journal homepage: www.intl.elsevierhealth.com/journals/cmpb

Like/dislike analysis using EEG: Determination of most discriminative channels and frequencies

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ARTICLE INFO

Article history:
Received 8 February 2013
Received in revised form
10 November 2013
Accepted 18 November 2013

Keywords:
Neuromarketing
EEG
Partiality
Power spectral density
Burg method
Logistic
Regression

ABSTRACT

In this study, we have analyzed electroencephalography (EEG) signals to investigate the following issues, (i) which frequencies and EEG channels could be relatively better indicators of preference (like or dislike decisions) of consumer products, (ii) timing characteristic of "like" decisions during such mental processes. For this purpose, we have obtained multi-channel EEG recordings from 15 subjects, during total of 16 epochs of 10 s long, while they were presented with some shoe photographs. When they liked a specific shoe, they pressed on a button and marked the time of this activity and the particular epoch was labeled as a LIKE case. No button press meant that the subject did not like the particular shoe that was displayed and corresponding epoch designated as a DISLIKE case. After preprocessing, power spectral density (PSD) of EEG data was estimated at different frequencies (4, 5, . . ., 40 Hz) using the Burg method, for each epoch corresponding to one shoe presentation. Each subject's data consisted of normalized PSD values (NPVs) from all LIKE and DISLIKE cases/epochs coming from all 19 EEG channels. In order to determine the most discriminative frequencies and channels, we have utilized logistic regression, where LIKE/DISLIKE status was used as a categorical (binary) response variable and corresponding NPVs were the continuously valued input variables or predictors. We observed that when all the NPVs (total of 37) are used as predictors, the regression problem was becoming ill-posed due to large number of predictors (compared to the number of samples) and high correlation among predictors. To circumvent this issue, we have divided the frequency band into low frequency (LF) 4–19 Hz and high frequency (HF) 20–40 Hz bands and analyzed the influence of the NPV in these bands separately. Then, using the *p*-values that indicate how significantly estimated predictor weights are different than zero, we have determined the NPVs and channels that are more influential in determining the outcome, i.e., like/dislike decision. In the LF band, 4 and 5 Hz were found to be the most discriminative frequencies (MDFs). In the HF band, none of the frequencies seemed offer significant information. When both male and female data was used, in the LF band, a frontal channel on the left (F7-A1) and a temporal channel on the right (T6-A2) were found to be the most discriminative channels (MDCs). In the HF band, MDCs were central (Cz-A1) and occipital on the left (O1-A1) channels. The results of like timings suggest that male and female behavior for this set of stimulant images were similar.

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http://dx.doi.org/10.1016/j.cmpb.2013.11.010

1. Introduction

The fundamental goal of marketing professionals is to guide the design and presentation of products in a way that they are well suited to consumer preferences. To understand the preferences, these professionals often use several standard research tools, such as one-on-one interviews with the consumers, general surveys, and focus group studies. These approaches are easy and inexpensive to implement but they provide data that can contain biases, and are therefore perceived as not very correct [1].

Neuro-marketing is a relatively new research field that studies human brain's response to commercials, brands, and other marketing stimuli. In this field, various neuroscientific methods are used to analyze and understand consumer behavior associated with purchasing preferences. These methods include the brain imaging technologies such as functional magnetic resonance imaging (fMRI), electroencephalography (EEG), magneto-encephalography (MEG), and steady state topography (SST), and physiological parameters like heart rate, respiratory rate, and galvanic skin response (GSR) [2,3].

The motivation behind the use of these technologies is to have access to hidden information about the consumer experience instead of just asking his/her preference. It is assumed that such hidden information may be used to influence purchasing behavior, thus the cost of doing neuro-scientific studies would be compensated by the benefit of better product design and sales [4].

Nowadays, functional Magnetic Resonance Image (fMRI) technique is drawing increasing interest from the neuromarketing community. It is based on imaging of the blood flow in the brain and helps identifying areas activated by a stimulus. The spatial resolution offered by this technology is superior to any other imaging method currently available. However, poor temporal resolution due to delay between a particular stimulus and the blood flow to the activated locations makes fMRI inappropriate for tracking the fast brain dynamics, and is an expensive technology. On the other hand, EEG and MEG are brain-imaging tools that provide high temporal resolution with inferior spatial resolution compared to fMRI. MEG systems are expensive and require shielded environments in order to detect very low magnetic fields generated by the brain. EEG technology is a relatively inexpensive, well established, and robust tool that has been attractive to neuro-marketing community since its first use in this field in 1971 by Krugman [5]. We also believe that we can enhance our understanding of the dynamics of brain (during some decision making processes) using EEG analysis as a practical and efficient tool.

