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Brain Effective Connectivity Comparison in the Four States of Confrontation to the Brands During Shopping

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ABSTRACT: Neuromarketing assists us to uncover the subconscious effects of marketing stimuli on consumers' brains from a neuroscientific perspective. One of the important effects of brands on human brain is in the level of directed relations between brain areas which were less considered in neuromarketing studies. In this paper, we used the EEG signals recorded during the confrontation of participants to the brands in the virtual shopping center. 20 participants (10 females and 10 men) were contributed to the experiment. After preprocessing, extracted brain sources were clustered to brain areas. Effective connectivity between brain areas was calculated using the Generalized Partial Directed Coherence (GPDC) index in four different states of watching brands (1. unfamiliar and undesired brands 2. familiar and undesired brands 3. unfamiliar and desired brand 4. desired and familiar brands). Statistical analysis between these states showed that in watching familiar brands, almost all brain areas have stronger relations. During watching unfamiliar brands, between hemispheric relations are stronger when brands are desired, and interhemispheric relations are stronger when brands are not desired. Additionally, during watching familiar brands, left-brain relations are stronger when the brands are desired and right-brain relations are stronger when the brands are undesired. As the brands were shown for 2 seconds, the connectivity values in 1st second and 2nd second of watching brands do not have significant differences. Moreover, connectivity values are stronger in lower frequency bands of the brain during watching the brands in the shopping center.

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1- Introduction

The development of technology in Biomedical engineering has encouraged neuroscientists to gain a better understanding of human brain features and complexities. One of the comprehensive applications of neuroscientific technologies is in the neuromarketing field, which tries to realize the brain transformation of consumers. Neuromarketing is an interdisciplinary field and contains form marketing, psychology, and neuroscience. Traditional marketing only considers people targets while neuromarketing looks deeper into humans and investigates their subconscious behavior. Not only a logical response but also the emotional response of consumers, which is nonconscious, are studied in neuromarketing [1].

Neuromarketing is also a profitable marketing approach since it can discover people's preferences and explain why they decide to shop for a product. One of the cognitive aspects of using neuromarketing techniques is to assess the brain pattern of brand recollection by watching them in advertisements or shopping centers. Thereafter, the marketing managers can consider more on their shoppers' minds and design more suitable advertising and marketing strategies [2].

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Drawing out information from human brains and their activities is vital and important in marketing research. Several tools are used in neuromarketing to extract information from customers brains and their behavior, such as Magnetoencephalography (MEG), Facial Recognition Coding System (FRCS), Heart Rating (HR), Electroencephalography (EEG), Galvanic Skin Response (GSR), Eye Tracking (ET) and functional Magnetic Resonance Imaging (fMRI) [2]. EEG is one of the most comprehensive neuroscientific techniques for marketing studies. High temporal resolution, noninvasiveness, and portability are among its prominent benefits. The EEG technique can of course complement traditional marketing in several ways and overcome its restrictions [3].

Generally, there are not abundant papers to work on the comparison between states in the neuromarketing field, using the EEG data analysis. However, we mention some of the searched studies in this field. One of these studies has done multiple univariate comparisons in the context of neuro-electric brain mapping. They extracted electrical data from the mannequin's head using a 61 channels EEG headset while the documents were presented on the screen (REST) and while commercial advertisements were presented on the screen (TASK). There will not be any differences between TASK and REST since the subject was a mannequin, not a human. At first, the results showed significant statistical differences between power spectra of signals during TASK and REST. However, it was corrected by using Bonferroni or Bonferroni-Holm adjustments[4]. Another study tried to investigate the impact of the reward system on reaction to a different type of consumer goods. They found the theta frequency band in the Dorsolateral Prefrontal Cortex (DLPFC) increases when the consumer sees preferred stimuli. In addition, they detected more consistent activity in response to consumer goods in the Left Prefrontal Cortex (LPFC). This study highlighted the coherence between EEG signals and preferred ranking [5]. In the same year, another study focused on gender differences between commercial categories and scenes of interest from cerebral indices. They recorded spontaneous recall value from theta power of the left frontal cortex and interest values from differences between average EEG power of the left and right channels. The results showed the perfume advertisement that is more active and swift, is more memorable for men than women. However, the calm perfume advertisement is more interesting for women than men [6]. A group of researchers inspected Evoke Related Potentials (ERPs) differences before and during the purchasing process. They suggested that when the consumer goods reveal, early ERPs like N200 indicate the preferences driven by an unconditional and automatic process. However, late ERPs like Positive Slow Waves (PSW) and Late Positive Potentials (LPP) represent the preferences carried out from more elaborative and conscious process [7]. Afterwards, a group of scientists measured the information flow between each electrode pair before advertising stimuli (Control stage) and during the advertising stimuli (Experience stage). The Wavelet Coherence (WC) and Phase Difference (PD), which are functional connectivity indices, were utilized in the mentioned study. WC values were generally higher in the experience stage than the control stage in the theta, alpha, and beta frequency bounds. However, PD values were generally lower in the gamma bound. They also observed an increase of interhemispheric coherence during observing the advertising stimuli in the anterior frontal-temporal-parietal area [8].

As the directed relations can gain us more information about the relations rather than the non-directed ones, for measuring the directed information flow between Brain channels or sources, many indices have been introduced. Granger causality is one of the famous effective connectivity indices which is based on multivariate autoregressive modeling between signals. Some of the other indices that were proposed in the context of granger causality are Granger Causality Index (GCI), Partial Directed Coherence (PDC), and Directed Transform Function (DTF) [9]. For example, by using PDC, L. Astolfi et al. showed differences in directed brain connectivity when subjects are watching TV commercials. Two types of commercials have been displayed. Those that will be remembered after several days of first watching (RMB) and those that will not be remembered after several days of first watching (FRG). They concluded output information flow from the Anterior Cingulate cortex (ACC) and Cingulate Motor area (CMA) and inflow information flow to Broadman areas 5,7 and 40 are significantly higher in RMB TV commercials than FRG TV commercials [10].

Among many indices of measuring directed connectivity, we chose Generalized Partial Directed Coherence (GPDC), since it can consider the causality and is based on the robust concept of Granger causality. GPDC is the extended method of PDC and it has a good performance on distinguishing between direct and indirect connections. More importantly, GPDC is a robust method of counteracting noisy data [11]. In addition, it measures effective connectivity for each frequency and time window. Thus, it gains us detailed information of the connectivity values [12].

