

Cortical correlations in wavelet domain for estimation of emotional dysfunctions

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Abstract In the present study, the level of nonlinear inter-hemispheric synchronization has been estimated by using wavelet correlation (WC) method for detection of emotional dysfunctions. Due to non-stationary nature of EEG series in addition to the assumption that the high-frequency band is possibly associated with emotional activation, WC has been applied to five distinct frequency band activities (fba) (Delta: 0.5–4 Hz, Theta: 4–8 Hz, Alpha: 8–16 Hz, Beta: 16–32 Hz, Gamma: 32–64 Hz) embedded in non-averaged single-trial EEG series mediated by convenient affective pictures from International Affective Picture System. Experimental data were collected from both healthy controls and patients, diagnosed with first-episode psychosis, through a 16-channel EEG cap. WC estimations, which are computed for eight electrode pairs (pre-frontal, antero-frontal, central, parietal, occipital, postero-frontal, antero-temporal, postero-temporal), in accordance with each specified fba and emotional state (pleasant, unpleasant, neutral) have been classified by using Least Squares Support Vector Machines with tenfold cross-validation to distinguish controls from patients. Results show that the highest classification accuracies of 88.06, 86.39, 83.89% are obtained in Gamma with respect to neutral, unpleasant, and pleasant stimuli, respectively. In each group

(controls and patients), the largest WCs are observed at antero-frontal and central lobes; however, controls generate the high WC in response to pleasant stimuli, whereas the patients generate the high WC in response to neutral stimuli in Gamma. In conclusion, fronto-central lobes are the most activated brain regions during emotional stimulation by means of inter-hemispheric correlation. Gamma is the most sensitive fba to visual affective pictures. Emotional dysfunctions are found to be characterized by decreased WC in pleasant state, increased WC in neutral state in Gamma.

Keywords Emotion · Hemispheric asymmetry · Wavelet correlation · Gamma

1 Introduction

Wavelet coherence is a time-frequency method which estimates the phase lag between two non-stationary time series in terms of wavelet transform (WT) [1, 2]. Due to requirement of Fourier transform (FT) on stationary assumption about EEG, this method has been used as better alternative to conventional coherence function based on FT to estimate the degree of cortical information flow between two brain regions [3–7]. WT has also been used in several algorithms for emotion recognition based on single-channel EEG analysis [8, 9]. Different from those studies, Wavelet correlation (WC) has been applied to five frequency band activities (fba) of EEG series, mediated by affective pictures from IAPS [10], for classification of controls and patients diagnosed with first-episode psychosis (FEP) in the present study.

Schizophrenia has been considered as the most devastating psychiatric disorder. Therefore, extraction of

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quantitative bio-markers for early detection of this important disorder has become attractive field. As well, EEG analysis could provide the appropriate and individual treatment of beginning phase of schizophrenia so named FEP. Instead of neuro-imaging modalities, EEG measurement provides the more sensitive analysis to understand cognitive brain functions during working memory activated by both auditory [11–15] and visual stimuli [16] as well as mental task [17]. The affective pictures from international database IAPS have been used for the first time in order to detect beginning phase of schizophrenia in the present study. Spectral power in Alpha has been frequently obtained to differ discrete emotions to each other [18–20]. Mostly, emotion recognition has been studied on EEG analysis including event-related potential synchronization in Gamma power [21–23].

Although, electro-myography (EMG) [29] and neuro-imaging modalities [30] were used for emotion recognition, EEG analysis was commonly found to be the most useful nervous system parameters [24–28]. In fact, cognition and emotion are commonly integrated by autonomic control system for both generation and representation of visceral changes in the human body. In detail, emotion is defined as neurological inter-correlations between thalamus, cortex, and limbic system [31–35]. In studies including inter-hemispheric asymmetry estimation in fba, experimental paradigm (memory working, attention, task-related, etc) and stimulus type (auditory, visual, audio-visual, static vs dynamic) are different from each other [25, 36, 37]. However, it was commonly stated that WT-based nonlinear methods are convenient due to non-stationary nature of EEG series. Therefore, WC has been applied to five fba of single-trial non-averaged EEG series mediated by affective pictures to obtain high-resolution phase coherence in both time and frequency in the present study.