In order to test a hypothesis in neuro-marketing or similar studies first a stimulus set and test protocol is prepared. The subject is exposed to the stimuli according to the protocol and electrical signals from different locations on the brain surface are acquired as multichannel EEG. After data acquisition, noise and artifacts that may overshadow the real changes in the signals are removed using various signal processing techniques such as filtering, independent component analysis and principle component analysis [6–8]. The resulting data set is then analyzed and some desired features (e.g., power spectra) are extracted [9]. These features coming from different stimuli and subjects are statistically analyzed to answer the questions under investigation.

In most of the EEG based studies, desired features are derived from frequency bands of the signal (especially theta, alpha, beta and gamma). The delta waves lie within the range of 0.5–4 Hz. These waves are mainly related with deep sleep and may exist in the waking state. It is very easy to confuse artifacts caused by the neck and jaw muscles with the real delta response. Theta waves, on the other hand, have been associated with access to unconscious material, creative inspiration and deep meditation. Theta waves arise from emotional stress, especially frustration or disappointment. In the alpha waves, the rate of change lies between 8 and 13 Hz. Alpha waves have been thought to indicate both a relaxed awareness and also inattention, and are strongest over the occipital and frontal cortex. Beta waves arise within the range of 13–30 Hz, and are associated with active thinking, active attention, and focus on the outside world or solving concrete problems. Gamma waves oscillate at frequencies beyond 30 Hz and mostly observed during cross-modal sensory processing, short-term memory matching of recognized objects, sounds, or tactile sensations [10–12]. A decade ago, Başar et al. [13] gave an overview on brain waves associated with different functions and mechanism of processing of emotional information. It has also been shown by several researchers that several brain regions such as the ventromedial and dorsolateral prefrontal cortex, amygdala, ventral striatum, anterior cingulate and insular cortex are important for human affective response [14].

In this particular study, we employed recordings from 19-channel EEG system in order to investigate the answers to the following two questions: (1) Which frequencies and channels (i.e., brain surface areas, not specific points) are critical and need special attention in the discrimination of like/dislike preference of products? (2) What is the characteristic of timings of like decisions?

2. Materials and methods

2.1. Study population and signal acquisition

In order to screen possible effects of 'age' (i.e., the reflection of decision processes on the EEG signals can be age dependent) in our analysis, we have recruited an age controlled group of 15 volunteers to participate in our study. We also aimed at exploring possible influence of gender in our results, so we have included both genders (10 female, 5 male) in our study group. Age profile of our subjects was as follows: Range 19–25, mean ± std age is 22 ± 1.6. All of the subjects signed an informed consent before the experiments and our study was approved by the Research Ethics Committee of Erciyes University.

In our trials, we recorded 21-channels of electroencephalography (EEG) signals using international 10–20 system [15]. We used 19 of these EEG channels in our analysis of characteristics of like/dislike decisions. Fig. 1 shows montage of these channels on a polar projected circular model head. Our recording system (EEG 1200, Nihon Kohden Co., Tokyo, Japan)

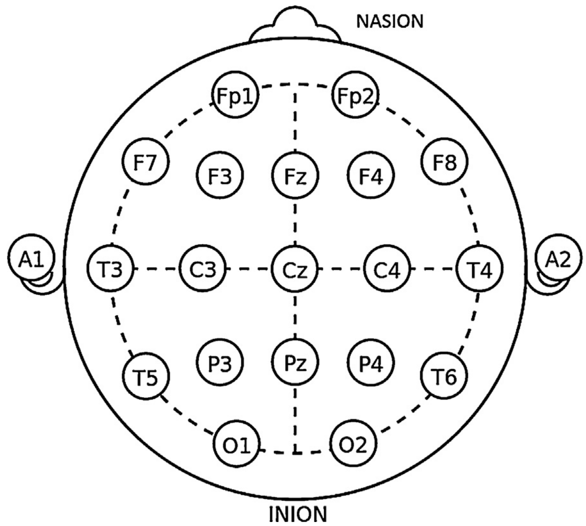

Fig. 1 – A schematic of 19-channel montage used in our experiments.

