangle, round), flavor (wheat, dark rye, plain) and topping (salt, poppy, no topping). We analyze the Electroencephalogram (EEG) signals collected from the different brain regions using the commercially available 14 channel Emotiv EPOC wireless EEG headset and relate the EEG data to the specific choice options with a Tobii X60 eye tracker. Fifteen participants were recruited for this experiment and were shown 57 choice sets; each choice set described three choice options. The patterns of cortical activity were obtained in the five principal frequency bands, Delta (0 - 4 Hz), Theta (3 - 7 Hz), Alpha (8 - 12 Hz), Beta (13 - 30 Hz), and Gamma (30 - 40 Hz). Our results indicate significant phase synchronization between the left and right frontal and occipital regions indicating interhemispheric communications during the choice task. Our experimental results also show that participants spent more time looking at the non-preferred items in each choice set at the beginning of the experiment (exploration mode), while reducing that time progressively to indicate significant amount of cognitive processing assigned to preferred items (exploitation mode).**

I. INTRODUCTION

Consumer neuroscience is an emerging discipline that employs methods originally used in brain research for investigating marketing problems, and furthers the advance of integrating neuroscientific findings into decision-making research [1]. To gain insight into decision-making, research has so far benefited from both revealed and stated preference perspectives by observing individuals' actual or stated behaviors. While useful, both approaches, however, ignore the black box in which decisions are made [2]. In such a case, human brain activity can act as a valuable tool providing marketers with information not obtainable via conventional marketing research methods (e.g., interviews, questionnaires, focus groups) [3]. Specifically, the change in the human brain signal, denoted as Electroencephalogram (EEG), and its main spectral bands of Delta (0-4 Hz), Theta (3-7 Hz), Alpha (8-12 Hz), Beta (13-30 Hz), and Gamma (30-40 Hz) is observed to examine consumers' cognitive or affective processes in response to prefabricated marketing stimuli [4], [5], [6], [7], [8]. As a result, one is in a better position to understand the contextual influences that may interact with the different neural circuitry leading to different choices.

Previous studies have mainly focused on the effect of observed TV commercials on the cortical activity and changes in functional connectivity in normal subjects (e.g. Ohme *et al.* [5], Astolfi *et al.* [9], Custodio [10] and Vecchiato *et al.* [11]). These studies found that the amount of cortical spectral activity from the frontal areas and parietal areas was higher for TV commercials that were-remembered, compared with the activity elicited by TV commercials that were forgotten [5], [9]. Alpha band activity was also observed in the occipital regions and theta activity in the midline and frontal cortical regions for the well-remembered advertisements [10]. Apart from such experiments focusing on the effect of TV commercials on brain signals, we recently proposed to incorporate EEG signals in discrete choice experiments (DCE's) [12], [13]. DCE's require participants to make a series of choices (in our context they were presented with 57 unique choice sets) and indicate their most and their least favorite options without requiring them to rate, rank or articulate why they chose the particular options. This allows us to avoid some of the more restrictive assumptions about how individuals compare competing alternatives (e.g. criticisms of ranking and rating tasks) and issues related to constructed reasoning (e.g. criticisms of retrospective reporting/thinking aloud tasks). In our previous research, we analyzed the EEG spectral changes in a simple choice (decision) context designed to measure specific features (i.e., shape, topping, and flavor) of the choice options (crackers) that individuals like/dislike. It was found that the various cracker flavors and toppings of the crackers were more important factors affecting the EEG power spectrum than the shapes of the crackers as measured by mutual information analysis [13].

In this paper, we extend our recent findings by analyzing the patterns of interdependency between different brain regions using EEG phase synchrony while the participants indicated their most preferred/least preferred items. We also investigate the timing effect in this experiment and the relation between the amounts of time spent on the cognitive processing associated with the preference elicitation task.

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II. Data Collection

The data collection process employed two sets of equipment; the first was a brain signal monitoring system represented by the Emotiv EPOC EEG wireless headset with 14 channels (`www.emotiv.com`); and the second is an eye-tracker system from Tobii technology (`www.tobii.com`), as shown in Fig.1. The Emotiv EPOC is a high resolution, neuro-signal acquisition and processing wireless headset that monitors 14 channels of EEG data and has a gyroscope measure for 2 dimensional control. 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 forming 7 sets of symmetric channels as shown in Fig.2. 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, and sends the data 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. Both of the EPOC and eye tracker were forced to start at the same time by means of synchronization software to start both modules together.