The purpose of the following study is to discover brain effective connectivity distinctions in different combinations of watching and choosing the brands. By using the GPDC index, we measured the effective connectivity between brain sources when the consumers are confronted with four different types of advertising stimuli. In particular, after preprocessing the gathered EEG signals from subjects during purchasing the products, we used K-means clustering to discover effective brain regions in this neuromarketing task. For each subject, we assigned specific time series to its brain regions by help of existing source signals in those brain regions. Finally, significant differences of each effective brain area relations between four states of watching and choosing brands were figured out using statistical analysis. To investigate brain area conversions among states, we then perform a statistical test among each pair of states.

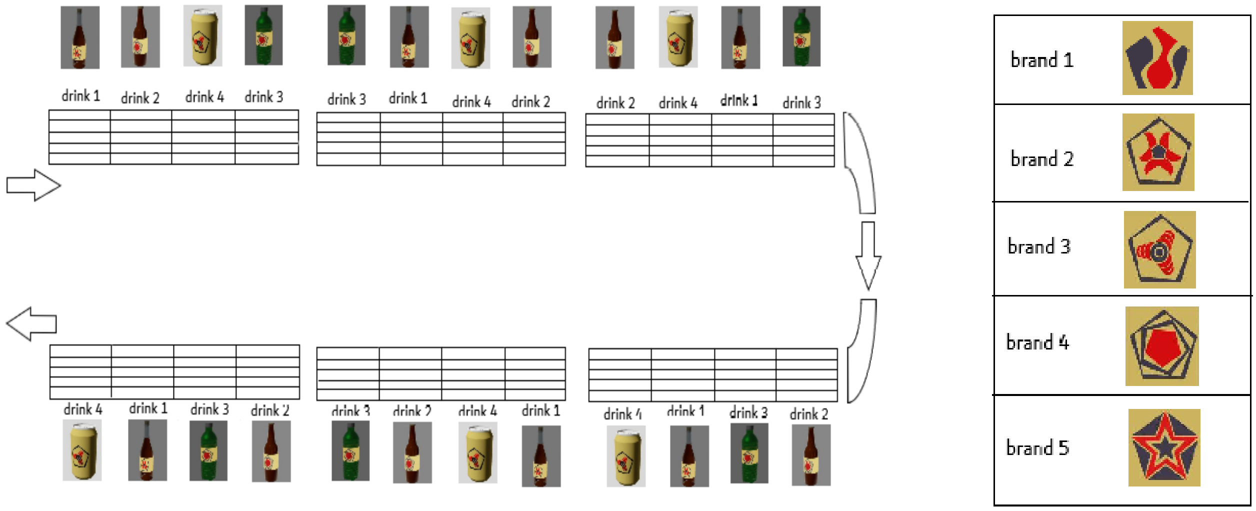
2- Materials and Method

In the following section, there will be some explanation about the dataset used in the project and how we treat these data to extract information from them.

2- 1- Subjects and Procedures of the Experience

In 2018, a comprehensive neuromarketing study was accomplished by M. A. Moosavi [13] and Z. Izadi [14] under the supervision of Dr. M. H. Moradi at Amirkabir University of Technology. We used the data collected in this neuromarketing study accomplished by our team to analyze the field of effective connectivity. 20 subjects (10 females and 10 men) participated with an average age of 26.17 ± 1.67. Each subject watched four background advertising videos. Videos were designed on the negative and positive themes. 6 females and 5 male participants watched four videos of the negative theme. 4 females and 5 male participants watched four videos of the positive theme. One specific brand existed somewhere in the videos for each one of the subjects. After watching the videos, subjects entered the virtual shopping center to purchase several beverages with brands on them.

Moosavi and Izadi designed a virtual shopping center with filled shelves with branded beverages. There were 24 shelves and each had five floors. Every floor of each shelf had one specific brand that was different from the brands of the other floors. Five different brands were used in the study



(a) (b)

Fig. 1. (A) a schematic of the virtual shopping center where participants walk to purchase among shelves in the direction of the arrows. 24 shelves of beverages exist in the virtual shopping center. Each has five floors with different brands. Beverages had four types which varied between shelves. (B) The five Brands that were used in the study are perched on one of the shelves as sample

and the sort of their presence on the floors varied randomly among the shelves. Additionally, four types of existing beverages changed stochastically between the shelves, but all floors of a shelf were from one type of beverage. The brands were new and the participants hadn't seen them before. These explanations are shown in Fig. 1. Therefore, participants were stimulated by a visual task when they were confronted with some beverages with brands on them on each one of the shelves' floor [13].

In the beginning the selves' floor door is closed. When participants would look at each of the floors, first the color of the door would change from green to pink for one second., then the door would open and the content of the self's floor would display for two seconds. This procedure is shown in Fig. 2 *with* more details [13].

2- 2- EEG Data

The participants entered the virtual shopping center using Oculus rift Virtual Reality (VR) equipment. Simultaneously their brain activity was recorded using 64 channels Ant-neuro EEG headset. Moreover, EEG recording was done during watching advertising videos but in this study, we focused on the EEG recording during watching and purchasing the branded beverages in the shopping center [13].

As we mentioned in the previous section, there were five different brands in the virtual shopping center. The point is; one of them was familiar to each one of the subjects because they watched that brand in the videos. Therefore, one floor of each shelf contains a familiar brand. After watching the brands of all floors of the shelf, subjects were able to purchase at most three beverages [13]. The brand which was bought by the subject is the desired brand for that shelf. Henceforth, when the subjects were confronted with the brands before purchasing them, we put the brand of each shelf floor to one of the following categories.

1. The brands which were not seen before and will not be chosen to purchase (Unfamiliar & Undesired state)
2. The brands which were seen before, but will not be chosen to purchase (Familiar & Undesired state)
3. The brands which were not seen before, but will be chosen to purchase (Unfamiliar & Desired state)
4. The brands which were seen before and will be chosen to purchase (Familiar & Desired state)

2- 3- Data Preprocessing

All the steps for EEG cleaning and preprocessing were performed in the EEGLAB toolbox that was implemented in MATLAB programming software (The Mathworks, Inc.) [15]. Harvard processing pipeline was also adapted for EEG preprocessing orders [16].