incorporated a timing marker button as well. To improve contact (i.e. to reduce contact resistance), electrode locations were cleaned with alcohol patch before attaching the electrodes. The recordings were unipolar with reference to the ear electrodes positioned on the side of the electrodes, i.e., for the electrodes sitting on the left side of the brain the reference electrode was on the left ear, and similarly for the ones on the right the reference electrode was on the right ear. All of our subjects were right-handed and none of them had any previously known neurological diseases.

During our recording sessions, subjects sat in a comfortable chair with a consistent posture. They were located next to the data acquisition (DAQ) system in such a way that they could not see it, and thus were not visually disturbed with the cables and signals running on the screen. At the same time, the researcher supervising/conducting the experiment sat behind the subject and was able to control the software on the DAQ system by placing fiducial points/markers (timings with labels) on the recordings as necessary. We asked subjects to blink or move their eyes minimally, or not to move any other part of their body as much as possible. The subjects were instructed to stay relaxed and keep their eyes open. They were presented full-screen, similar size high-quality shoe photographs from a fixed laptop computer with 15-inch monitor, at eye distance of 1 m. Using PowerPoint (Microsoft Corp., Redmond, WA), we have prepared a presentation including 16 ten-second slides of some women's shoes, which had different styles and colors. The photographs were obtained from an electronic trade web site. In an attempt to create/establish a rest state before each shoe photograph stimulus, a slide with 5-s plain color (same with the background color of the next shoe photograph) slide was presented. The subjects were allowed to use this time slot to blink and move.

Online monitoring of EEG signals began before any slide presentation. Once the subject was ready for the experiment, the slide show and data acquisition to the hard disk was activated by the researcher using a wireless mouse. First the subject encountered a plain-color screen for 5 s then the first shoe photograph was presented. At that transition moment from the plain-color screen to the first photograph the researcher overviewing the experiment carefully put a fiducial on the screen by just clicking on the space bar of the keyboard on the DAQ system.

We have used MATLAB Software (Matlab R2011b, The MathWorks Inc., Natick, Massachusetts) to carry out our data analysis tasks. We have both developed our own in-house software and used readily available Matlab subroutines in our data processing. To transport EEG data from equipment format into Matlab environment, we have first exported the EEG data into plain text (ASCII) format using EEG equipment's software and loaded this text data into Matlab. We have recorded EEG signals at a sampling rate of 500 samples/s and during analog to digital conversion our amplitude resolution was 16 bits.

Each trial epoch was of 15 s (5 s background recording plus 10 s of photograph display), and as there were 16 trial epochs (shoe photographs shown) for each subject, total length of EEG recordings were $15 \times 16 = 240$ s. Using a custom data reading/formatting code, we formed matrices with 19 columns corresponding to 19 channels and 120,000 ($240\,\text{s} \times 500$ samples/s) rows corresponding to signal samples over time. These raw data sets were then used in the preprocessing and power spectral density analysis stages to be described in Section 2.2. In summary, we have used a manual and offline synchronization, which was also checked/confirmed and fine-tuned by observing noticeable changes in the brain activity and/or eye movements on the signals.

During the experiments we asked subjects to concentrate on the photographs and instructed them to press on the marker button when they thought they liked the particular shoe being displayed and the software automatically recorded the time of corresponding 'like decision.' We used this information in two ways: (1) determining whether they liked it or not, (2) determining the timing characteristics of the like decisions (TLD).

