ISSN: 2458-8989

Natural and Engineering Sciences

NESciences, 2022, 7(2): 148-168 doi: 10.28978/nesciences.1159248

# Detection of EEG Patterns for Induced Fear Emotion State via EMOTIV EEG Testbench

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## Abstract

In this study, International Affective Picture System (IAPS) were used to evoke fear and neutral stimuli using EMOTIV EPOC EEG recognition system (n=15). During the experiments, EEG data were recorded using the Test bench program. To synchronize the EEG records, IAPS pictures were reflected on the screen. A Python script was written in the Open Sesame program to provide a synchronized data flow in the Input/Output channels of the installed virtual serial port. The Event-Related Oscillations (ERO) responses and Event-Related Potentials (ERPs) were calculated. Statistically significant differences ($p<0.05$) were observed among the mean amplitude differences in the P7, O1, F3, AF3, P8 channels at 200-400 milliseconds in the ERP analysis, and also significant ($p<0.05$) differences were found in alpha($\propto$) and beta($\beta$) brainwaves compared to neutral stimuli, in the Fast Fourier Transform (FFT) analysis. After these evaluations, different time-spectral signal activity patterns occurred in the right frontal lobe (F4) at the ($\propto$) band, and in the left parietal lobe at the ($\beta$) band, respectively.

**Keywords:**
EEG Fear-type emotion signal processing, ERP, FFT, IAPS, EROs

**Article history:**
Received 04 January 2022, Accepted 18 May 2022, Available online 08 Agust 2022

## Introduction

Emotions are mainly defined with their somatic markers (Ekman & Friesen, 1971), which describe the reason for emotional mechanisms and reveal the role of the body and interceptions in reflecting emotions (Pessoa, 2018).Understanding emotional signals should offer insightful knowledge of both verbal and nonverbal communication as well as intentions between individuals reflected through feelings, moods, and affects (Hassouneh et al., 2020; Suhaimi et al., 2020). Emotions are responses triggered using neural and humoral pathways (Damasio, 1998). People often do not

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convey the emotions they experience correctly. Difficulties are experienced in detecting instantaneous emotions (Ciuk et al., 2015). Commonly, self-evaluation reports such as the Self-Assessment Manikin (SAM) (Bradley & Lang, 1994) produce visually-illustrated images to project the triggers of pleasure-displeasure, degree of arousal, and dominance-submissiveness (Morris, 1995). Other studies have used the SAM question type but, except for the current study, none has shown manikins as arousal/valence ratings (Warriner et al., 2013; Kumar et al., 2016). For experimental conditions, mainly IAPS pictures were used for emotional stimulations. The IAPS images contain a large database of images reflecting various emotions based on subjects' statements (Lang et al., 1997). We used the pictures from the IAPS database to analyze fear- and neutral-stimuli in the literature (Yuvaraj et al., 2014). By relying on technological achievements in brain-computer interface and neuroimaging devices such as functional magnetic resonance imaging (fMRI), galvanic skin response (GSR), facial coding, EEG, it becomes possible to capture neurophysiological signals originating from the brain (Shu et al., 2018). The development in EEG technology as well as machine learning programming has led scientist to utilize EEG signals in diverse research like detecting spatial attention(Altan & Inat, 2021), predicting imagined hand movements on a subject (Altan et al., 2021), detecting potential problems associated with brain disorders(Altan et al., 2016) and deep learning approaches in brain activity analysis(Altan & Kutlu, 2018). The variety of capable EEG headsets allows us, to gather emotion-based signals from the brain (Mauss & Robinson, 2009). EEG devices capture responses to emotional stimuli by recording brain signals in high time resolution. Generally, EEG devices are distinguished by specific features, such as their resolution, number of channels, and reliability. In addition to the large EEG devices used in clinics, smaller portable and easy-to-use EEG devices have been recently invented (Soufineyestani et al., 2020). It has been reported in previous studies that the EMOTIV EPOC EEG device, which is one of the portable EEG devices, could provide sufficient temporal resolution using 14 channels (Badcock et al., 2013). These non-invasive and transportable devices have advantages for neurophysiological measurements of cerebral studies (Di Flumeri et al., 2019). Additionally, the development of EEG devices, such as source imaging and classification has made it easier to identify cortical areas and present the relationship between ERP or oscillatory rhythms and cognitive mechanism. EEG devices include fast and easy positioning due to dry or saline electrodes (Lau-Zhu et al., 2019) using wireless Bluetooth or Wi-Fi data transmission allowing faster mobility at relatively cheap prices (Cruz-Garza et al., 2017). Several studies using EMOTIVTM devices have investigated emotional responses or P300-based applications via assessment of neurophysiological changes (Fakhruzzaman et al., 2015; Ramirez et al., 2018). However, only a few studies on fear-type stimulus-response have been performed to understand emotional progress using EMOTIV devices, such as the wireless saline-based dry electrode for the EMOTIV EPOC device (Chabin et al., 2020).

The major concern of the study is to evaluate neutral and fear stimulation of ERP and oscillatory activity. The stimulations were applied by the IAPS pictures, which were added to the Open Sesame program (version 3.3.8), to create a stimulus paradigm which we synchronized with the EMOTIV device. To synchronize the EEG records with the IAPS pictures, a virtual serial port was installed on the computer. A Python software (version 3.8.7) script program that runs in the Open Sesame program was written to provide a synchronized data flow to the input and output channels of the virtual serial port.