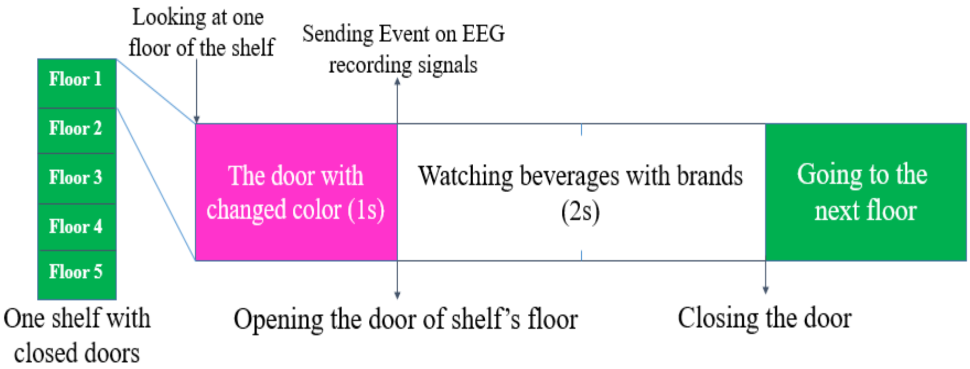


Fig. 2. Procedure of watching brands in virtual shopping center

2- 3- 1- Filtering and Component Extraction

By using a 1Hz high pass fir filter, low frequency moving artifacts were removed from the EEG signals. As the active bound of EEG signals could not exceed 60Hz, the components of the signals which has more than 60Hz were removed by a 60Hz low pass fir filter. For the strong and important line noises in EEG signals, the 48 to 52 notch filter was utilized.

In this study, one or two channels were sometimes noisy because of the VR mechanical pressure on the EEG headset [17]. For distinguishing these noisy channels, the channel which had heterogeneous behavior in time and frequency was excluded from the dataset. Afterwards, the mean of other channels data was put in substitute of the excluded channel.

Afterwards, the ICA method with the Infomax algorithm was used for cleaning the EEG dataset from extra brain signals like eye blinks and EOG, body movement, ECG, channel noise, etc. Noisy components were removed by distinguishing noisy using the ICA algorithm [18].

2- 3- 2- Signal Segmentation

The EEG signals gathered during the confrontation with the bands in the virtual shopping center were segmented into epochs. Each epoch lasts for three seconds from one second before watching the brand to two seconds after watching the brand. The first seconds of the epochs were used for baseline removal since that's before watching the stimulus. Therefore, we used two last seconds of each epoch to continue the processing.

2- 3- 3- Dipole Fitting

Every brain component obtained after execution of the ICA were assigned to the dipoles inside the 3D model of the scalp. These dipoles are localized and fixed as stationary brain sources. The localization process of the dipoles in the scalp 3D model was done using a nonlinear optimization source inversion algorithm which is implemented in the EEGLAB toolbox [19]. Immediately after dipole localization, some of the dipoles might take a place far from the brain area. Thus, we excluded brain components that correspond to outside brain dipole. The signals of the EEG channels are highly correlated due to the undesired volume conduction effect [20]. The signals assigned to the brain dipoles by brain components are the brain source signals and these dipoles are brain sources. The volume conduction effect is highly reduced in source signals [21]. Therefore, we considered the source signals for the calculation of brain connectivity.

2- 3- 4- Rereferencing and Down Sampling

After removing all the artifacts, signals of the channels were a reference to the mean of them. To reduce the dataset amount, they were down sampled 1000 sampling frequencies to 250 sampling frequency.

2- 4- Finding Effective Brain Area

The location and numbers of the brain areas varies between each person. This issue causes a problem in group statistical analysis. Therefore, we utilized some clusters and put the brain sources in these clusters to make the synchrony between participants. Clustering performance was done by the K-means algorithm. Input features to the algorithm were x,y,z coordinates of the brain sources. Hence, the brain sources were put to brain clusters by their coordinates.

One important point in this issue is the number of clusters. As the number of clusters grew, the inner cluster dispersal reduced, but the between cluster dispersal increased. They were calculated by the equations (1) and (2). In addition, with the growing number of clusters, the number of clusters that don't have any dipoles increased in some subjects. Thus, we chose the number of the clusters with these three criteria (inner cluster dispersal, between cluster dispersal, and number of without dipole clusters).

$$J_{in} = \frac{1}{N}\sum_{i=1}^{N}\sum_{\substack{t=1 \\ x\in c_i}}^{n_i}\left\|x_{it} - \mu_i\right\|^2 \tag{1}$$

$$J_{out} = \frac{1}{m}\sum_{\substack{i,j=1 \\ i\neq j}}^{m}\left\|\mu_i - \mu_j\right\|^2 \quad , \quad m = \binom{N}{2} \tag{2}$$

where N is the number of clusters and n_i is number of samples in each clusters. μ_i and μ_j are centers of clusters c_i and c_j, respectively.

We named these clusters brain areas. We also devoted one signal for each brain area by calculating the median of brain source signals that had dipoles in that brain area. If some brain areas missed dipoles in a participant, we assigned the mean of the signals of other persons corresponding brain area for these without dipole brain areas.

2- 5- Connectivity Calculation

We calculated the effective connectivity between brain areas' signals using the GPDC index. For this issue, some steps of processing must be done. These steps are expressed in the following section.

2- 5- 1- MVAR Modeling

As the GPDC index is based on the Granger causality approach, the first step is to calculate the Multivariable Autoregressive (MVAR) model and get the connectivity matrix. The set of each time series at the nth sample is expressed in equation (3). MVAR models were determined by equation (4). Afterwards, equation (5) helped to show the model residuals, which has zero mean and a Σ_w covariance matrix.

$$X(n) = \{x_1(n), \ldots, x_N(n)\} \tag{3}$$

$$x_i(n) = \sum_{k=1}^{p}\left(\sum_{m=1}^{N-1} a_{im}(k)\, x_m(n-k)\right) + w_i(n) \tag{4}$$

$$W(n) = \{w_1(n), \ldots, w_N(n)\} \tag{5}$$

where $a_{ij}(k)$ is one element of $N \times N$ the connectivity matrix A_k, which demonstrates the influence of time series j to time series i in kth order. We chose the order of the model using Akaike (AIC) method that is written in the equation (6) [22].

$$AIC(p) = Ln\left|\Sigma_{w_p}\right| + \frac{2}{\hat{T}}\, p\, N^2 \tag{6}$$

where $Ln\left|\Sigma_{w_p}\right|$ is the logarithm of the determinant of the covariance matrix Σ_w for the test in a model by order p. N is the number of time series and $\hat{T}$ is total number of samples [22].