2.2. *Preprocessing*

Each one of 15 subjects EEG data matrices was first filtered using a 100th degree FIR1 (window-based linear-phase finite impulse response digital filter design) band-pass filter with cut-off frequencies of 1 and 45 Hz. In FIR1 the filter is normalized in order to adjust the magnitude response of the filter at the center frequency of the passband to 0 dB. Once the filter coefficients were computed a *filtfilt* function (a built-in Matlab function) was employed in order to avoid the phase shift in the data. Later, using a custom Matlab-based EEG viewer software that we have developed, we have visually checked the EEG time series data channel by channel or all channels at once for any abnormalities or glitches. This viewer also allowed us to manually clean eye blinking or eye movement related noise from the EEG data. Each 15-s data corresponded to an epoch (data chunk) to be studied carefully. After removing initial 5-s portion of the data chunk, corresponding background or resting state recording, we visually determined the onset and ending points of each noisy portion of the data in the remaining 10-s part of the epoch. We have then cropped those portions and formed a clean data chunk containing crucial/critical information brain activity signal obtained during shoe presentation from each epoch. Mean duration for crucial data chunks was approximately 7.2 s. However, there were 31 epochs whose duration after cleaning dropped below 5.0 s. We left these epochs out of the analysis, and the data set coming from the remaining 209 clean and long-enough epochs formed the basis/material for the subsequent analysis.

2.3. Power spectral density computation

The power spectral density (PSD) of each epoch (16 epochs) for each subject (15 subjects) was estimated using the Burg method [16]. The Burg method is an autoregressive (AR) prediction model based parametric spectral estimation method and yields a PSD estimate given by

$$\hat{P}(f) = \frac{1}{fs} \frac{\varepsilon_C}{\left|1 + \sum_{k=1}^{c} \hat{a}(k) e^{(2\pi jkf/fs)}\right|} \quad (1)$$

where fs is the sampling frequency, c is the order of the model, f is the frequency, and $\hat{a}(k)$ are the AR model parameters. These parameters are computed by the minimization of the backward and forward prediction errors while satisfying a specific recursion scheme called the Levinson–Durbin recursion. In the Burg method the signal whose PSD to be estimated is assumed to be the output of an all-pole linear system driven by white noise. In our study, the model order was taken as 15 after literature [17]. This method estimates the model parameters directly without a need for the autocorrelation function calculation. The main advantages of this approach are resolving closely spaced sinusoids in signals with low noise levels, and successfully estimating power spectral densities of short data recordings. In addition, this technique guarantees a stable autoregressive model and is computationally efficient [18].

For each epoch, we computed/estimated PSD values at each integer frequency. To be more specific, we have computed the spectrum at $f = 4, 5, 6, \ldots, 39, 40$ Hz, total of 37 frequency points. We then normalized the power values using the sum of all power values in that segment to minimize inter-subject and intra-subject variability. Therefore, we obtained 37 normalized power values (NPVs) for each epoch (totally 16 epochs), channel (totally 19 channels), and subject (totally 15 subjects) and created a Matlab cell array with size $15 \times 16 \times 19$. In each cell there were 37 NPVs. We used this data structure for the subsequent statistical analysis.

2.4. Statistical analysis

Because we knew which subject liked which shoe from the button usage, we created two data sets of NPVs. One data set was composed of the collection of all NPVs of 19 channels coming from the LIKE cases (the shoes that the subjects liked), and the other one DISLIKE cases (the shoes that the subjects did not like). This way we were able to investigate the general characteristics in PSD of EEG signals by comparing the LIKE and DISLIKE cases in terms of discriminative channels or frequency values.

In order to determine the most discriminative frequencies, we have used "logistic regression" [19,20] on each channel, where our categorical (binary) dependent variable was LIKE/DISLIKE status and continuous independent variables were the NPVs. One major advantage of logistic regression is that the influence/contribution of all predictors are taken care of all at once, i.e. logistic regression is very similar to analysis of variance (ANOVA), in terms of avoiding misleading conclusions that may arise due to multiple testing [21].

In our implementation of logistic regression, we have utilized *glmfit* generalized linear model (GLM) fit function/subroutine of Matlab Statistics Toolbox, as logistic regression is a special case of GLM where response distribution is binomial and the link function is the logistic sigmoid function that maps the real line between 0 and 1.