## Materials and Method

### *Participants and Experimental Procedure*

15 healthy subjects (8 women and 7 men) in Turkey (SD = 11.8, range 44–33) were included to the study. Participants included in the study had normal vision and hearing, no history of epilepsy, no difficulty using computers, no obstacles using EEG, and no neurological or psychiatric disorders. They were over 18 years of age and right-handed. All individuals were informed and were not paid for their assistance. Local ethics committee was validated protocol of the study.

### *Procedure*

We selected fear-related and neutral pictures among IAPS (Lang et al., 1997) pictures to evoke a fear and neutral stimuli experimental paradigm. The IAPS pictures selected were used in previous studies for fear stimuli using the following numbers: 1050, 1120, 1200, 1201, 1270, 1274, 1280, 1300, 1302, 1930, 1931, 2770, 2811, 3001, 3061, 6021, 6313, 6315, 6370, 6510, 8160, 8480, 9000, 9050, 9440, 9584, 9590, and 9600, and for neutral stimuli using the following numbers: 5621, 5629, 5001, 5300, 5410, 5594, 5600, 5814, 7175, and 7235. The numbers themselves were used in a random order, but in the same order for each participant (Yuvaraj et al., 2014) in front of a computer screen. After each picture appeared on the screen for 3 seconds, participants answered the SAM questions about the fear and neutral stimulus as the valence/arousal scale rating SAM scale rating (Kumar et al., 2016). The SAM form is used to determine the emotional state of the participants through responses to stimulus. Self-evaluation measures are often used for the evaluation of emotions in terms of arousal, valence, and dominance (Morris, 1995). The research process of the study is shown in Figure 1.

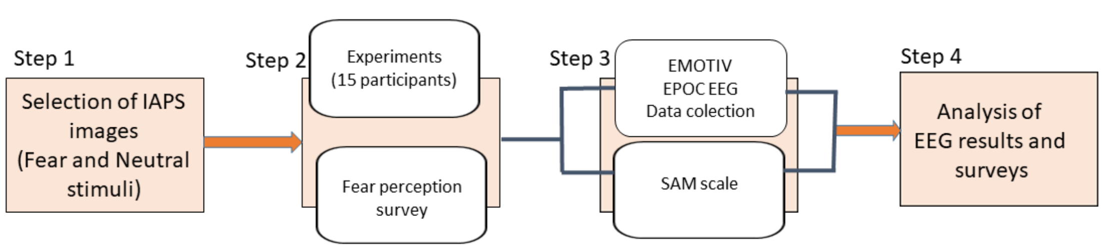


Figure 1. Reseach process of the study

### *EMOTIV EPOC EEG Recordings*

EEG device was a portable, practical and inexpensive model compared to the clinical EEG devices of the EMOTIVTM brand as seen in Figure 2a. This headset EMOTIVTM (2015 version) is made up of 14 usable saline as sensor electrodes (work with gold-plated) positioned according to the 10/20 system (AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4) (Figure 2b) in addition to 2 references on parietal sites (P3 and P4), CMS/DRL canals were used as references at right and left mastoids. The Emotiv EPOC electrodes were in a fixed position. Low electrode impedances were achieved using a saline solution as indicated by Test bench. A wireless computer connection was provided via a low-energy Bluetooth. The USB receiver transmits data over 2.4 GHz. The technical specifications of EPOC is listed in user manual (EPOC User Manual, n.d.).

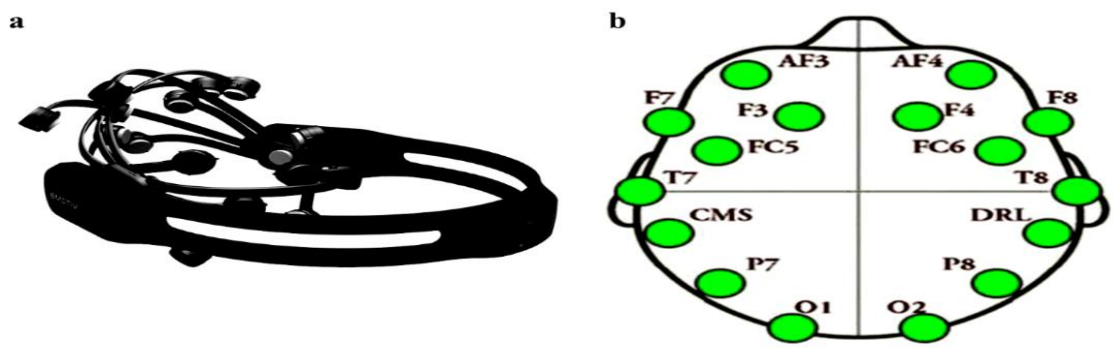


Figure 2. (a) Presentation of EMOTIVTM EPOC EEG headset (b) Electrode configuration of the Emotiv Epoc + system included in the analysis over the scalp according to the 10–20 system (Emotiv Home Page, n.d.)

EEG data were recorded using the Test bench program and synchronized using the Open Sesame program (version 3.3.8), which is an open-source software. To synchronize the EEG records with the IAPS pictures, a virtual serial port was installed on the computer. A Python software (version 3.8.7) script that runs in the Open Sesame program was written to provide a synchronized data flow to the input and output channels of the virtual serial port. As soon as the pictures were on the screen, the Open Sesame program sent a trigger to the Test bench program on the same computer and via a virtual serial port. Impedance was checked at the beginning of the recording using the Test bench program.