In addition to the EPOC, a Tobii X60 eye tracker system was used to record the choice experiment (i.e. what each participant saw and when), thus, helping with post-experiment processing of the EEG data. The Tobii X60 eye tracker is 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 a sampling rate of 60 Hz. The X60 monitor mount accessory provides fixed geometry for the eye tracker and screen, allowing the setup to be adjusted for each participant without impacting data quality.

Fifteen participants (including males and females), were recruited for the study. All participants were aged between 25 and 65 years (average age 38 years). Eleven participants were right-handed, and four were left-handed; nine participants wore medical glasses. The experimental procedure was approved by the human research ethics committee in the University. The eye tracker was re-calibrated for each subject to provide accurate measurements for the participant's gaze.

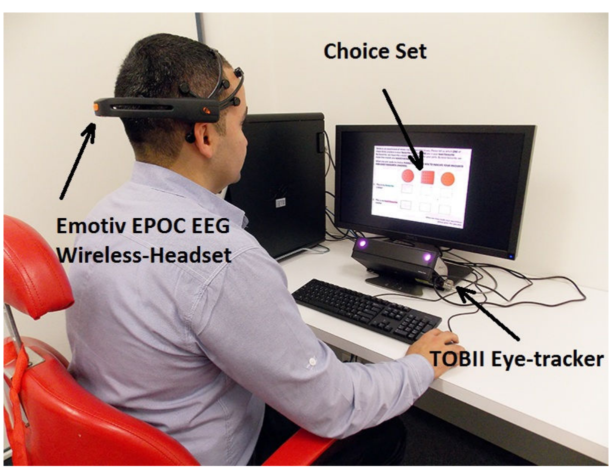

Fig. 1. The experimental setup utilized in this paper.

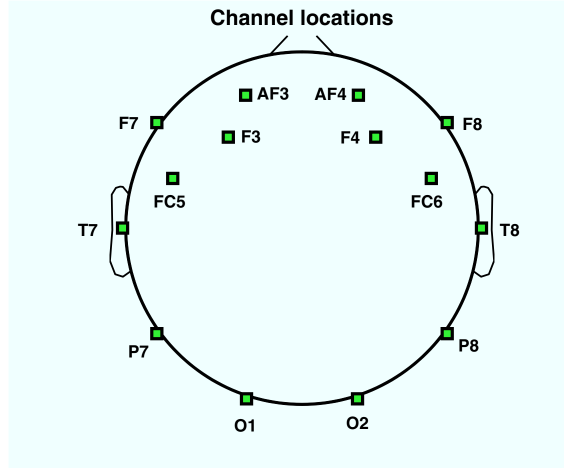

Fig. 2. Emotiv EPOCs electrode positioning

A sequence of 57 choice sets was developed. Each described three crackers that varied in shape, flavor and topping. The context was choosing crackers for a party that the participant would host. Three shapes (round, triangle and square), three flavors (wheat, dark rye and plain) and three toppings (salt, poppy seed and plain) were used to create the objects as shown in Fig.3. The three cracker features were varied using a full factorial design producing 27 unique crackers. We then used a balanced incomplete block design to assign the 27 different crackers to 57 choice sets. Each of the 57 choice sets contained three crackers; the design also controls for order of appearance, which ensures that each of the 27 crackers appears in every order. The design also insures that each of the 27 crackers appears equally often across the 57 sets, and co-appears with every other cracker equally often. Each of the 57 choice sets was shown on the screen one-at-a-time. Each set consisted of a screen with the 3 crackers aligned on the left, middle, and right positions, with options displayed below the crackers to indicate preferences.