2- 5- 2- Model Validation

The MVAR model validation was examined in three steps:

a) Model Stability and Stationarity

The random process $X(n)$ is considered White Sense Stationary (WSS) if absolute values of the eigenvalues of the matrix below were less than one [22]:

$$S_{Np\times Np} := \begin{bmatrix} A_1 & A_2 & \cdots & A_p \\ I_N & 0 & \cdots & 0 \\ \vdots & \ddots & \ddots & \vdots \\ 0 & \cdots & I_N & 0 \end{bmatrix} \tag{7}$$

b) White Residuals in the Model

The efficient MVAR model of each signal has uncorrelated and small residuals. The whiteness of residuals was tested by the Autocorrelation Function (ACF) test. The autocorrelation matrix in lag k was given by $R_k = D^{-1} C_k D^{-1}$, where $C_k = E[w_i, w_{i-k}]$ is the auto-covariance matrix, and D is a diagonal matrix with diagonal elements equal to the square root of C_0 diagonal elements. Finally, for the statistical test of ACF, $\rho = \dfrac{count\left(|R_k| > \pm 2/\sqrt{\hat{T}}\right)}{count(R_k)}$ was used as a statistic [22].

c) Model Consistency

To check the consistency, a series of a dataset with the same dimension and sample number by the MVAR model were produced. After that, $PC = \left(1 - \dfrac{\|R_a - R_r\|}{\|R_r\|}\right)\times 100$ value were computed. R_a and R_r are vectorized autocorrelation matrices of the artificial and real datasets. If PC is higher than 80%, we conclude that the model is consistent [22].

2- 5- 3- Effective Connectivity Measuring

The value of connection from signal $x_j(n)$ to signal $x_i(n)$ in each frequency is measured by formula (8). Unlike the PDC index, the GPDC index considers the variances of the innovation processes. This notion will result to have purer directed connectivity values. Measurements of the GPDC index is brought in the formula (9) and (10) [12].

$$\overline{A}_{ij}(f)=\delta_{ij}-\sum_{i=1}^{P}a_{ij}(k)\,e^{-j2\pi fk} \quad (8)$$

$$\pi_{ij}^{(w)}(f)=\frac{\frac{1}{\sigma_i}\overline{A}_{ij}(f)}{\sqrt{\sum_{k=1}^{N}\frac{1}{\sigma_k^2}\overline{A}_{kj}(f)\overline{A}^{*}_{kj}(f)}} \quad (9)$$

$$\left|\pi_{ij}^{(w)}(f)\right|^2\le 1 \quad , \quad \sum_{i=1}^{N}\left|\pi_{ij}^{(w)}(f)\right|^2=1 \quad (10)$$

where δ_{ij} is the Heaviside function equal to 1 when i=j. In the formula (9) and (10), w represents the window time. σ_i is the variance of the innovation process $w_i(n)$ and σ_k is the variance of the innovation process $w_k(n)$.

2- 5- 4- Actual Connectivity Specifying

After calculating GPDC to find the effective connectivity between brain areas, we had to make sure whether those connectivity values were significantly demonstrating the existence of effective connectivity or not. In order to find a significant relationship between brain areas, we used nonparametric surrogate statistics tests. Surrogate datasets were constructed by the phase randomization method. This method represents each signal in the frequency domain using a Fast Fourier Transform (FFT) and replaces its phase with a random signal, and later gets inverse FFT to produce a surrogate signal for the original ones. If in 95 percent, surrogate datasets had a lower connectivity value between two brain areas than the original dataset, we concluded that the directed relation between those areas is significant [22].

2- 6- Statistical Analysis

As our goal is to compare each directed brain area relation between four states of watching the brands, we just held significant brain areas relation for all four states of watching the brands. It is obvious that samples in four states of watching the brands may be related to each other, because they are from a specific person, frequency, and epoch time. Statistical distribution of every brain area relation was examined by the Kolmogorov-Smirnov test and Shapiro-Wilk test. We found that all brain area relations values are from a non-normal distribution [23]. Therefore, we had to use a nonparametric Friedman test to distinguish differences between states of brand watching [24].

By using the Friedman test, we found whether there are statistical differences between four states of brand watching or not. We need to know what state or states cause this difference when there is a statistical difference between brain areas relation. Hence, we implemented the Wilcoxon sign rank test with Bonferroni correction and showed which brain areas relations have significant differences between states of brand watching. If we have a large number of samples, Wilcoxon distribution gets near to normal distributions [25]. Thus, we can use the one-sided test for the median difference of two populations and see which brain areas have a significantly higher value of effective relations compared to two states of watching brands. In order to define the superiority of connectivity differences between states, we used effect size calculations in the Wilcoxon signed-rank test [26].

What we have done, from preprocessing to statistical analysis, is shown in summary mode in Fig. 3.

3- Results and Discussion

The following section contains the important information gained from each of the processing blocks of the previous section.

3- 1- Choosing Brain Area Number

As mentioned earlier, between cluster dispersal increases and inner cluster dispersal deceases when number of clusters go up. Also, number of without dipole clusters increases by number of cluster increment. The result values of these three parameters for choosing one cluster to 20 clusters are shown in Fig. 4. The growth of inner cluster dispersal reduction after 5 clusters was continued with lower speed than before 5 cluster. In addition, the growth speed is lower after 10 clusters than before 10 clusters for between cluster dispersal increment. If we chose 10 as a number of clusters, some clusters didn't have any dipoles in more than 3 subjects, which is not desired. According to 3rd plot of Fig. 4, for more than 7 clusters number of the number of dipole-less clusters increase severely. Hereupon, we decided to choose 6 as a number of clusters, since only 2 people don't have any dipole in just one of their clusters in this number of clusters.

3- 2- Showing Effective Brain Areas

Center of each brain areas are shown by a dipole in Fig. 5. Table 1 explains the names of the brain areas that these dipoles exist in or are near to by using the Human Brainnetome Atlas.

3- 3- Statistical Differences

According to the Friedman test results, all effective relations between brain areas had significant differences among states of watching brands. To know the details about the differences between states, Wilcoxon signed-rank test with Bonferroni correction outcomes are shown in Fig. 6 to Fig. 8. The superiority of significant differences between effective connectivity in each pair of brand watching states by colored arrows between brain areas. The superiority is calculated by effect size. Stronger differences between brand watching states are shown by warmer colors in the figures.