We used the EEGLAB Software program (version 2021.0), an open-source program that runs on MATLAB© (version R2020b), to preprocess all the EEG data as used in previous studies (Badcock et al., 2013). All processing code is available at Open Science Framework (EEGLAB Download Page, n.d.). Following preprocessing, EEG data was stored on the Testbench program as an .edf extension. Then, these files were transferred to the EEGLAB program, while channel and electrode location information were obtained from the data file. Signals were filtered between 0.2-45 Hz using the Basic FIR band-pass filter method and artifacts were determined. Afterward, epochs in the range of 100-1,000ms were determined to evaluate stimuli responses. A 1 Hz Basic FIR high-pass filter was applied to the data. Independent Component Analysis (ICA) was applied and the determined components were transferred to the data file that was filtered to 0.2-45 Hz (Klug & Gramann, 2020). Following filtering, all epochs were visually scanned, and artifacts caused by motor, visual, or muscular movements were rejected in the preprocessing stage using the EEGLAB Software program. After the preprocessing stage, the analysis part was started on EEGLAB. To determine the differences between two levels of emotion, EEG data was divided into two sub-data files as Fear and Neutral and included into the analyses.

### *ERP Analysis*

ERPs are electrical potentials in the EEG that map specific events (Sokhadze et al., 2017). ERP analyses were performed by calculating the average amplitudes of the data recorded using the EEG device from the moment the participants saw a visual stimulus. To perform these analyses, two separate EEG datasets were created, including fear stimuli and neutral stimuli. These datasets contain preprocessed EEG data. In the analyses, fear stimuli and neutral stimuli were recorded separately as both channel information and participant information in the EEGLAB and it was possible to compare neutral and fear stimuli by using analysis methods such as ERP, ERO, spectral power analysis based on electrodes and overall. The mean amplitude values of the fear and neutral stimuli were calculated for each channel. Statistical significance analysis of the differences between the ERP values which are obtained against the fear stimulus group and neutral stimulus group was performed using a paired t-test ranked with Wilcoxon. During the analysis, permutation statistics were used, and the statistical significance p-value was taken as $\leq 0.05$. To compare the ERP outputs as fear stimulus and neutral stimulus, the participants' EEG recordings were screened for evaluation based on electrodes. Thus, channels with significant differences in mean amplitude values in 250-500 milliseconds against fear and neutral stimuli were obtained because they were frequently encountered in the literature (Patel & Azzam, 2005; Duvinage et al., 2013).

### *Emotiv EPOC EEG Fourier Analysis of Oscillations*

With FFT analysis, it is possible to understand the emotional states of participants such as arousal, valence (Reuderink & Mühl, 2013), attention, and sleep (Abhang et al., 2016). Thanks to the right-left asymmetry in the frontal region, the valence status of the participants was determined (Harmon-Jones et al., 2010). In our research, we focused on the topographical power spectra differences against fear and neutral stimuli. We did not use a fixed duration time window for all frequencies. FFT was performed using EEGLAB (version R2020b), on each epoch of each condition according to the frequency bands of (delta: 0.5-4 Hz; theta: 4-8 Hz; alpha: 8-13 Hz; beta: 13-32 Hz; gamma: 35-140 Hz). We used the Hanning window no overlap based on the FFT magnitude squared to estimate the Power Spectral Density (PSD). In our study, the average power distributions of the response to fear and neutral stimuli in the I-theta, II-delta, III-alpha, IV-beta, and V-gamma bands were examined on the topography map. EEG data used in ERP analyses were also used for the ERO analysis. While performing these analyses, the frequency ranges determined for each band were entered into the program, and scalp maps were displayed on the power scale according to the channels as described in tutorial (EEGLAB Plotting Channel Spectra Tutorial, n.d.). Group-averaged spectrograms were computed by taking the median power across subjects at each time and frequency at the electrode of interest for each condition. Then, they were computed by taking the median power across subjects at each frequency across the entire 5 min epoch, and the median power at each frequency was calculated for each group. The significance was calculated with the paired t-test ranked with Wilcoxon statistic method. The power (voltage) differences for each band against fear and neutral stimuli were shown on the scalp map. The map was prepared in such a way that the red regions show statistically significant ($p \leq 0.05$) differences. Thus, it was determined what brain regions and what frequency bands were significant differences in the visual IAPS of fear and neutral stimuli.

## Results

### *SAM Scale Results*

During the experiment, the participants evaluated the fear and neutral stimuli selected from the IAPS pictures using the SAM criterion. The score given by each participant for each picture was examined, and pictures that included emotions of fear, high excitement (arousal), and negative (valence) were used in the EEG analysis. Table 1 shows the SAM scores of fear and neutral stimuli. Pictures that did not meet this criterion were removed from the database separately for each participant. For example, if a participant evaluated the snake picture as a fear stimulus, the picture for that participant was included in the analysis; if another participant indicated low excitement or a positive emotion when looking at the snake picture, then it was not included for that participant. All neutral images were included in the analysis for each participant. The pictures included in the study are pictures that have values close to negative (<5) in the valence evaluation of the SAM scale, and close to excited (>3) in the arousal evaluation. They are matched with feelings of fear, startle, anxiety, and disgust as emotions indicated.

