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ORIGINAL ARTICLE

Resting State Functional Connectivity in PTSD Veterans: An EEG Study

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Abstract

Purpose Posttraumatic stress disorder (PTSD) is a chronic debilitating disorder which may occur as a result of life-threatening mental trauma. Combat experience may lead to PTSD in veterans. In this paper we study resting state functional connectivity based on EEG signals of Iranian veterans with PTSD. We investigate whether there is a significant difference among PTSD group and two control groups including trauma exposed non-PTSD veterans and healthy controls who has not experienced any trauma.

Methods Preprocessed signals are divided into epochs. ciPLV (corrected imaginary part of phase locking value) is calculated between each pair of channels, in each sub band as well as the whole band. After studying networks, three graph features are extracted from networks: nodal degree, nodal efficiency and betweenness centrality. Repeated measure ANOVA is used at confidence level of 99%.

Results Results demonstrate consequent networks are significantly different among three groups. Moreover, *p*-values illustrate three groups are significantly different. They also suggest which features and which channels can be proper choices for automatic classification.

Conclusion In addition to achieved results, our work shares two main features. First, we study combat related PTSD which lasts at least 30 years. Second, brain networks in PTSD group are compared to not only healthy controls, but also trauma-exposed non-PTSD participants.

Keywords Posttraumatic stress disorder · Combat veterans · Resting state EEG · ciPLV · Functional connectivity

1 Introduction

According to American Psychiatric Association, post-traumatic stress disorder (PTSD) refers to a psychiatric disorder which may occur following a traumatic event [1]. It is a chronic debilitating anxiety condition caused as a result of encountering life-threatening mental trauma. PTSD is characterized by symptoms including unremitting distressing repetition of the traumatic experience, hypervigilance, hyper-arousal, emotional numbing, avoidance, dissociation and negative alternation in cognition [2].

fMRI studies on PTSD patients indicate functional abnormalities in cortical and subcortical circuits including insula, amygdala, hippocampus, anterior cingulate cortex (ACC), ventromedial prefrontal cortex (vmPFC) and posterior cingulate cortex (PCC) [3, 4]. Functional connectivity is a powerful tool for studying sophisticated networks such as brain. It was used for many disorders including Alzheimer's disease [5–7], schizophrenia [8] and PTSD. Investigation of functional connectivity in MRI reveals increased hippocampal and limbic activation associated with PTSD pathology as well as decreased ventromedial prefrontal cognitive control [9]. In addition to studies which investigate abnormal patterns in the presence of emotional elicitations like traumatic event cues, dysregulated patterns of the resting state functional connectivity is of great importance in providing

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insights into the pathophysiology of PTSD [10, 11]. Resting state functional connectivity addresses correlations embedding in hemodynamic activity among various brain regions; based on the synchronization of neural activation of those regions [12]. Resting state functional connectivity has been used to study intrinsic brain activity with various modalities. An increased nonlinear dynamics in the left hemisphere of PTSD patients is reported in a resting state EEG study as well as a decreased nonlinear dynamics in the right hemisphere [13]. Moreover, positive correlation between right frontal lateralization and PTSD symptom severity is reported [14].

EEG, as an available, low-cost, high temporal resolution modality, provides optimal observation of ongoing changes of brain activities [15, 16]. However, few studies have investigated resting state functional connectivity in PTSD based on EEG. Their results are reported based on comparing the PTSD group with none trauma exposed controls [13, 17–21]. In [17] studying PTSD subjects with childhood trauma reveals enhanced coherency in alpha and beta band over the temporal and central areas. Moreover, [19] reported increased alpha band functional connectivity between the precuneus and the right inferior parietal lobe in PTSD participants. In [20] network indexes based on graph theory have been used. They reported reduced values in two graph features (nodal connection strength and communication efficiency) in beta and gamma bands for PTSD participants. In their next study [21] they use a source level weighted network analysis rather than sensor (electrode) level which was used in their previous study.

There are studies which consider participants suffering from various types of PTSD in the same group [11, 21] and in contrast, other work are focused on a particular kind of trauma [22]. Furthermore, one of the recent work uses functional connectivity biomarkers for the purpose of identifying PTSD subtypes based on EEG signals [23].