When subjects were confronted with undesired brands, if those brands were familiar to them, almost all their brain areas showed stronger relations than if the brands were unfamiliar (Fig. 6. A). This remarkable effect of confrontation to familiar brands was also acquired when subjects watched desired

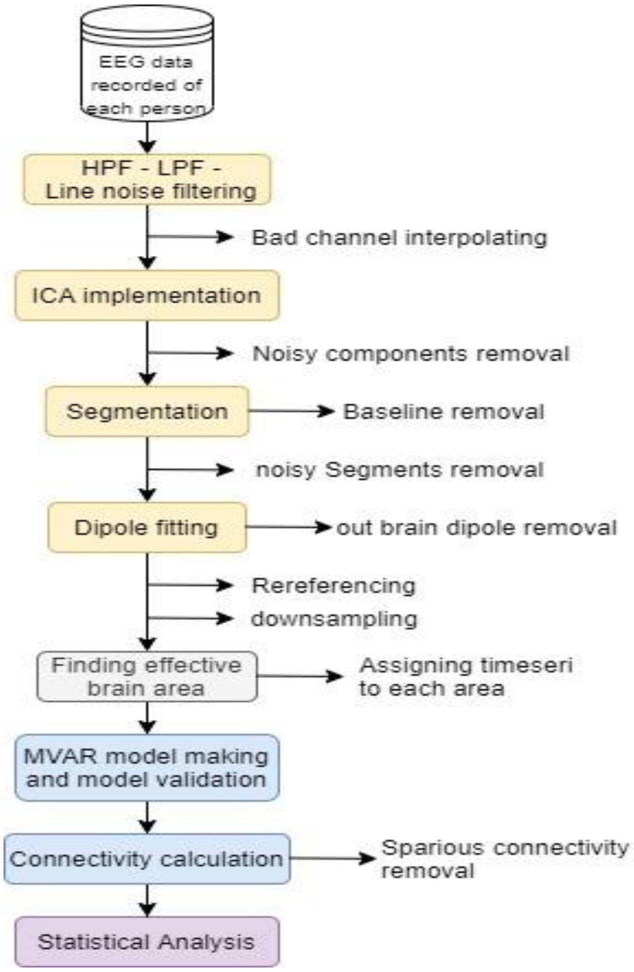


Fig. 3. Steps of the all processing blocks in this study for finding effective brain areas and connectivity measuring

brands (Fig. 6. B). The only relation which was stronger in watching unfamiliar desire brands than the familiar desired brands was from FUG.L to FUG.R (Fig. 6. c). There was no brain relation stronger when subjects watched unfamiliar undesired brands than the familiar undesired brands.

Fig. 7. A presents that most brain areas directed relations were significantly stronger when participants watched familiar and desired brands rather than unfamiliar and undesired brands. Additionally, most brain areas directed relations were stronger in familiar and undesired brands to unfamiliar and desired brands (Fig. 7. B). Thus, we can realize that the effect of watching familiar brands is pretty more than the effect of watching desired brands in the brain effective connectivity.

When subjects watched new brands that they hadn't seen before, mostly their between hemispheric relations were stronger if they wanted to purchase those brands, and if they didn't want to purchase, mostly their interhemispheric relations were stronger (Fig. 8. (A, B). According to Fig. 8. (C, D), when subjects watched desired brands among familiar brands, the interhemispheric interactions of their left brain areas were significantly stronger than observing undesired brands of familiar ones. Likewise, when subjects watched undesired brands among familiar brands, the interhemispheric interactions of right-brain areas were significantly stronger than observing desired brands of familiar ones. Based on Fig. 8. (A, C) the effective connectivity from LCG-R area (in limbic lobe) to ORG-R area (in the frontal lobe) was significantly stronger when subjects watched desired brands if brands were equal as familiarity. This finding is important to distinguish subject buying decisions when they see only familiar or only unfamiliar brands.

In Fig 9, box plot values of brain effective connectivity are compared in different states of watching brands in females and males who have experienced advertising videos in positive or negative genre. It is obvious that in both females and males and both positive and negative genres of watching videos, values of confronting familiar brands were higher. In addition, when females watched negative advertisements, their brain

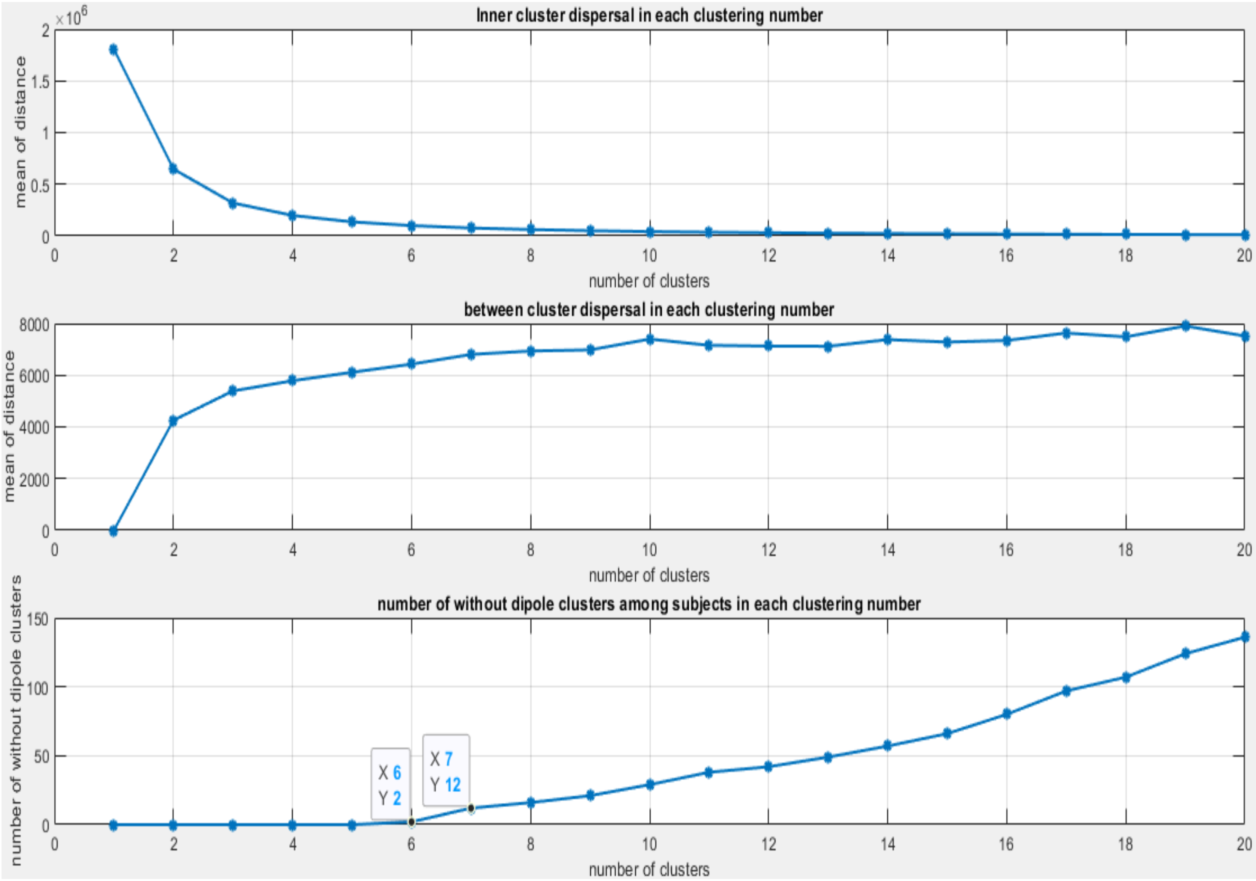


Fig. 4. (up) mean of inner cluster dispersal reduction (center) mean of between cluster increment (down) number of without dipole clusters increment as number of cluster increases