2 Methods

2.1 Data acquisition

2.1.1 Participants

In the present study, surface EEG series were collected from 10 healthy male volunteers (aged from 19 to 24 with mean age of 20.90 ± 2.6 years) and 10 young male volunteers who had been diagnosed with first-episode psychosis (aged from 19 to 23 with mean age of 20.77 ± 2.31 years). In controls, the inclusion criteria are non-smoking, right-hand use, lacking a history of epilepsy and stroke, and not to use medication. Experimental data were collected by volunteers in Department of Biophysics at Gülhane Research and Education Hospital (GREH) at

Table 1 Clinical test scores of patients (dm: duration in month)

Subject	dm	-n	-p	-si	BPRS
1	4	35	21	51	48
2	1	25	19	42	36
3	0.5	16	28	46	45
4	4	14	11	33	29
5	2	17	19	44	40
6	1	17	13	34	30
7	1	32	15	59	58
8	5	34	24	47	55
9	1	21	18	36	34
10	2	21	18	36	34

University of Health Sciences, Ankara, Turkey. Committee of GREH approved the research protocol of this study on November 4, 2014. In patients, the inclusion criteria are stated by an expert physician with respect to international clinical tests [Positive and Negative Syndrome Scale (PANSS) and Brief Psychiatric Rating Scale (BPRS)] which were presented by American Psychiatric Association in references [38–40]. The quantitative test results of patients are listed in Table 1. In this table, PANSS scores are given in terms of negative (-n), positive (-p), and psycho-pathology sub-index (-si).

2.1.2 Emotional stimuli and experimental protocol

Emotional stimuli were 56 static and colored affective pictures (18 were pleasant, 18 were un-pleasant, and 20 were neutral) from a database so called IAPS which is described in [10]. The categorization of pictures was done by a rating policy such that a 9-point scale refers the level of arousal (1 and 9 refer calm and excited, respectively) and another 9-point scale refers the level of valence (1, 5, and 9 refer unpleasant, neutral, and pleasant, respectively). The IAPS database includes 956 images with a wide range of subjects such as happy human faces, happy couples, cute babies, animals, household objects, car accidents, and war. Each image was rated with two parameters (valence and arousal) by a large group of participants. The request form of images can be found on this link <http://csea.phhp.ufl.edu>. The scoring policy on the pictures was verified by the other physiological parameters such as skin conductance, startle reflex, and heart rate in references [41, 42].

The average arousal and valence scores of selected 18 pleasant pictures were 7.5 and higher scores. The average arousal and valence scores of selected 18 un-pleasant pictures were 3.5 and lower scores. The average arousal and valence scores of selected 20 neutral pictures were between 4.5 and 5.5. The number of those pictures is listed in “Appendix”.

In each individual experimental session, emotional visual stimuli were presented on 17-inch computer screen with a refresh rate of 60 Hz. During data collection, volunteers were placed in a recording room (band cut filter of 0.5500 MHz, attenuation of 40 dB, temperature of 22 °C) in a sitting position on a comfortable chair across the screen with distance of 1.5 m. The experiments did not include either working memory or oddball task. At the beginning of each experiment, two different neutral pictures were presented for 6 s followed by a 6-s inter-trial interval. Just after showing these adaptation stimuli, the other pictures were also displayed on that screen of 6 s with a visual angle of 16° horizontally and 12° vertically in the following order: 6 pleasant, 6 neutral, 6 unpleasant, 6 neutral, 6 unpleasant, 6 pleasant, 6 unpleasant, 6 neutral, 6 pleasant. Each picture was shown once in a single experimental session. Following each affective picture, white blank screen was shown of 6- to 12-s inter-trial interval. The volunteers viewed the same 56 pictures in the same order in individual session. They were not familiar with the affective pictures selected.