Table 1. Mean and Standard deviations of fear stimulus in SAM measurement of 'Arousal' and 'Valence' using International Affective Picture System (IAPS) pictures.

| **SAM scale for Fear Condition** | | | **SAM scale for Neutral Condition** | | |
|---|---|---|---|---|---|
| **IAPS (n; the number of pictures)** | **Arousal (High 0/Low 8) (Mean±SD)** | **Valence Pos 0/Neg 8 (Mean±SD)** | **IAPS (n; the number of pictures)** | **Arousal (High 0/Low 8) (Mean±SD)** | **Valence Pos 0/Neg 8 (Mean±SD)** |
| **n1050** | 5,0±2,6 | 4,0±2,0 | **n5621** | 2,5±2,7 | 3,1±2,2 |
| **n1120** | 3,7±2,5 | 5,1±2,5 | **n5629** | 3,1±2,8 | 3,1±2,5 |
| **n1200** | 4,6±2,3 | 4,5±1,7 | **n5001** | 7,0±1,4 | 1,1±1,6 |
| **n1201** | 2,4±2,0 | 5,6±2,0 | **n5300** | 6,1±2,2 | 2,2±2,3 |
| **n1270** | 4,7±2,4 | 5,4±2,1 | **n5410** | 6,7±1,4 | 1,2±1,6 |
| **n1274** | 2,9±1,7 | 6,3±1,7 | **n5594** | 5,8±1,9 | 1,8±1,7 |
| **n1280** | 3,5±2,3 | 6,4±1,5 | **n5600** | 5,1±2,8 | 2,1±2,5 |
| **n1300** | 2,8±2,0 | 5,7±1,4 | **n5814** | 5,5±2,4 | 1,8±2,2 |
| **n1302** | 2,7±1,8 | 4,5±2,1 | **n7175** | 6,6±1,7 | 1,5±1,6 |
| **n1930** | 3,7±2,2 | 4,7±2,2 | **n7235** | 5,7±2,8 | 1,9±1,9 |
| **n1931** | 2,7±1,7 | 4,9±1,6 | | | |
| **n2770** | 4,8±2,1 | 3,3±1,4 | | | |
| **n2811** | 3,0±2,6 | 5,7±1,8 | | | |
| **n3001** | 2,1±1,8 | 7,0±1,4 | | | |
| **n3061** | 2,7±1,8 | 6,2±1,3 | | | |
| **n6021** | 3,1±1,5 | 5,9±1,5 | | | |
| **n6313** | 1,8±1,7 | 6,7±1,1 | | | |
| **n6315** | 2,1±1,2 | 6,1±1,5 | | | |
| **n6370** | 2,5±1,5 | 5,7±1,2 | | | |
| **n6510** | 1,9±2,1 | 5,6±2,0 | | | |
| **n8160** | 1,8±1,7 | 5,2±1,6 | | | |
| **n8480** | 2,9±1,9 | 5,4±1,7 | | | |
| **n9000** | 4,6±1,8 | 4,5±2,0 | | | |
| **n9050** | 2,9±2,5 | 5,1±1,9 | | | |
| **n9440** | 3,5±1,7 | 4,7±1,6 | | | |
| **n9584** | 4,1±2,5 | 4,4±2,3 | | | |
| **n9590** | 3,9±2,7 | 4,3±2,6 | | | |
| **n9600** | 2,5±2,4 | 6,1±1,2 | | | |

### *ERP Results*

ERPs are electrical potentials in the electroencephalogram that are linked to specific events. In this study, EEG data, including visual fear stimulus pictures and reactions to neutral pictures, were evaluated according to the results of the paired t-test ranked by the Wilcoxon statistical analysis.

Results with a statistical significance value of p <0.05 were accepted as significant differences. During the ERP analysis, the average amplitude values of all participants were calculated based on each channel. The number of participants was small and the values did not provide normal distribution. For this reason, analyses were performed using permutation statistics software in the EEGLAB and MATLAB, which were then evaluated by a paired t-test using SPSS software. Descriptive of all channels with mean and standard deviation values are shown in Table 2. As seen in Table 2, there was a significant difference at P7 channels (p=0.01) and T8 channels (p=0.04) under fear and neutral stimuli conditions.

Table 2. Descriptives of all channels amplitude with mean and standard deviation and comparison of Fear stimuli vs Neutral stimuli determined by paired t-test ranked by Wilcoxon test (*p <0.05 is noted as significant). The statistical significance of the channels are noted in descending order.

| **Electrodes** | **Neutral stimuli (mean±SD)** | **Fear stimuli (mean±SD)** | **p value** |
|---|---|---|---|
| P7 | 0.23±2.12 | 11.9±2.12 | *0.01 |
| T8 | 3.76±3.94 | 1.54±3.66 | *0.04 |
| AF4 | 3.21±4.11 | 0.92±2.99 | 0.14 |
| F8 | 3.11±4.76 | 0.26±3.24 | 0.26 |
| O1 | 1.24±1.24 | 2.35±2.78 | 0.32 |
| P8 | 0.96±0.96 | 1.46±1.89 | 0.48 |
| FC6 | 11.0±2.69 | 0.29±1.39 | 0.53 |
| FC5 | 0.43±1.28 | 0.47±3.76 | 0.54 |
| F3 | 1.16±2.48 | 1.75±2.18 | 0.56 |
| F7 | 0.07±0.89 | 0.41±2.11 | 0.69 |
| T7 | 0.28±1.25 | 0.10±1.25 | 0.75 |
| O2 | 1.45±1.16 | 1.61±1.38 | 0.77 |
| AF3 | 0.36±2.04 | 0.46±1.65 | 0.81 |
| F4 | 0.18±2.76 | 0.27±1.96 | 0.92 |

ERPs were obtained to highlight the brain activity in response to fear and neutral stimuli conditions. In the ERP comparisons, AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4 channels were evaluated. The analysis was made according to the averages of amplitudes. Our results showed that there was a sign at 250–500ms in responses to fear stimuli compared to neutral pictures. Significant differences were observed in the AF3 (250–300ms) and FC5 (330–500ms) electrodes in the left parietal region as seen in Figure 3.