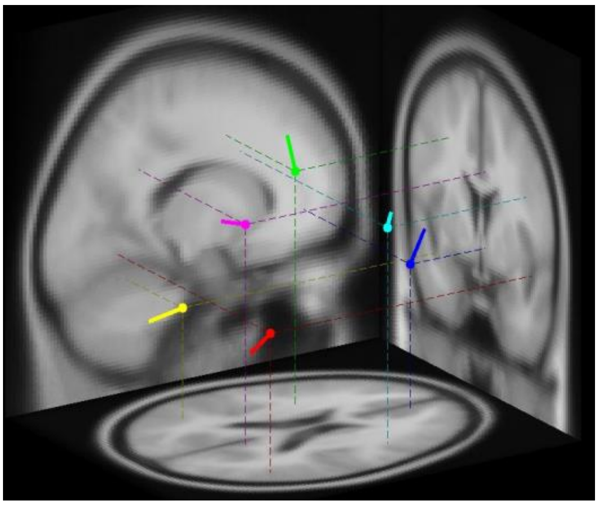


Fig. 5. Center of the clusters exhibited using dipoles

Table 1. Name of effective brain areas using Brainnetome

Effective brain areas number	Name of effective brain areas	Abbreviation name
Area 1	Frontal lobe – Medial frontal gyrus – left hemisphere	MFG-L
Area 2	Frontal lobe – Orbital gyrus – Right hemisphere	OrG-R
Area 3	Temporal lobe – Fusiform gyrus – Right hemisphere	FUG-R
Area 4	Limbic lobe – cingulate gyrus – Right hemisphere	LCG-R
Area 5	Frontal lobe – Inferior frontal gyrus – Right hemisphere	IFG-R
Area 6	Temporal lobe – Fusiform gyrus – Left hemisphere	FUG-L

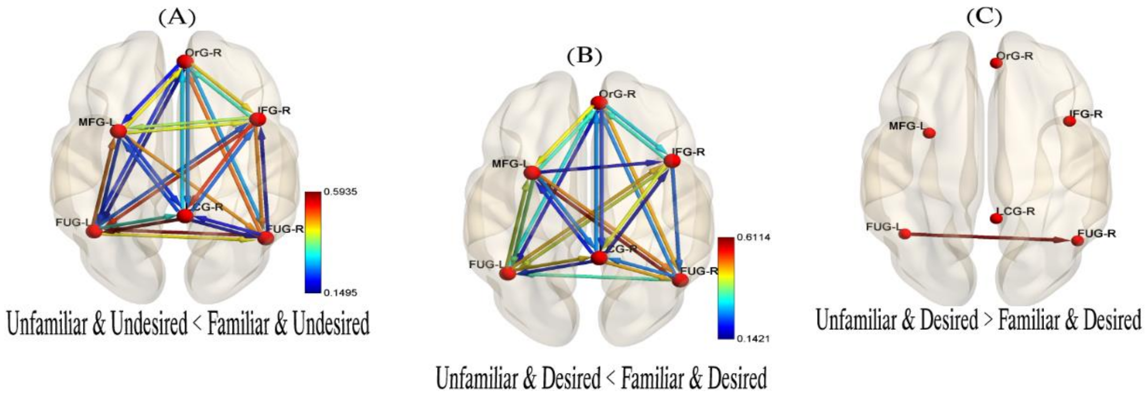


Fig. 6. significant differences in brain area relations between states of watching familiar brands and unfamiliar brands. The color of the arrows shows the power of differences. It shows in (A) and (B) that almost all brain areas have significantly stronger directed relations during watching familiar brands rather than watching unfamiliar brands. It shows in (C) Only one directed relation in watching unfamiliar & desired brands is stronger than familiar & desired brands

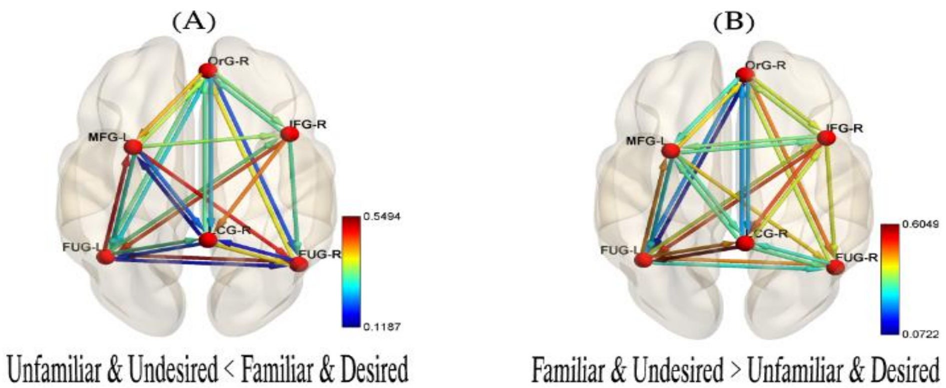


Fig. 7. Significant differences between interaction states of familiar and desired states