2.1.3 EEG measurements

Each affective stimulus was shown once in every individual session. The recording systems were 16-channel Glonner Neurosys system-2000 (Glonner, Munich, Germany). Prefrontal (Fp1, Fp2), frontal (F3, F4, F7, F8), central (C3, C4), parietal (P3, P4), temporal (T3, T4, T5, T6), and occipital (O1, O2) scalp activities were recorded by using Ag/AgCl surface electrodes with respect to international 10–20 electrode placement system. The electrical impedances of electrodes were kept less than 5 kΩ. Analog signals were sampled by sampling frequency of 250 Hz and were converted to digital sequences by using 16-bit analog-to-digital converter. The temperature of the light-controlled recording room was set during experiments. Both band-pass filter (0.318–70 Hz) and notch filter (50 Hz) were applied to raw data. Single-trial raw EEG measurements were also passed through an artifact detection algorithm described in [43].

2.2 Extraction of EEG frequency band activities

Five well-known EEG fba can be mentioned as follows: Delta (0.5–4 Hz) observed during deep sleep with large amplitudes about 75–200 μV, Theta (4–8 Hz) observed in drowsiness, Alpha (8–16 Hz) observed eyes opened awake states and attenuated by not only visual attention but also mental effort, Beta (16–32 Hz) observed during working memory when alertness is increased, and, Gamma (32–64 Hz), observed during both processing and

recognition of sensory stimuli as well as voluntary movements [44, 45].

Since waveform of Daubechies wavelet is highly similar to the waveform of limited duration of EEG sequences [46–48], db-8 was used in sixth-level wavelet decomposition for estimation of those FBAs from non-averaged EEG series mediated by pictures. The final approximation (A6) and last four details (D6, D5, D4, D3) were assumed to be equivalent to individual sub-bands so called Delta (0–4 Hz), Theta (4–8 Hz), Beta (8–16 Hz), Alpha (16–32 Hz) and Gamma (32–64 Hz), respectively, with respect to resulting sixth-level decomposition for each single trial of 6 s.

2.3 Estimation of inter-hemispheric correlation

In the present study, 16-channel emotional surface EEG series were collected from volunteers mediated by 18 × 3 times (18 pleasant pictures, 18 un-pleasant pictures, 18 neutral pictures). Assuming x refers a particular EEG sub-band in non-averaged single-trial emotional EEG series, recorded from right hemisphere, while y refers the same frequency range of another non-averaged single-trial emotional EEG series which is simultaneously recorded from left hemisphere, WT representations of x and y are defined by following equations,

$$WT_x(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} x(t) \Psi^* \frac{t - \tau}{s} ds \quad (1)$$

$$WT_y(\tau, s) = \frac{1}{\sqrt{s}} \int_{-\infty}^{+\infty} y(t) \Psi^* \frac{t - \tau}{s} ds \quad (2)$$

where $\Psi(t) = \pi^{-1/4} e^{j\omega t} e^{-0.5t^2}$ named as mother wavelet function. Here, τ , s and $*$ denote the scale, translation, and complex conjugation. The parameters of translation and dilation (τ, s) correspond to time and temporal period, respectively. Adjusting the scale provide to obtain different frequency components of x and y . By using Eqs. 1 and 2, WC is computed to quantify the level of similarity between x and y by using the following equation,

$$WC_{x,y}(\tau, s) = WT_x(\tau, s) WT_y(\tau, s)^* \quad (3)$$

Here, WC is computed in units of normalized variance [49]. WC was used to observe statistical differences between controls and patients with autonomic failure in estimating the possible the relationship between low-frequency oscillations in near-infrared spectroscopy and mean arterial blood pressure [50]. WC does not depend upon the power of sub-bands [51]. The stronger synchronization between two non-stationary time series produces the higher WC [51]. The more detailed explanation of this method can be found in reference [52].