Combat experience may cause PTSD in military deployments [24]. Although network connectivity of combat exposure PTSD have been studied previously, conflicting results have been reported due to considering different control groups [10]. fMRI studies reported combat exposed PTSDs have different resting state networks comparing to none trauma exposed controls [25, 26], and also in comparison with trauma exposed ones [9, 25, 27–29]. Some other work consider a combination of none trauma exposed and trauma exposed subjects as control groups [28, 30, 31].

In [26], three groups have been investigated. However, PTSD associated differences was just observed in comparison with none traumatized control group. In contrast, in [10] differences in fast temporal of dorsal default mode network are reported based on analyzing simultaneous EEG and fMRI signals. They also reported differences in anterior and posterior salience networks. These differences are reported between combat-related PTSD veterans comparing to none PTSD combat-exposed controls.

In this paper resting state eyes-closed EEG is recorded from combat related PTSD veterans, combat exposed non PTSD veterans and healthy controls without being exposed to combat or any serious other trauma. PTSD group in our study is consisted of Iran-Iraq war veterans. This war had been terminated 30 years ago. Therefore, PTSD participants are engaged with the disorder more than 30 years. To our knowledge this is the first work which investigates EEG in three aforementioned groups. Most importantly, this is the first study which investigates resting state EEG of participants suffering PTSD symptoms for such a long period.

After de-noising and preprocessing, corrected imaginary part of phase locking value (ciPLV) is calculated for each epoch of the signals. Based on the obtained connectivity matrices differences among three groups are identified in sub-bands as well as the whole band. Moreover, three graph features are extracted from each network. Statistical analysis is applied to reveal the ability of features in making distinction among three groups (PTSD, non-PTSD and Control). We also investigate the ability of each feature associated to each channel in making significant difference between each pair of classes.

The rest of the paper is organized as follows: the next section is dedicated to material and method, which will cover participants, EEG recording and preprocessing, and the synchrony measure and graph features. Results are reported in the third section. Finally, the last section is dedicated to discussion and conclusion.

2 Materials and Methods

2.1 Participants

Forty-five right-handed men have been involved in the study. Among them 30 had participated in the Iraq-Iran war (September 1980-August 1988). $n = 15$ were diagnosed with chronic PTSD, $n = 15$ trauma exposed but non-PTSD. $n = 15$ of the participants were healthy non trauma exposed controls.

Exclusion criteria is included current symptoms or history of psychosis, a diagnosed neurological disorder (i.e. stroke, head injury, etc.), and a current substance dependence or abuse.

PTSD subjects are recruited from the hospitalized patients of the Sadr Hospital, Tehran, Iran (October 2018-April 2019). They were diagnosed with chronic PTSD at least by a neurologist and a psychiatrist.

Participants of the two control groups are recruited from the local community, specially Amirkabir University of Technology and Sadr Hospital via local announcements.

The healthy non trauma exposed participants did not express any history of a major trauma including combat experience, car accident, sexual assault, serious disease, physical injury or surgery. Moreover, none of the participants of the two control groups are taking medications with potential psychoactive effects.

All participants were asked to answer the structured clinical interview for Diagnostic and Statistical Manual of Mental Disorder DSM, 5th edition. In addition, they underwent a physical examination by a psychiatrist and a psychologist to confirm the PTSD or non-PTSD label. Moreover, they asked to answer 20 item self-report questionnaire of PTSD check-list (PCL). This questionnaire rates each item on a scale of 0–4. It measures severity of symptoms of posttraumatic intrusion, hyper-arousal and avoidance associated to a particular trauma in the previous week. Participants are also asked to answer depression, anxiety stress scales (dass-21), which contains 21 item self-reported questionnaire which measures stress, anxiety and depressive severity during the last 2 weeks. It rates each item on a scale of 0–3. Table 1 contains demographic and clinical characteristics for three groups. For the sake of simplicity, we will mention the combat related PTSD, combat exposed non-PTSD and not trauma exposed healthy controls as PTSD, non-PTSD and control, respectively.