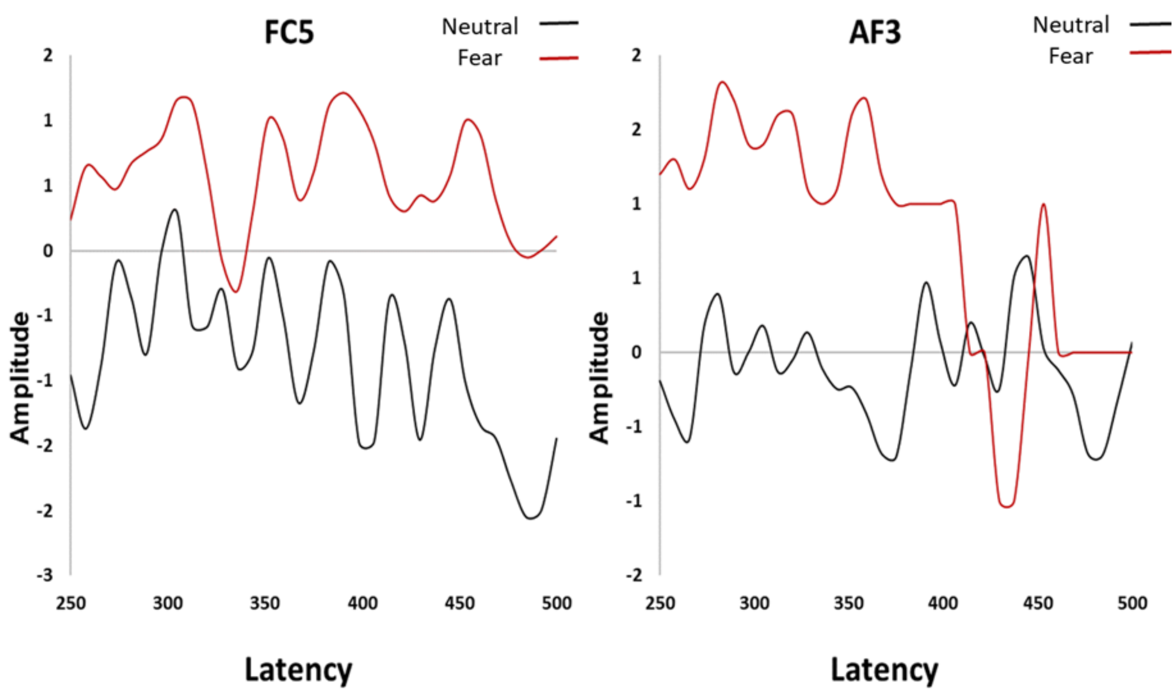


Figure 3. EMOTIV EPOC ERP mean amplitude values for Fear (red color) and Neutral stimuli (black color) of IAPS picture for (a) AF3, (b) FC5 electrodes. (*p<0.05 noted as significant).

***EMOTIV EPOC EEG Fourier Analysis of Oscillations***

The differences in the FFT analysis were in the left parietal lobe in the beta band and the right frontal region in the alpha band (Figure 4). We used the paired t-test without correction of the p-value by frequency band ($p = 0.05$). Significant differences were found between neutral and fear conditions for oscillations of alpha F4 ($p=0.02$), O2 ($p=0.05$), P7 (0.009), P8 (0.026). There was also a significance for beta oscillations in the electrodes F4 ($p< .001$), F8 ($p=0.003$), P7 ($p< .001$) and P8 ($p< .001$) as seen in Figure 4. The topographic map for all oscillations is illustrated in Figure 5. The amplitudes of the ERPs are shown in Figure 4 for the following brands: alfa (8-13 Hz) and beta (15-25 Hz) frequencies. As seen in Figure 4a the amplitudes of alpha bands from F4, O2, P7, and P8 channels were significantly higher for fear vs neutral stimuli. The amplitudes of beta bands from F4, F8, P7, and P8 channels were significantly higher for fear vs neutral choice ($p <0.005$) as presented in Table 3. Significant differences were seen in the left hemisphere, especially in the occipital, parietal, and frontal lobes. The P7 and P8 electrodes are closest to the amygdala and hippocampus in the brain, which are fear-related areas (Pizzo et al., 2019). In addition, there were no significant differences in delta, theta, and gamma bands in the topographic map of responses to IAPS pictures.