Although the WC method has been applied in diverse fields from engineering to physiology [53, 54] and neuroscience [55, 56], it has been adopted to analyze fba embedded in non-averaged EEG series mediated by static pictures for detection of emotional dysfunctions in the present study.

2.4 Classification of emotional features

SVMs are supervised machine learning derived methods based on statistical learning theory of Vapnik Chervonenkis dimension theory [57]. Least squares (LS)-SVM is modified version of SVM leading a cost function to obtain a linear set of equations in dual space [58–61]. Therefore, LS-SVMs have been frequently used to classify EEG features in detecting various disorders [62–66]. In the present study, two-class problem was solved to classify controls (labeled by 0) and patients (labeled by 1).

Controls and patients were classified with respect to eight emotional features for both pleasant and un-pleasant as well as neutral states in each fba. The number of participants was 10 in each group. Multi-channel emotional surface EEG series were collected from participants 18 times to obtain electrophysiological waves mediated by every specified emotional state. Inter-hemispheric phase coherence was computed individually for eight electrode pairs (Fp1–Fp2, F3–F4, C3–C4, P3–P4, O1–O2, F7–F8, T3–T4, T5–T6). Accordingly, we obtained eight emotional features 180 times (the number of participant \times the number of trials = $10 \times 18 = 180$) in both pleasant and un-pleasant as well as neutral states for each fba (Delta, Theta, Alpha, Beta, and Gamma). Tenfold cross-validation was performed in classification steps. Gaussian radial basis function was used as kernel function in training the data where the box constraint and scaling factor were 0.05 and 1, respectively.

It is known that spontaneous EEG series are not stationary, and amplitude-latency parameters of evoked potential vary from sweep to sweep [67–70]. In studies including emotion recognition, the same brain functions are observed controls when the same emotional stimulus is received by individuals [71–73]. Therefore, estimation of two-channel inter-hemispheric correlation between two separate non-averaged EEG series has been aimed in the present study. Regarding the applications in both brain-computer interface studies [74, 75] and emotion recognition papers [76–78], the number of individuals is not classified; indeed, the number of instances, i.e., the number of EEG segments mediated by the identical stimuli, is classified. To perform tenfold cross-validation (CV), the features are divided into two spaces to firstly train a model and then to validate this model in LS-SVM applications where onefold of the feature set is held out for validation,

while the remaining ninefold are used for learning within each iteration.

3 Results

The classification performance statistics [Sensitivity (SNS), Specificity (SPC), and classification accuracy (CA)] were computed in classifying controls and patients with respect to each specified EEG fba. In addition, three feature sets are organized as follows: The feature set so named Lower Bands (LB) includes the features obtained from low fba (Delta and Theta), the feature set so named Higher Bands (HB) includes the features estimated from high fba (Alpha, Beta, and Gamma), and the final feature set so named All Bands (AB) includes the features estimated for each fba. The classification performance results are given in Table 2.

Regarding this table, it can be said that the best classification performance is provided by the highest EEG band, Gamma, such that controls can be classified with the CA values of 88.06, 86.39, and 83.89% considering neutral, un-pleasant, and pleasant pictures, respectively. The relatively lower performance is obtained by using the features generated by Beta in neutral, un-pleasant, and pleasant states with the CA values of 88.06, 82.22, and 78.33%, respectively. The useful classification performance can not be obtained when the features are estimated from other separate fba (Alpha, Theta, Delta). The LB provided the lower performance than HB in each emotional state; moreover, AB produced the lowest classification performance in comparison with both LB and HB as well as individual fba in each emotional state. However, the highest classification performance was obtained for the features which were estimated from Gamma in each emotional state.