Ethical approval was provided by Amirkabir University of Technology, and Shahid Beheshti University on behalf of Sadr Hospital, Tehran, Iran. After describing the study procedure in details, written consent form was signed by all participants. At the end of the session, they received financial compensation for their participation.

2.2 EEG Recording and Preprocessing

EEG has been recorded in 16 channels using active electrode g.Tec system in a quiet room. Signals were recorded at 1200 Hz sampling rate. Recording sites were chosen at AF3, AF4, F3, Pz, F4, F8, FC3, FC4, T8, CP3, P5, P6, PO3, PO4, O1, O2 according to the standard 10/20 system. In the following, these sites are called channels 1–16, respectively. Fz was the ground and the left ear considered as the reference. We used 0.1 Hz and 100 Hz as the cut-off frequencies of the system filters, in addition to a 50 Hz Notch filter during signal acquisition. The electrode impedance was less than 5 kΩ during data acquisition. Resting state eyes-closed EEG signals were recorded for 5 min while participants were asked to get relaxed and try not to think to a particular topic.

First of all, gross movement artifacts are removed visually. Then independent component analysis (ICA) is employed for de-noising. Then, signals are divided into epochs of 1 s length.

2.3 Phase Synchrony Calculation

In order to generate connectivity matrices a phase synchrony measure is used. Nonlinear dynamic methods, specially phase synchronization have devoted considerable attention recently [32]. We used ciPLV as one of the state of the art powerful fast metrics which is explained in this section, briefly.

For two given signals, S_1 and S_2, phase Locking Value (PLV) is defined as a connectivity measure tailored to investigate evoked activity as a function of time [33]:

$$PLV_{S_1,S_2}(t) = \frac{1}{N}\left|\sum_{n=1}^{N} \exp\left(-j\left(\varphi_{S_1}(t,n) - \varphi_{S_2}(t,n)\right)\right)\right| \tag{1}$$

where j represents the imaginary part, N is the number of trials $\varphi_{S1}(t,n)$, and $\varphi_{S2}(t,n)$are respectively the corresponding phases of signals S_1, S_2 at time point t, in the nth trial. The above definition has been extended to the resting state time series via assessing PLV as a stable phase difference over the signal's time. Mean Phase Coherence (MPC), which is also called PLV, was introduced for this purpose [34]:

$$PLV_{S_1,S_2} = \frac{1}{T}\left|\sum_{t=1}^{T} \exp\left(-j\left(\varphi_{S_1}(t) - \varphi_{S_2}(t)\right)\right)\right| \tag{2}$$

where T represents the length of data.

Bruna et al. proposed a new version of PLV in 2018 [35]. They re-formulated PLV based on the similarity of PLV and

Table 1 Demographic and clinical characteristics of three groups

Characteristics	PTSD ($n=15$) Mean($\pm$SD)	non-PTSD ($n=15$) Mean($\pm$SD)	Control ($n=15$) Mean($\pm$SD)
Age (years)	52.818(4.283)	53.111(2.0276)	50.867(3.870)
Marital state (1: married, 0: divorced)	0.818(0.395)	1(0)	1(0)
Number of children	2.500(1.012)	2.444(0.7265)	1.800(0.775)
Years of education	9.000(3.532)	14.778(1.856)	11.867(2.475)
Age of trauma	18.591(3.202)	17.556(1.236)	–
Depression and anxiety	50.046(6.897)	8.667(6.801)	9.133(3.829)
PTSD	55.476(12.734)	7.650(4.012)	–

coherence, and achieved a computationally efficient formulation. They proposed the imaginary part of PLV (iPLV) and its corrected counterpart (ciPLV) as two new indexes. iPLV and ciPLV are obtained based on calculating phases using Hilbert transform.