An excellent discussion of GLMs can be found in Ref. [21], here we will briefly explain GLM approach for sake of completeness. GLMs were first formulated in 1972 by Nelder and Wedderburn to unify different statistical models, like linear, logistic, or Poisson regression [19]. It is well known that linear regression predicts the expected value (EV) of a given response variable having a normal distribution as a linear combination of a set of predictors. In GLMs, by incorporating a link function the linearity assumption is relaxed, and the response variable can be modeled with a distribution other than normal. The linear predictor (LP) is the quantity that incorporates the information about the independent variables into the model. LP is connected to the EV of the data through the link function. η (=$\mathbf{X}\beta$) is expressed as linear combinations of unknown parameters β. The coefficients of the linear combination are characterized as the matrix of independent variables $\mathbf{X}$. In our problem, LIKE and DISLIKE datasets with NPVs comprised predictors and the response variable was 1 for 65 LIKE cases and 0 for 144 DISLIKE cases. The distribution of the response variable was binomial, and the link function was assigned as the "logit function," i.e., the inverse of the sigmoidal 'logistic' function.

We observed that when all the NPVs used as predictors, the regression problem/model was becoming ill-posed, as indicated by the warning messages of the *glmfit* subroutine. This could be due the fact that there were only 65 LIKE and 144 DISLIKE cases versus total of 37 NPVs, i.e. too many predictors. Further, high frequency tails of the PSDs were very similar to each other, i.e. too much correlation among predictors. In order to alleviate these problems, we divided the frequency range into two bands, low frequency (LF) 4–19 Hz and high frequency (HF) 20–40 Hz. (This way, we had respectively 16 and 21 NPVs/predictors in LF and HF bands.) The *glmfit* returns weight coefficients of predictors (β parameters) and corresponding p-values indicating statistical significance of estimated predictor weights, i.e. whether or not they are significantly different than zero. Hence, for each channel and frequency band, we computed a matrix of p-values (significance results) by feeding appropriate parts of NPVs to the *glmfit*.

Along with this analysis, for each case we have also checked if the overall model that was fit to our data was statistically significant from the one constructed using only the constant term (no predictor information). This comparison was performed based on the Chi-square statistics using the deviances and likelihood ratio test (LRT) [22]. LRT allows for the comparison of two models by looking at the difference in the deviances.

2.5. *Discriminative channels and frequencies*

The next step of the analysis whose aim was to determine discriminative channels and frequencies used the *p*-value matrix (37×19 matrix, i.e., 37 frequencies and 19 channels). Using this matrix, *p*-values that are less than 0.05 (which we called low p values) was determined corresponding to different channels and frequencies. For a frequency, if the number of low *p*-values was greater than 3 (a figure/threshold that approximately corresponds to 10% of the cases), then that frequency value was assigned as one of the most discriminative frequencies (MDFs). This examination of *p*-values was carried separately in LF and HF bands. Similarly, for a channel, if number of low *p*-values was greater than 3 (15% of the cases), then that channel was designated as one of the most discriminative channels.

3. Results

In Fig. 2a, we have included three most liked shoes that were preferred by 8, 8, and 12 subjects (out of 15 subjects) from left to right panel. Fig. 2b shows three least liked shoes that were preferred only by 2 subjects for each photograph.

In the first step of our analysis, we have manually processed (removed several types of artifacts) on a total of 240 epochs each of which was 10 s long (we discarded 5 s long portions shown before shoe slide presentation). While removing artifacts from multichannel EEG recordings by excluding certain parts from the signal, we worked on a window depicting Fp1-A1 channel as a reference signal while visually checking all channels on a separate window.

As for the breakdown of LIKE and DISLIKE cases, LIKE cases included 37×68 values for each channel, i.e., 68 shoes were liked (by 22 male and 46 female subjects) out of 209 shoes with proper data. The DISLIKE cases included 37×141 values for each channel, i.e., 141 shoes were disliked (by 40 male and 101 female subjects) out of 209 shoes with proper data. Fig. 3a and b shows EEG signals obtained from F7-A1 (upper panel) and its corresponding normalized power values (lower panel) from one of the LIKE conditions (the most liked shoe among all subjects) and one of the DISLIKE conditions (one of the most disliked shoes among all subjects).