The statistical spectra (mean std) of WC values which were estimated for relatively high fba (Alpha, Beta, and Gamma) in accordance with emotional states are shown in figures for both patients and controls. Figure 1 shows that patients produced the lower WCs at three lobes (anterio-frontal, central, parietal) in response to pleasant pictures in Alpha. In controls, the highest WCs were observed at pre-frontal lobe in each emotional state.

In addition, controls and patients commonly provide the higher WCs for all states at pre-frontal lobe in Alpha.

Figure 2 shows that both controls and patients produce the lower WCs at postero-frontal, occipital, and temporal electrode pairs in comparison with other electrode pairs including anterio-frontal, central, and parietal lobes for each emotional state in Alpha.

In addition, patients produced the lower WCs at postero-temporal region for each emotional state in Alpha. Figure 3 shows that the highest WCs were produced by

Table 2 Statistical results of classifications

	Delta	Theta	Alpha	Beta	Gamma	LB	HB	AB
P								
SNS	67.22	66.11	76.11	78.89	96.67	73.06	80.00	43.56
SPC	70.00	66.11	81.11	77.78	71.11	46.11	74.26	67.44
PPV	69.14	66.11	80.12	78.02	76.99	57.55	75.66	57.23
NPV	68.11	66.11	77.25	78.65	95.52	63.12	78.78	54.44
CA	68.61	66.11	78.61	78.33	83.89	59.58	77.13	55.50
UP								
SNS	65.00	65.56	75.56	82.78	92.78	64.17	79.81	43.89
SPC	66.11	61.11	81.11	81.67	80.00	56.67	73.89	67.89
PPV	65.73	62.77	80.00	81.87	82.27	59.69	75.35	57.75
NPV	65.38	63.95	76.84	82.58	91.72	61.26	78.54	54.75
CA	65.56	63.33	78.33	82.22	86.39	60.42	76.85	55.89
N								
SNS	74.44	72.78	78.33	88.89	96.67	66.94	81.85	44.78
SPC	73.89	65.56	83.33	87.22	79.44	55.83	74.63	70.44
PPV	74.03	67.88	82.46	87.43	82.46	60.25	76.34	60.24
NPV	74.30	70.66	79.37	88.70	95.97	62.81	80.44	56.06
CA	74.17	69.17	80.83	88.06	88.06	61.39	78.24	57.61