III. Data Analysis

Detecting and removing artifacts produced in the EEG data by muscle activity, eye blinks and electrical noise, etc., is an important problem in EEG signal processing research. Initial processing starts with a baseline removal due to the included DC offset in the EPOC EEG readings. A band-pass filter with a cut-off of 0.5Hz-to-40Hz was designed (filter implemented using Matlab's fast Fourier transform (FFT) functions through EEGLAB[1]). Discrete wavelet transform (DWT) based denoising was then utilized to clean the EEG

[1] http://sccn.ucsd.edu/eeglab/

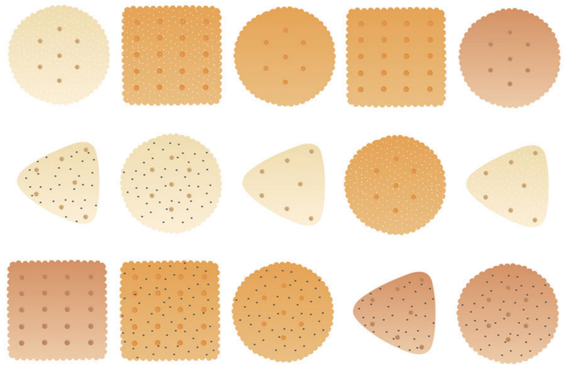

Fig. 3. Illustration of the developed choice set objects which vary shape, flavor and topping.

signals collected by the EPOC headset from noise and remove artifacts [14]. For a signal $s_i(t)$ composed of m samples, DWT is applied with a scale factor of 2^j and is given as

$$w_k^j = 2^{-j/2} \sum_{t=0}^{m-1} s_i(t) \psi(\frac{t}{2^j} - k) \tag{1}$$

where the scale factor j is related to the frequency, the parameter k is related to the time at which a frequency component occurs, w_k^j is the wavelet coefficient of $s_i(t)$ at scale index j and time index k, and $\psi(n)$ is an orthogonal basis. Fifth-order Daubechies compactly supported wavelet was utilized in this study with 5 decomposition levels, as it provided to give good empirical results. A hard-thresholding step was then implemented on the wavelet coefficients in which only those coefficients with values less than a specific threshold T were maintained, while all other coefficients were replaced by zeros. The value of T was selected empirically as the median of the signal plus 3 times its standard deviation. The inverse wavelet transform was then utilized to acquire the denoised version of the EEG signals.

After cleaning the signals, we employed the phase of the EEG signals to provide a direct quantification of frequency-specific synchronization (i.e., transient phase-locking) between two EEG signals. The phase values, referred to as $\phi_i(n)$ for each signal indexed by i, were obtained by using the angle of the Hilbert transform. Direct evidence supporting phase synchronization during emotional response to positive and negative film stimuli has already been provided [15]. However, no further studies were conducted to evaluate EEG phase synchrony while the participants were actually indicating their like/dislike decisions on a product. The phase locking value (PLV) employed in this paper as a measure of synchrony is then defined as the average value [15], [16]

$$PLV = \frac{1}{N} \left| \sum_{n=1}^{N} \exp(j\phi(n)) \right| \tag{2}$$

where n is the frequency index and $\phi(n)$ is the phase difference $\phi_1(n) - \phi_2(n)$ of the EEG signals from two brain regions, representing the inter-trial variability of this phase. The eye-tracker was used here to mark the preferences related EEG segments for PLV analysis. Here, we introduce our method of detecting synchrony in a precise frequency range between two recording sites, i.e., the PLV value is calculated for each of the δ, θ, α, β, and γ bands to detect what brain regions and which EEG bands are mostly getting phase synchronization.

IV. Experiments and Results

In the first part of the experiment, we employed the PLV measure to detect phase synchronization while the participants were indicating their preferences on the different attributes of the crackers. Each pair of electrodes from the left and the right hemispheres were analyzed together to study the symmetry between these regions and their relation to the preferences elicitation task. As mentioned previously, this was done along each of the δ, θ, α, β, and γ bands for which the computed average PLVs are shown in Fig. 4.