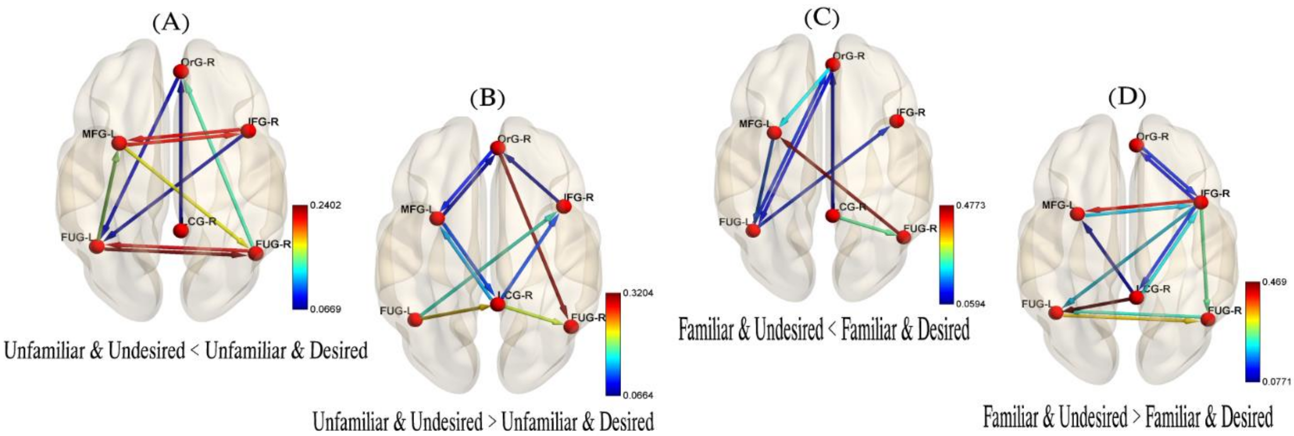


Fig. 8. Significant differences between states of watching desired brands and states of watching undesired brands.

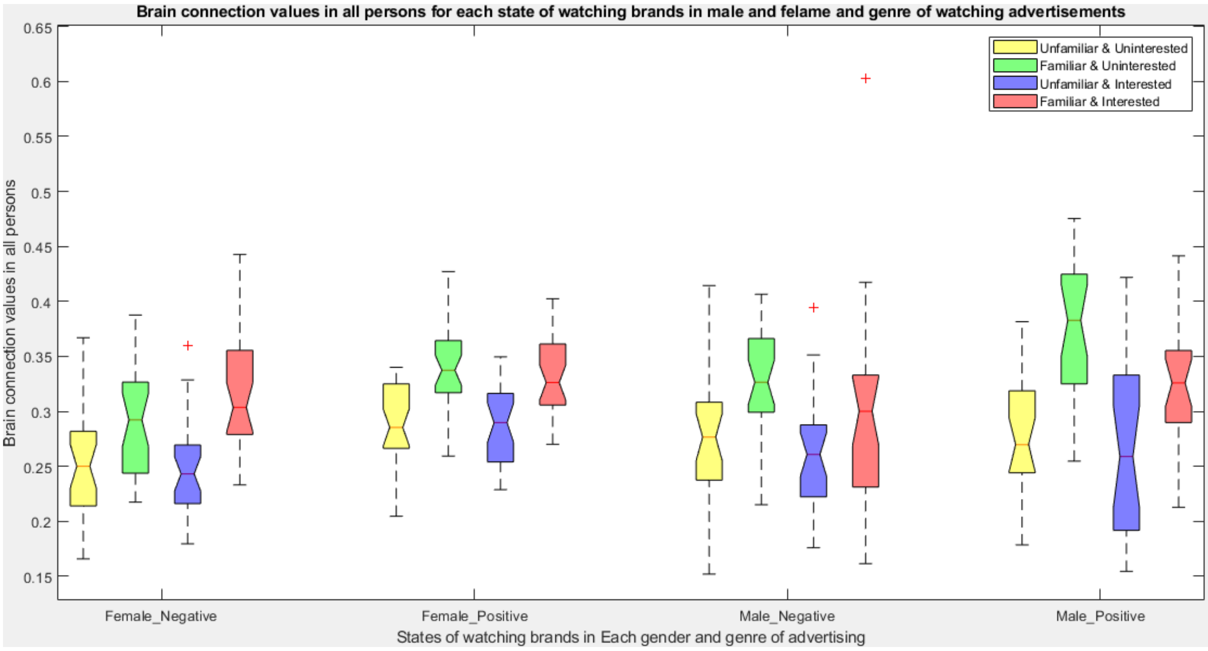


Fig. 9. Brain connection values for different states of brand confrontation comparison in females and male who watched positive or negative genre of advertising videos

connectivity in confrontation to familiar and desired brands was higher than the confrontation to other brands. When males watched positive advertisements, their brain connectivity in confrontation to familiar and uninterested brands was higher than the confrontation to other brands.

By visual comparison of all states of watching brands using boxplot, there were no significant differences between 2 seconds of watching brands. In Fig 10, we can see that brain connection values in the 1st second and 2nd second of brand confrontation are almost equal for all states. Therefore, we can conclude that only one second of brand confrontation would be enough to have its all effects on brain area connection.

The differences in brain effective connectivity values between the 5 frequency bands of EEG signals are shown in Fig. 11. Here, the effect of familiarity in strengthening the connectivity values is obvious as the connectivity values for the states of watching familiar brands are higher. In addition, the values of connectivity for lower frequency bands are higher than the other frequency bands. In another word, as the frequency band increases the values of connectivity decrease.