Table 3. Descriptives of alpha and beta frequencies with mean and standard error (SE). Significance is noted as p<0.05. The statistical significance of the channels are noted in descending order.

| **EROs Descriptives (Peak Detection, mean±SE)** | | | | | | | |
|---|---|---|---|---|---|---|---|
| | **Alpha** | | | | **Beta** | | |
| **Electrodes** | **Neutral** | **Fear** | **p-value** | **Electrodes** | **Neutral** | **Fear** | **p-value** |
| P7 | 35.4±0.08 | 35.2±0.10 | *0.009 | AF4 | 32.1±0.16 | 32.9±0.16 | *< .001 |
| F4 | 37.5±0.14 | 38.2±0.21 | *0.02 | P7 | 32.2±0.22 | 32.2±0.21 | *< .001 |
| P8 | 40.1±0.12 | 39.4±0.22 | *0.026 | P8 | 32.3±0.13 | 32.2±0.12 | *< .001 |
| O2 | 39.3±0.25 | 38.9±0.29 | *0.05 | F8 | 32.1±0.08 | 32.1±0.09 | *0.003 |
| T8 | 40.0±0.07 | 39.8±0.10 | 0.094 | F7 | 32.1±0.19 | 32.1±0.22 | 0.071 |
| F7 | 36.3±0.10 | 36.4±0.13 | 0.105 | FC6 | 32.2±0.09 | 32.2±0.09 | 0.173 |
| AF3 | 35.5±0.08 | 35.8±0.13 | 0.106 | AF3 | 32.1±0.16 | 32.9±0.16 | 0.18 |
| FC5 | 35.2±0.06 | 35.0±0.05 | 0.147 | T8 | 32.3±0.07 | 32.3±0.10 | 0.228 |
| FC6 | 35.2±0.06 | 35.0±0.05 | 0.147 | F4 | 32.1±0.17 | 32.1±0.17 | 0.238 |
| F3 | 36.8±0.22 | 36.6±0.07 | 0.336 | O1 | 32.2±0.13 | 32.2±0.14 | 0.251 |
| O1 | 36.6±0.17 | 36.4±0.13 | 0.394 | F3 | 32.1±0.2 | 32.1±0.2 | 0.349 |
| T7 | 35.3±0.28 | 35.5±0.08 | 0.476 | FC5 | 32.2±0.17 | 32.1±0.18 | 0.483 |
| AF4 | 37.9±0.21 | 37.7±0.22 | 0.552 | O2 | 32.2±0.19 | 32.2±0.21 | 0.749 |
| F8 | 38.4±0.16 | 38.3±0.15 | 0.741 | T7 | 32.3±0.20 | 32.3±0.18 | 1.000 |

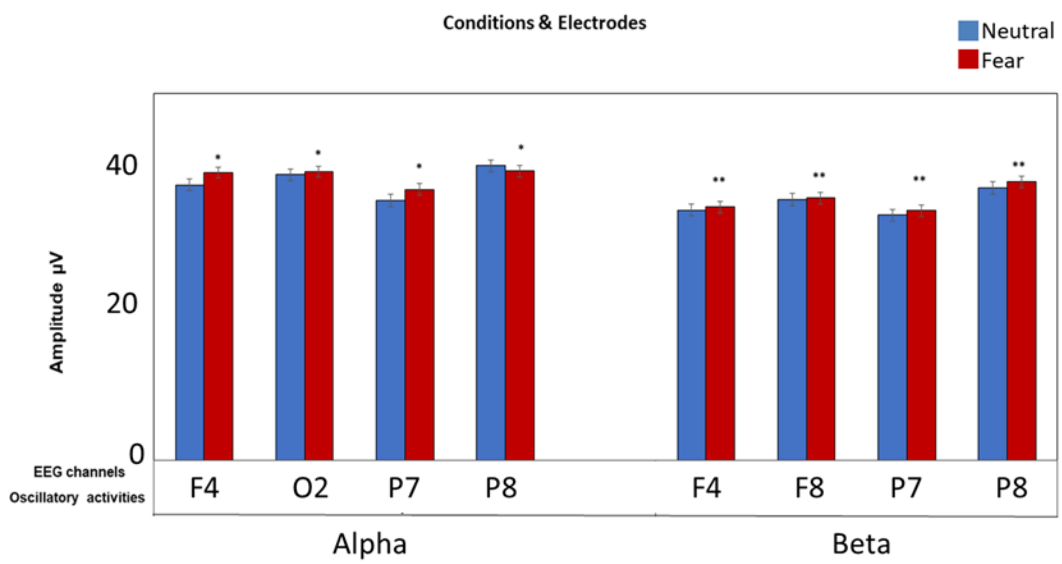


Figure 4. EMOTIV EPOC EEG Fourier analysis of oscillations results for Fear and Neutral IAPS Fear (red color) and Neutral stimuli (blue color) of IAPS picture for oscillations of alpha F4, O2, P7, P8, and beta F4, F8, P7, P8 channels (p<0.05 noted as significant)