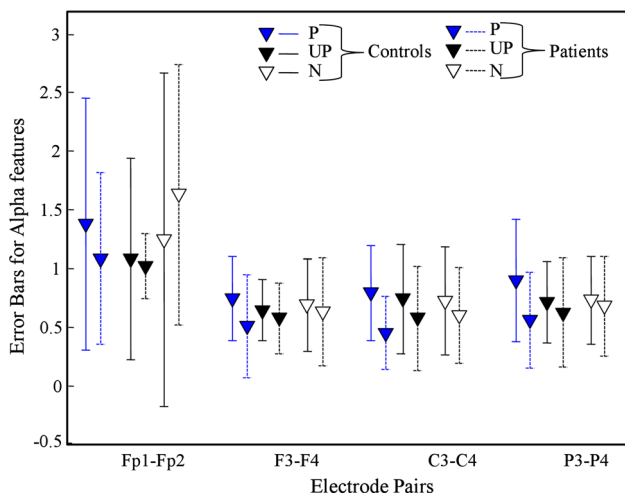


Fig. 1 Error Bars in Alpha at antero-frontal, central, and parietal regions

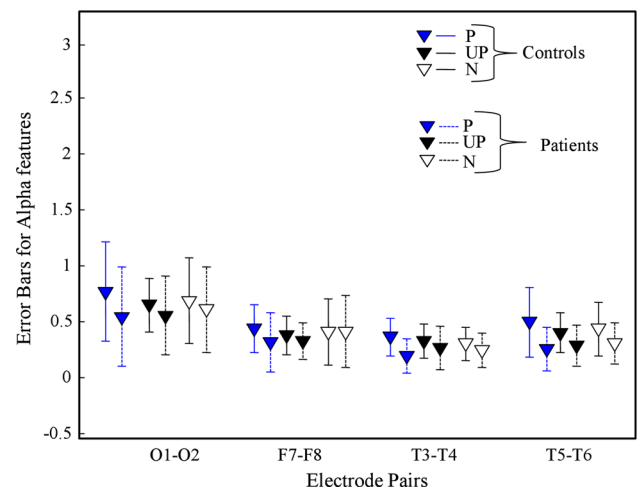


Fig. 2 Error Bars in Alpha at postero-frontal, occipital, and temporal regions

controls at antero-frontal and central regions for pleasant state, while patients produce the lower level of WC at antero-frontal and central lobes for neutral state in Beta. Regarding Fig. 4, patients produce the higher level of WCs at temporal lobes for neutral state in Beta.

Figure 5 shows that the highest WCs were produced by controls at antero-frontal and central regions for pleasant state, while the patients produce the higher-level WCs at the same regions for neutral state in Gamma. Regarding Fig. 6, patients produce the higher level of WCs at temporal lobes for neutral state in Gamma. By comparing all figures, it can be said that the largest WCs were obtained

from Gamma at antero-frontal and central electrode pairs in pleasant state.

We also used analysis of variance (ANOVA) test to study the contribution of each pair of EEG channels, located on scalp symmetrically, in discriminating controls from patients with FEP in accordance with specified emotional state. The most useful differences between controls and patients were observed in Gamma. Therefore, the related results (*p* values) are listed in Table 3.

Regarding Table 3, the highest statistically meaningful differences between controls and patients were observed at both pre-frontal and occipital regions of the brain for un-pleasant

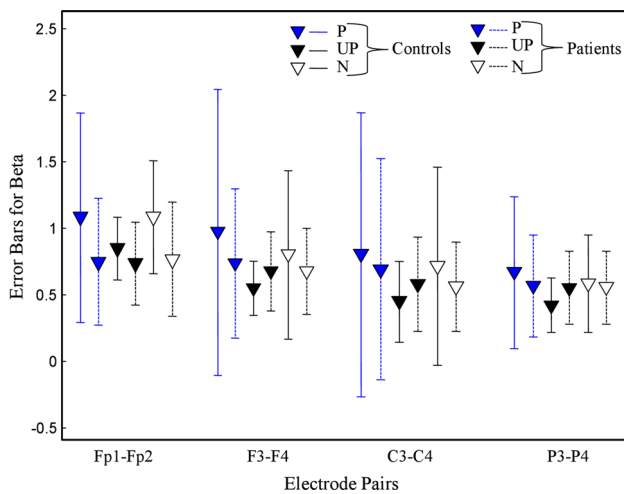


Fig. 3 Error Bars in Beta at antero-frontal, central, and parietal regions

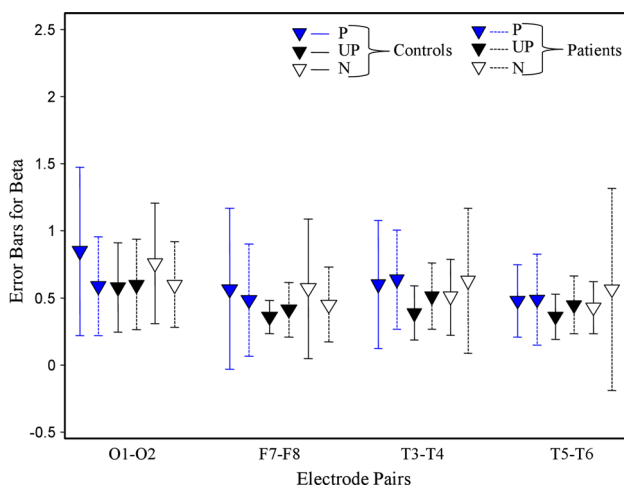


Fig. 4 Error Bars in Beta at postero-frontal, occipital, and temporal regions

($p \ll 0.0001$) and neutral ($p \ll 0.0001$) pictures in studying contribution of each electrode pair. When the groups were compared to each other with respect to eight electrode pairs, the clear difference between groups could be observed for both unpleasant ($p \ll 0.0001$) and neutral ($p < 0.001$) pictures.