In the male subjects group one subject liked 9 out of 16 shoes, another subject liked 2 out of 16 shoes. A similar trend was valid for female subjects group, one subject liked 12 and another one liked only 1 shoe. Approximately 5 shoes were liked on average for both male and female subjects. Table 1 shows the general portrait of the relationship between number of LIKE cases, average timing of the like decisions (TLD) and range of TLD for each subject. We used M and F to code male and female subjects. For example, M1 is the first male subject and F1 is the first female subject. We should here note that in the TLD analysis we did not leave out short epochs (less than 5 s that was excluded in PSD estimation), and thus used 74 LIKE cases (instead of 68 as stated above) and 146

Fig. 2 – (a) Three most liked shoes out of 16 shoes used in the experiments. (b) Three least liked shoes out of 16 shoes used in the experiments.

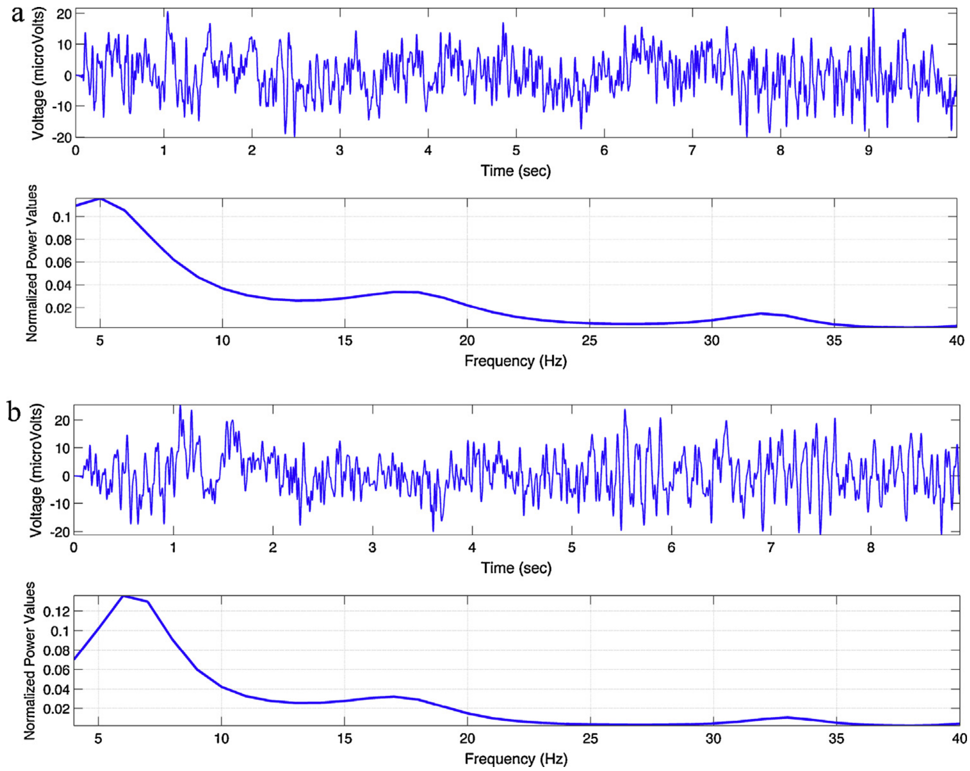

Fig. 3 – (a) An EEG signal taken from F7-A1 (upper panel) and its corresponding normalized power values (NPVs, lower panel) from one of the LIKE conditions (the most liked shoe among all subjects). In the upper panel vertical axis corresponds to voltage values in microVolts and horizontal axis is time in seconds. In the lower panel vertical axis shows the normalized power values and horizontal axis shows the frequencies in Hz. (b) An EEG signal taken from F7-A1 (upper panel) and its corresponding normalized power values (NPVs, lower panel) from one of the DISLIKE conditions (one of the most disliked shoes among all subjects). Same display style is used with the one in (a).

Table 1 – The statistics showing the number of likes, mean of TLD (timing of the like decision) and minimum and maximum TLD obtained for each subject in our experiments.

	Num. LIKE	Mean TLD	Min-Max TLD
M1	9	0.55	0–2
M2	6	0.33	0–1
M3	6	2.0	0–3
M4	2	2.5	1–4
M5	3	3	3–3
F1	2	2.0	1–3
F2	5	3.2	2–8
F3	7	3.7	1–8
F4	12	1.2	1–2
F5	5	2.4	1–4
F6	1	0	0–0
F7	4	2.5	1–5
F8	5	5.0	2–9
F9	3	1.6	1–2
F10	4	1.0	1–1

DISLIKE cases (instead of 141 as stated above). In 38 out of 74 LIKE cases (approx. 51%) subjects made their decisions (in other words, pressed the button) in the first second; 21 of these 38 early decisions were made by female subjects. Another 16 LIKE decisions were reached between 1 and 2 s (approx. 22%). Only 6 decisions were made in more than and equal to 5 s. These 6 late decisions were made by 4 female subjects. All male subjects made decisions in less than 4 s.