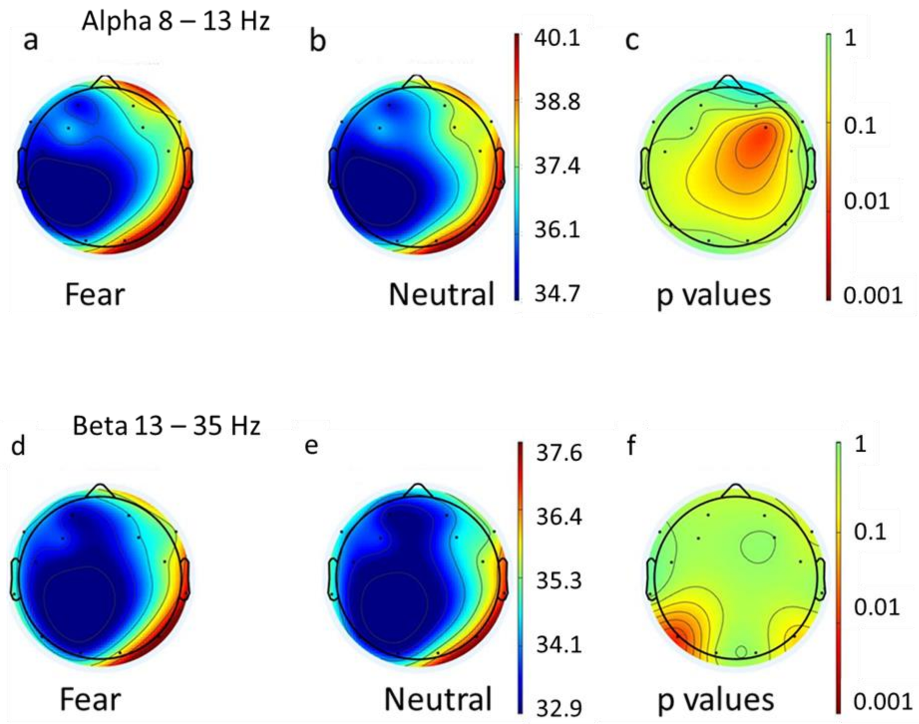


Figure 5. Topographic map of responses to IAPPS picture. FFT analysis and p values at the alpha band (8-13 Hz.) a) Fear stimuli b) neutral stimuli. c) p values according to paired t-test of differences in power distribution of Fear and Neutral stimuli. FFT analysis of beta band (13-35 Hz.) for (d) Fear stimuli (e) Neutral stimuli (f) p values

**Discussion**

In this study, we aimed to determine the electrophysiological process via EMOTIV EPOC EEG records related to fear and neutral emotions while observing visual IAPS pictures used in previous studies (Frantzidis et al., 2010; Yuvaraj et al., 2014). Our results showed that IAPS pictures are as appropriate for EMOTIV EPOC EEG recording studies as they were in previous studies (Sánchez-Reolid et al., 2018).

Referring to other studies in terms of detecting fear and neutral stimuli was evaluated using potential differences in the mean responses elicited by ERP and FFT measurements (Joshi & Ghongade, 2020). Firstly, we focused on the results of fear-related emotion stimuli using fundamental measurements of valence and arousal. Since we presented neutral and fear stimuli based on EEG recordings in the current design, there was a negative affectivity for fear stimuli as a valence response to IAPS pictures, but no findings appeared about affective arousal space (from rest to arousal) (Kumar et al., 2016). Therefore, we speculate that valence processes may be effective in this study. Briefly, arousal and valence cannot fully explain the reason: the classified emotion fear and other emotional stimuli disgust are accepted in a very similar way (in the same quadrant within the valence-arousal space), but our concept is a classification model quite capable of distinguishing fear from neutral stimuli. Using altered stimuli, Lin et al., (2010) illustrated participants' emotions as differing in valence and arousal too. However, earlier studies have shown that through the central gyri area stretching the parietal and occipital lobes, suppression of emotion appeared in emotional states of sadness and fear with high arousal and low valance as an imaging method through EMOTIV (Ros et al., 2013). The scalp topography of the distinctions was examined for fear and neutral stimuli. Interestingly, the variations were rather generalized peripherally and were distributed locally. Thus, we investigated how fear-related emotional reactions differ from one another in terms of frequency distribution patterns and topography, as based on earlier studies (Murugappan & Murugappan, 2013; Basar et al., 2020). In this way, we tried to explain the alterations in neural activity and emotional stimuli to determine the underlying processes (Barrett & Wager, 2006). Despite all the variations in stimuli and class precision, the connection between research on phrases with unique fear type emotion distributions of frequency in EEG recordings and their topography, claimed to reflect mental approaches to interactive problems as a classification of the monitoring method. In order to determine oscillations' response to fear, the FFT analysis was done. There were significances at alpha and beta frequencies. Earlier studies had shown that the range of alpha-band oscillations, which are the dominant oscillations in the human, are related to the processing of information and selective attention (for review see) (Klimesch, 2012). As a result, oscillations of the alpha band represent one of the most fundamental cognitive processes and have been proven to play a significant role in the integration of brain activity at various frequencies. Besides, desynchronization of alpha during the sessions of facilitated connectivity changes across brain regions, which might lead to reductions in oscillatory power in specific regions, such as the amygdala. Studies showed that a stronger response in the alpha band was elicited when expressing emotions of joy and fear than in states of calm and sadness from the frontal lobe. In another study, to assess responses to visual stimuli using video clips, including several emotions, different frequency bands were instantly determined by the FFT analysis. Our study illustrated that there was a significant difference in the alpha frequencies' response to fear stimuli (Eijlers et al., 2019). In another work, a negative correlation between activity of the brain in parietal and cortices of lateral frontal for alpha power (Laufs et al., 2003) were found. However, several works have concluded a negative correlation between attention and task demands for alpha activity. More specifically, a decrease in alpha power was related to a rise in emotional arousal (Aftanas et al., 2002; Simons et al., 2003; de Cesarei & Codispoti, 2011; Uusberg et al., 2013; Eijlers et al., 2019). Our results did not contradict these observations: the activity in the alpha frequency band was decreased predominantly for the fear response at centro-posterior sites, in channels O2, P7, and P8, and an increase in frontal sites in the F4 channel in comparison to the neutral emotional responses. Several studies focused on the frontal, parietal and temporal electrodes (Xu et al., 2019; Lakhan et al., 2019). The beta activity was correlated with emotional arousal modulation (Yuvaraj et al., 2014). Regarding the beta band, the higher the beta amplitudes, the higher the anxiety. Both horror movies and virtual reality exposure to horror gameplay yielded an increase of 24 microvolts, 33 microvolts in the range of the beta waves respectively (Bălan et al., 2019). Soleymani et al. showed that the higher frequency components of EEG signals gave more important information regarding positive emotions compared to negative ones (high and low valence respectively), while a correlation between increased beta power and positive emotional self-induction has also been reported (Katsigiannis & Ramzan, 2018; Zhuang et al., 2018). Another finding was the significance at beta frequencies in the electrodes F4, F8, P7, and P8. In their work on the assessment of fear stimulation, Masood et al., (2019) reported that the highest accuracy was reached at the beta frequency and at AF3, F4, T7, P7, F3, O1, P8, and AF4 electrodes (Masood & Farooq, 2019). In our research, there were differences between fear and neutral pictures based on electrodes. In earlier studies, the beta band and F3/F4 electrodes were found to have the highest accuracy as emotions classifiers (Bazgir et al., 2018). Significant ($p<0.05$) differences were observed in the P7 channel at 200–400ms. The P7 electrode contains signals from the left parietal lobe and T8 electrodes from the right temporal region. The relationship between fear and the amygdala has been shown in a number of studies (Ledoux & Ledoux, 2000). Although EEG instruments are not expected to detect amygdala activation, this difference in mobility in the P7 region may indicate a relationship between the parietal lobe and amygdala. Significant differences were also determined in other channels, including T8, which was found to have the highest classification accuracy at distinguishing disgust and relaxation (Iacoviello et al., 2015). Our ERP results were significant in AF3 and FC5 electrodes as seen in Fig.4a–b in the scale of negative valence and the arousal behavior in states of fear and anger according to the valence-arousal model of Kumar et al. (2016). Visual inspection of the data revealed clear at-time latencies and with topographic characteristics as reported in AF3 (250–300ms) and FC5 (330–500ms) electrodes in the left parietal region. ERP-based methods can be classified into two different paradigms based on the task that participants performed. In current studies using IAPS pictures, many ERP components have been evaluated using recordings of the electrodes in the frontal region to classify IAPS pictures according to SAM criteria (Olofsson et al., 2008; Lee et al., 2020; Singh & Singh, 2021). Our study found that different emotions, such as happiness, sadness, fear, calmness and P300 were observed in the parietal and occipital region (Schupp et al., 2008). Finally, this work showed that classifying emotions via EMOTIV EPOC EEG recordings can be applied to emotion evoked responses. It is necessary to confirm that variation in responses of emotions is shown in a set of active stimuli experienced under different conditions.