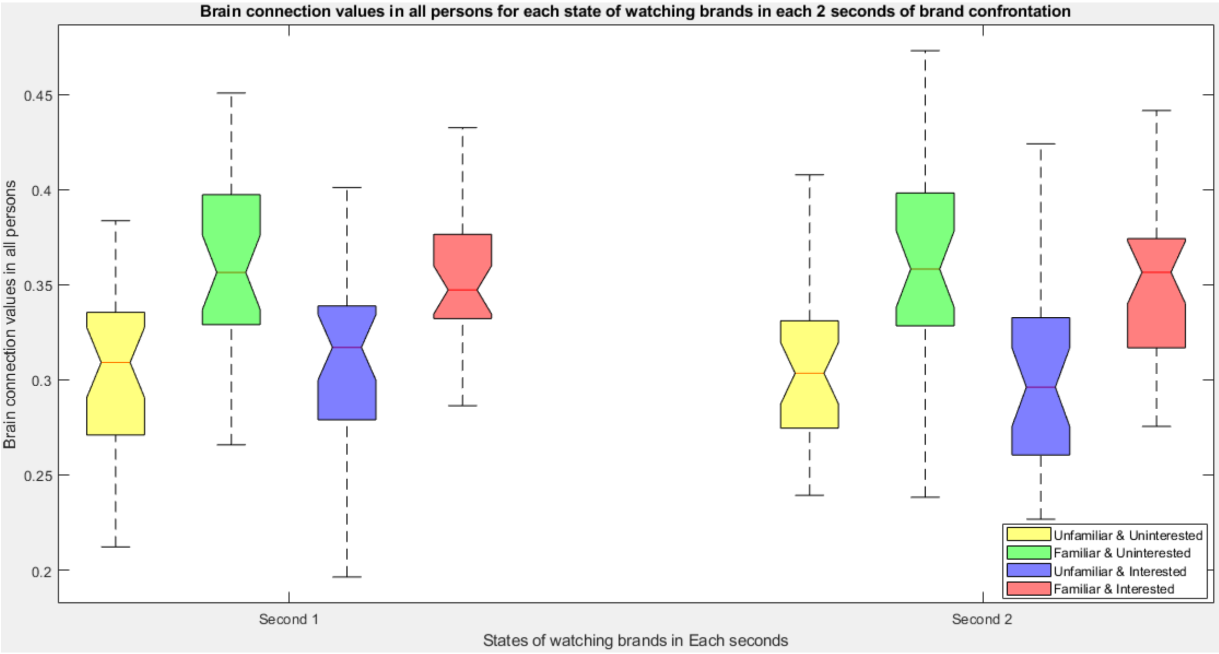


Fig. 10. Brain connection values for different states of brand confrontation comparison in two seconds of presenting brands

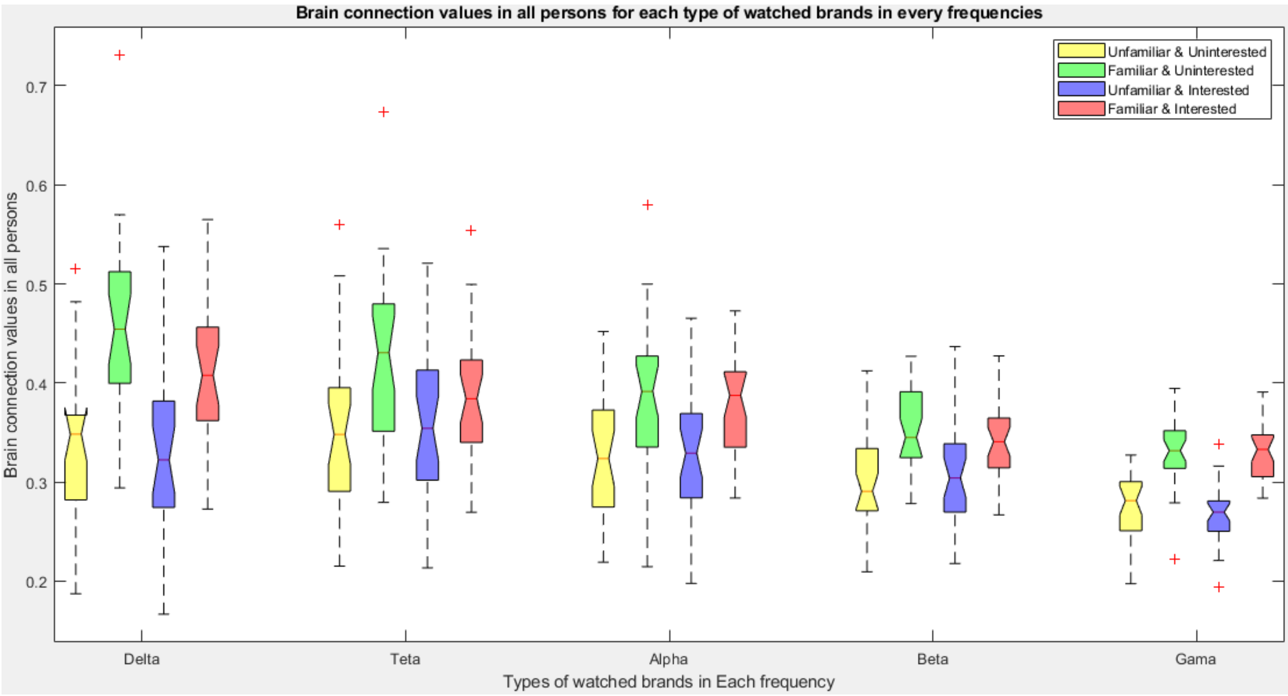


Fig. 11. brain connection values for different states of brand confrontation comparison in 5 frequency bands of presenting brands

4- Discussion

In statistical analysis, we used Bonferroni correction for the Wilcoxon sign rank test. As it divides the alpha level by the number of comparisons, it will reduce the total error rate and get more accurate results [4]. As researchers have mentioned in their previous studies, there are consistent activities in the prefrontal cortex in response to consumer goods [5], the relations corresponding to the frontal area of the brain like OrG-R in this study are so considerable. Astolfi et. al. figured out outflow of information from ACC and CMA areas and inflow of information to Brodmann areas 5,7,40 are higher when the advertisements were remembered than when they didn't [10]. In the result section of our study, we showed almost all of the brain areas inflow and outflow of information are higher when subjects watched familiar brands without considering buying or not buying that brand. In this matter, Astolfi's study and our study acknowledge each other.

People experience the states of brand watching during purchasing the brands, so memory has a critical point in their thoughts in these states. The study [9] mentioned that the memory process is in low-frequency bands. Additionally, here in Fig. 11, we can see the effective connectivity values are stronger in the low-frequency band during watching brands in the shopping center, which is along the memory process in the brain.

5- Conclusion

In this study, we tended to know brain effective connectivity differences between four states of watching brands. After preprocessing the EEG signals gathered during the confrontation with the brands in the virtual shopping center, the brain sources were extracted. We put these brain sources into six brain areas. Afterwards, directed relations between brain areas were calculated using the GPDC index. We found that when participants are watching familiar brands, almost all their brain areas have a stronger relation to each other rather than when watching unfamiliar brands. In watching desired brands, the only relation which is stronger in watching unfamiliar desire brands than the familiar desired brands is from FUG.L to FUG.R brain area. We also conclude that the effect of watching familiar brands is pretty more than the effect of watching desired brands in the brain effective connectivity. If the presented brands are unfamiliar, the between hemispheric relations are stronger when brands are desired to subjects, and the interhemispheric relations are stronger when brands are undesired to subjects. Additionally, if the presented brands are familiar, the left brain relations are stronger when the brands are desired and right brain relations are stronger when the brands are undesired. By comparing times, we conclude that the values of brain relation areas don't have significant differences between the 1st second and 2nd second of brand presentation in all four states of watching brands. This means that only one second would be enough for brands to have their influence on brain area directed relations. We also found that effective connectivity values are stronger for lower frequency bands than higher frequency bands during confrontation to the brand in virtual shopping center.

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