The PLV results clearly indicate the frontal (AF3-AF4 and F3-F4) and occipital channel (O1-O2) were the most synchronized channels, which in turn indicates the importance of the cognitive processing taking a place at these brain regions. Such large phase synchronization values were previously attributed to the dynamic cooperation between cortical areas which highlights the role of information exchange during emotional response [15]. In contrast, this paper considers the EEG phase synchronization in an actual decision making task that required the participants to indicate their preferences on a product. Our findings support the theory that there was wide inter-hemispheric communication during preferences elicitation task. The results presented in this paper also clearly show the importance of all of the θ, α, and β that reflected the highest PLV at the aforementioned frontal and occipital regions. These EEG bands and their corresponding regions with highest PLV values were indicated in the literature as very relevant for tasks involved with emotional processing of preferred vs. non preferred marketing stimuli when these regions were studied separately [7], [8]. The PLV was also calculated at each frequency band for all the couples of possible electrodes, rather than just the symmetric ones. In this case the set of frontal channels represented by AF3, F3, F4, and AF4 showed the highest PLVs among each other at all of the θ, α, and β bands. On the other hand, the occipital channels (O1 and O2) showed its highest PLVs with the parietal channels (P7 and P8) rather than with the frontal channels as indicated by Costa *et al.* [15], a difference which could be related to the nature of the task itself (preference judgment on crackers in our case in comparison to watching emotional video scenes in [15]). Thus, our results further support the idea that synchronization provides an interesting and useful tool for studying and understanding the variation in brain activity that occurs during an actual decision making task that was related to subjective preferences on a number of attributes in a marketing product.

In addition, we also analyzed the time taken by the participants to indicate their preferences on the crackers that

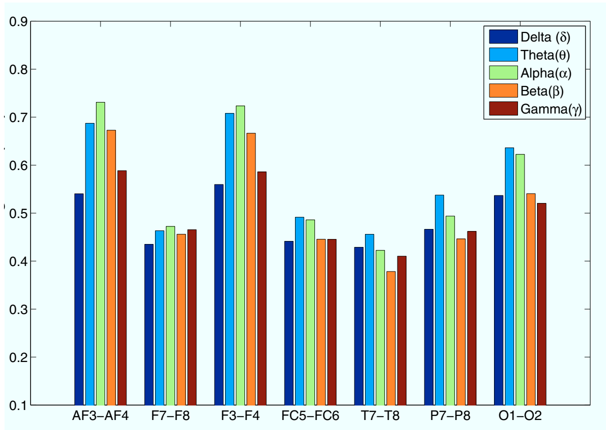

Fig. 4. Phase locking values between all of the δ, θ, α, β, and γ bands at each symmetric pair of electrodes.

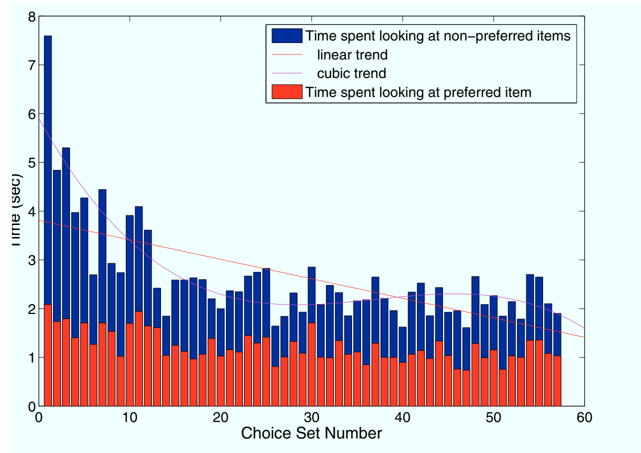

Fig. 5. Average time taken by all participants to indicate their preferences on each choice set.

was calculated per each of the 57 choice sets and averaged across all participants as shown in Fig.5. One can clearly see that during the initial choice sets (e.g. choice sets 1-10) there was a clear trend in which the participants spent more time looking at the objects they did not end up selecting, while less time is spent looking at preferred items. This can be justified by that the participants were exploring all the possible items in the set spending more cognitive processing on the other items (e.g. thinking if they like a cracker or not). In contrast, processing of the remainder of the choice sets (e.g. choice sets 11-57) is focused upon the preferred items. As participants became familiar with the choice task and the competing options, they had established their preferences and as a result, were able to quickly indicate their most and least preferred options (i.e. they could exploit the best available options). As a consequence, we show that the preferences elicitation task can be characterized as a search process, involving a trade-off between exploring new solutions and exploiting old solutions and that such trade-offs influence a wide range of everyday decisions.

V. CONCLUSIONS

This paper uses both EEG and eye tracking systems to study the decision-making process in a simple choice context. Our results showed clear EEG phase synchronization on the symmetric frontal and occipital regions while indicating the importance of θ, α, and β rhythms of EEG at those regions. The results also clearly showed the trade-off between exploring and exploiting possible preferences indicating the role of such a trade-off in the decision-making process. Our experiments continue as we seek to further advance the research into the field of consumer neuroscience.

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