4 Discussion and conclusion

The possible dependency of emotional activities on inter-hemispheric correlation has been studied to classify healthy controls and patients diagnosed with FEP. The results show that patients provide the high level of inter-hemispheric correlation in response to neutral pictures, whereas controls provided the high level of inter-hemispheric correlation in response to pleasant pictures at commonly antero-frontal and central lobes in Gamma.

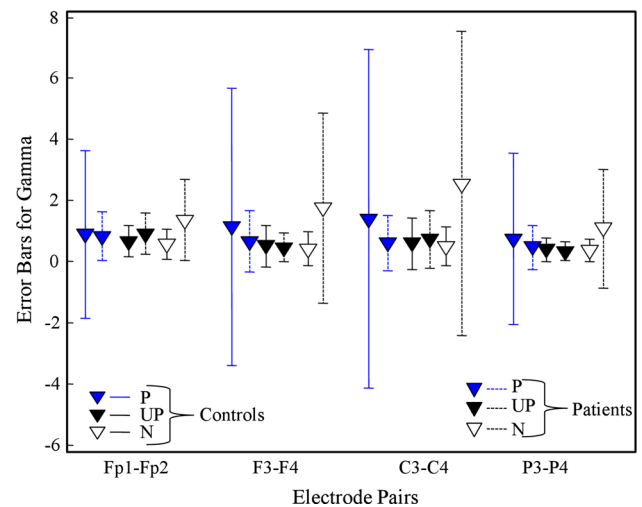


Fig. 5 Error Bars in Gamma at antero-frontal, central, and parietal regions

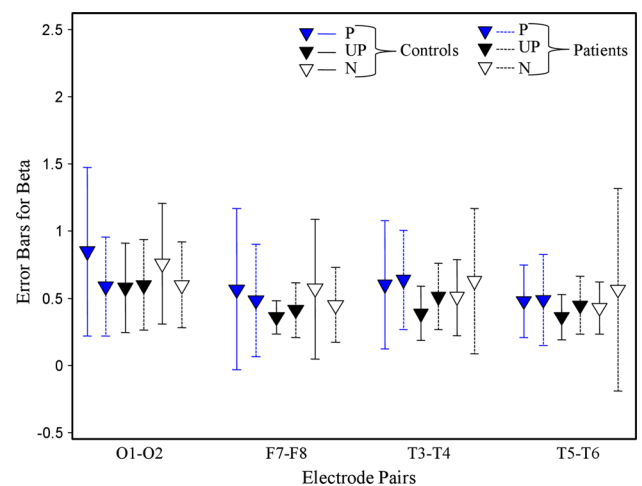


Fig. 6 Error Bars in Gamma at postero-frontal, occipital, and temporal regions

The best classification performance was obtained in Gamma. Although, the useful results could be observed in other high fba (Alpha, Beta) to classify the data mediated by neutral and un-pleasant pictures, combination of the separate features extracted from each sub-band produced the poor performance.