Fig. 4 depicts NPVs computed for the frequencies between 4 and 40 Hz from 209 clean epochs of all subjects for channel number 3 (F7-A1). Upper and lower panels show NPVs for DISLIKE and LIKE cases, respectively.

Fig. 5 shows p-values of the β parameters as a matrix. Rows and columns are channel numbers and frequency values, respectively. The p-values that were less than 0.05 are represented with a black square and the rest as white. This matrix representation and visualization helped us see the global picture corresponding to our results with ease. If on a row at one frequency value there are more than 3 (approx. 10% of the frequency values) black squares then this frequency was noted as the frequency with high discrimination power. If on a column at one channel number there are more than 3 (approx. 15% of the channels) black squares then this channel was noted as the channel with high discrimination power. The above panel corresponds to low frequency band (4–19 Hz) and the below panel corresponds to high frequency band (20–40 Hz).

This figure demonstrates that in the LF band 4 and 5 Hz were found to be the most discriminative frequencies (MDFs). In the HF band for none of the frequencies low p values occurred more than 3 times. In the LF band, a frontal channel on the left (F7-A1) and a temporal channel on the right (T6-A2) were found to be the most discriminative channels (MDCs). In

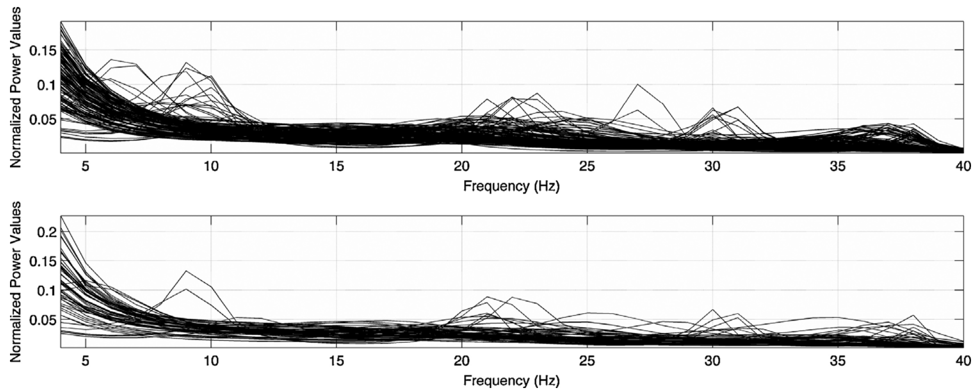

Fig. 4 – Normalized power values (NPVs) versus frequency values between 4 and 40 Hz for all channels and all epochs. Upper panel shows DISLIKE cases and lower panel shows LIKE cases.

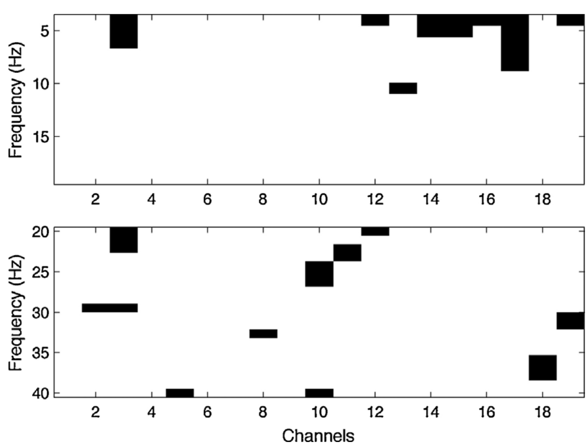

Fig. 5 – The *p*-values of the β parameters are represented as a matrix. Rows are channel numbers and columns are frequency values. The *p*-values that were less than 0.05 (important *p* matrix) are marked as a black square and the ones greater than 0.05 are depicted as white. Black–white contrast helps the viewer to see the channels and frequencies that have the highest discrimination power. The upper panel corresponds to low frequency band (4–19 Hz) and the lower panel corresponds to high frequency band (20–40 Hz).

the HF band, MDCs were central (Cz-A1) and occipital on the left (O1-A1) channels.