Our study supplies significant information however, as a limitation, number of participants were relatively low at 15. Additionally clinically approved EEG device with more electrodes would have given the opportunity to compare.

Understanding emotions would be strong evidence of the status of human’s physiology and psychology. In this study, statistically significant differences were observed between fear-type stimuli and neutral stimuli according to ERP and FFT results. According to the ERP results, left hemisphere P7, O1, F3, AF3, and P8 channels, mostly in the left hemisphere are the most discriminative electrodes for characterizing the distinction between fear-type stimuli and neural ones. There were no statistically significant variations in other channels. For the frequency response, the most discriminative bands were alpha and beta as compared to the other three sub bands i.e. theta, delta, and gamma. After the evaluations, it can be concluded that fear-type emotion can be detected via the EMOTIV EPOC EEG device. Hence, we have demonstrated that we can distinguish between the specific emotional experiences, neutral and fear, and validated that the specific emotions that the IAPS picture were meant to elicit, corresponded with what the participants described to have experienced during viewing the pictures. Thus, even though we cannot answer fundamental questions about the basic or specific emotions in the brain, the results do suggest that representations of these emotional experiences, described as, neutral and fear and disgust by our participants, can be distinguished in EMOTIV EEG data. However, this study is limited to eliciting mainly one emotion to an extreme extent, at a high temporal resolution. Further research is however needed in order to confirm the differentiation of emotional responses over time for a more diverse set of dynamic stimuli. Additionally, future studies are required about the emotional experiences for clinical settings to consumer settings such as the consumption of digital media (such as movies, TV shows, and broadcasted sports events), gaming, and online shopping. This paper gives also contributive information for developing real-time EEG-based studies. For future works, we expect to expand our studies by adding new sound, video, and picture validations to validate emotion classification algorithms. Also, we predict increasing the number of participants may help to achieve confidential results.

**Author Contributions**

Ahmet Ergun Gümüş: Performed the experiments and analyzed the results. Writing the manuscript. Çağlar Uyulan: Analyzed the results. Reviewing and editing the manuscript. Zozan Guleken: Analyzed the results. Reviewing and editing the manuscript and supervision.

**Data Availability Statement**

The data that support the findings of the present study are available from the corresponding authors [ZG] upon request.

**Conflict of Interest**

The author declares there is no conflict of interest in this study.

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