In conclusion, emotional functions of the brain could be observed in relatively higher fba (16–32 and 32–64 Hz). The lower fba (0.5–4 and 4.5–8 Hz) do not reflect the emotional functions in detail. Visual and static pictures activated mostly antero-frontal and central lobes in Gamma. The largest level of inter-hemispheric correlation was observed at mostly frontal lobe in Gamma in response to pleasant pictures in controls, while the largest level of inter-hemispheric correlation was observed at mostly frontal lobe in Gamma in response to neutral pictures in patients. In Alpha, the lowest level of inter-

Table 3 Statistical results (*p* values) of ANOVA in studying the contribution of each electrode pair in addition to all pairs with respect to emotional states in Gamma

Electrode pair	For pleasant stimuli	For unpleasant stimuli	For neutral stimuli
Fp1–Fp2	0.7196	1.85×10^{-15}	2.66×10^{-12}
F3–F4	0.4637	0.0723	0.1170
C3–C4	0.4170	0.0921	0.2183
P3–P4	0.4407	0.0045	0.2471
O1–O2	0.1940	3.90×10^{-13}	2.37×10^{-14}
F7–F8	0.3751	0.1573	0.2234
T3–T4	0.0806	0.0881	0.2598
T5–T6	0.2131	0.4880	0.1391
All pairs	0.0818	1.07×10^{-7}	0.0065

hemispheric correlation in addition to the narrower interval of correlations ($mean \pm std$) was observed at temporal lobes (T3–T4, T5–T6) in response to un-pleasant and neutral pictures in controls and patients, respectively. In Gamma, the lowest level of inter-hemispheric correlation was observed at parieto-central lobes (P3–P4, O1–O2) in response to un-pleasant pictures in both controls and patients.

Our results are compatible with the previous findings, including three main statements as follows: decreased hippocampal volume closely linked with emotional dysfunctions [79], functional insufficiency at mostly the right hemisphere in depression [80], and increased emotional coherence in controls in Gamma (low Gamma: 30–50 Hz and high Gamma: 50–80 Hz) [80]. In addition, the relatively decreased cortical activities at right and left hemispheres were found to be related to withdrawal and approach motivations, respectively, in MDD [81]. In detail, the relatively higher EEG asymmetry was reported as associated with motivational system and affect at anterior-frontal (F3–F4) and posterior-frontal (F7–F8) regions in Alpha in depression before treatment [82]. Depression was also reported as connected with not only increased resting-state activities at left hemisphere but also decreased resting-state activities at right hemisphere in Alpha [83–85]. Commonly, depressive inter-hemispheric emotional dysfunctions were correlated with relatively higher fba in the literature.

The amygdala having the main role in existing an emotion, includes perceptual pathways (from primary visual cortex to inferior temporal cortex) and reciprocal connections (between prefrontal cortex and orbito-frontal cortex) in humans. The orbito-frontal cortex, located at the base of the frontal lobes, receives direct neural inputs such as emotional stimuli from medial thalamus. Then, sensory information is received and strengthened by amygdala. In summary, once the brain is mediated by an affective picture, the thalamus and cortex interact to each other through not only firing of individual neurons but also transient functional integrations of local neuronal assemblies across

right and left brain regions. Therefore, our results support that cortical EEG series can be analyzed by means of neuronal inter-hemispheric correlation in wavelet domain in high fba (16–32 Hz and 32–64 Hz) for early detection of FEP.

In future work, both POMS scale [86] and theta coherence analysis [87] would be examined to re-analyze the emotional data explained in the present study.

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Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

Appendix

In the present study, several pictures were selected from IAPS as emotional stimuli as follows: Adaptation (Neutral) pictures: 2745 and 2191. Pleasant pictures: 1440, 1460, 1610, 1710, 1920, 2035, 2071, 2311, 2347, 2550, 4626, 5210, 5621, 5760, 5780, 5833, 7330, 8170. Unpleasant pictures: 1111, 3185, 3195, 3213, 3550.1, 6312, 6313, 6520, 7359, 8230, 9043, 9075, 9291, 9300, 9413, 9560, 9600, 9940. Neutral pictures: 2026, 2102, 2273, 2377, 2411, 2512, 7001, 7002, 7004, 7009, 7014, 7019, 7032, 7050, 7052, 7081, 7179, 7211.

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