4. Discussion and conclusions

The aim of this study was to investigate the performance of logistic regression approach used to determine the EEG channels and frequencies that best discriminate a group of subjects' partialities (like or dislike decision). Our case study focused on women's shoes in order to test the partiality of 10 female and 5 male subjects. In addition, we explored the timings of like decision and whether they were different between male and female subjects. We can summarize our key findings as follows:

- The mean time of LIKE decision for male subjects was almost half of that for the female subjects. This and some other individual statistics also support the idea that young female college students make decisions in a longer period of time than male students do.
- 9 out of 10 female subjects and 3 out of 5 male subjects preferred the same most liked shoe. The other most liked shoes were preferred by 5 out of 10 female subjects and 3 out of 5 male subjects. Average number of LIKE decisions for male and female subjects were almost the same (5 out of 16 shoes). These numbers suggest that male and female behavior for this set of stimulant images were similar.
- Some subjects liked only 1 or 2 shoes; some others liked 9 or 12 shoes. This was true for both male and female subjects. This shows that it is hard to generalize any kind of preference. However, the most or least liked models can give a general clue for marketing professionals and shoe designers.
- In the frequency analysis 4 and 5 Hz were found to be the most discriminative frequencies (MDFs). In the 4–19 Hz band, frontal and temporal channels (F7-A1 and T6-A2) were found to be the most discriminative channels (MDCs). In the 20–40 Hz band, central and occipital channels (Cz-A1 and O1-A1) were determined as the MDCs.

In neuro-marketing field using partiality analysis we can evaluate whether a consumer likes a certain design of a product or not. In our approach we propose using less number of electrodes and focusing on specific frequency values in such analyses in order to make the whole process cheaper and less time-consuming. As a result of our study we found that only 4 channels and 2 frequency values are enough (or possess the most discriminative power) for the partiality analysis research.

There are numerous studies examining emotional processes by using visual, auditory, and combined stimuli to evoke emotions. The pictures from the International Affective Picture System (IAPS) developed by Lang et al. [23] have been frequently employed as the stimulant for the investigation of various questions [24–26]. In addition, Vecchiato group in Italy [3,27] recently showed that during the observation of the TV commercials cortical activity in the theta and gamma bands was higher and localized in the frontal areas for the commercials judged pleasant when compared with disliked ones. Many studies also showed that both subcortical areas like amygdala and cortical areas like prefrontal cortex, cingulate cortex, and temporal cortices are critical in emotion processing [28–32]. Activity from the amygdala and the remaining parts of the limbic system cannot be sensed directly in surface recordings because they lie deep in the brain. The relation between the amygdala and the prefrontal and temporal cortices produces an intentionally experienced sensation of an emotion [32]. The temporal lobe corresponding to the channels T3 to T6 is important for emotion, language, hearing, and memory. The prefrontal lobe is part of the frontal cortex and is involved in the cognitive, emotional and motivational processes. In addition, recent studies show that the emotional meaning of a stimulus controls the visual cortex including the visual areas V1 and V2 [33].

We must note here that instead of using the total power in different frequency bands (e.g., delta, theta, alpha, beta), which is the common practice in the context of EEG analysis and emotion processing, we have chosen to use the power at each frequency in the 4–40 Hz range in our comparisons. This corresponds to better frequency resolution, compared to the lumped approach of band type analysis. Although we believe that our results and findings are interesting and the methodology that we have introduced may help pave the way for future studies to be carried out in the same field, we must acknowledge that these findings need to be validated or augmented by future, possibly larger, studies, where the number of subjects is higher. One of the main limitations of this study is that since the number of trials is very low (and since the number of likes is very low for some subjects) the statistical power of their tests and generalizability of the results is limited. Further, the influence of type or nature of stimulus on the study also deserves attention.

Conflict of interest

The authors declare that they have no competing interests.

Acknowledgment

We would like to extend our special thanks to the students of Biomedical Engineering Dept. of Erciyes University, Kayseri, Turkey, who have volunteered to participate in our study.

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