The oscillatory part of an analytical signal, S_k, is obtained by the following normalization:

$$\dot{S}_{BP,H,k}(t) = \frac{S_{BP,H,k}(t)}{\left|S_{BP,H,k}(t)\right|} \tag{3}$$

where H denotes the Hilbert transform, BP stands for band pass filtering, and dot is used for derivative. Based on the above formulation, we have:

$$PLV_{S_1,S_2} = \frac{1}{T}\left|\sum_{t=1}^{T} \dot{S}_{BP,H,1}(t).\left(\dot{S}_{BP,H,2}(t)\right)^*\right| \tag{4}$$

or by using the vector form:

$$PLV_{S_1,S_2} = \frac{1}{T}\left|\dot{S}_1 \cdot \dot{S}_2\right| \tag{5}$$

where $\dot{S}_1$ is the vector representation of $\dot{S}_{BP,H,1}(t)$ and $\dot{S}_2'$ shows the transpose conjugate of S_2. By generating vectors with the t th sample of each trial, the formulation can be expressed as follows:

$$PLV_{S_1,S_2}(t) = \frac{1}{T}\left|\dot{S}_{1,t} \cdot \dot{S}_{2,t}\right| \tag{6}$$

Finally, iPLV is defined as follows:

$$iPLV_{S_1,S_2,t} = \frac{1}{T}\mathfrak{I}\left\{\dot{S}_{1,t} \cdot \dot{S}_{2,t}\right\} \tag{7}$$

where $\mathfrak{I}$ denotes the imaginary part. To address the problem arising from not being normalized, ciPLV is proposed as follows [35]:

$$ciPLV_{S_1,S_2,t} = \frac{\frac{1}{T}\mathfrak{I}\left\{\dot{S}_{1,t} \cdot \dot{S}_{2,t}'\right\}}{\sqrt{1-\left(\frac{1}{T}\mathfrak{I}\left\{\dot{S}_{1,t} \cdot \dot{S}_{2,t}'\right\}\right)^2}} \tag{8}$$

ciPLV is insensitive to zero lag synchronization while working correctly in the case of nonzero-lag synchronization. Moreover, it can tackle the issue of volume conductance as well as source leakage effects [35].

2.4 Functional Connectivity Graph Indices

Three nodal centrality measures are extracted from the network including nodal degree, nodal efficiency (measure of communication efficiency) and betweenness centrality. The aforementioned features are defined as follows:

Let us consider a graph with $\mathcal{N}$ nodes. Nodal degree (ND) is defined as the total weight connected to a given node i:

$$ND(i) = \sum_{j\in\mathcal{N}} w_{ij} \tag{9}$$

where w_{ij} represents the connection weight between nodes i and j. It indicates the strength of the connection at a particular node.

Nodal efficiency of node i (NE), is illustrated as the inverse of the harmonic mean of the shortest path length between this node and all other nodes in the network. It is quantified as [36]:

$$NE(i) = \frac{1}{n-1}\sum_{j\in\mathcal{N},j\neq i}\frac{1}{d_{i,j}^{w}} \tag{10}$$

where $d_{i,j}^{w}$ is the shortest weighted path length corresponding to the path between i and j nodes which calculates as follows:

$$d_{i,j}^{w} = \sum_{wst\in g_{i\to j}^{w}} f(wst) \tag{11}$$

where f is considered as the inverse of weight to length and $g_{i\to j}^{w}$ indicates the shortest weight path between i and j [37].

Betweenness centrality measures how often nodes occur on the shortest paths between other nodes. For a given node betweenness centrality is the fraction of the shortest paths in the network passing through it. It is calculated as:

$$unBC = \sum_{\substack{h,j\in N \\ h\neq j, h\neq i, j\neq i}} \frac{g_{hj}(i)}{g_{hj}} \tag{12}$$

where, $g_{hj}(i)$ is the number of the shortest paths between node h and j passing through i. Moreover, g_{hj} is the number of shortest paths between node h and j. Finally, it is normalized by the mean valve of unBCs in a network, which will be denoted as BC.

2.5 Calculations

First of all, de-noised preprocessed signals are filtered. The following processes are applied to the delta (1–4 Hz), theta (4–8 Hz), alpha (8–13 Hz), beta (13–25 Hz) and gamma (25–40 Hz) sub-bands as well as the whole band signals. Each of the filtered signals, are divided into 1 s epochs as well as the whole band signal. We use an undirected weighted graph generated based on ciPLV values. Actually, our networks contain n = 16 nodes (corresponding to the number of the surface sensors). Links between each pair of nodes are associated with the connecting weights calculated using ciPLV. For given nodes i and j, w_{ij} is the synchrony measure which is in [0, 1], where 1 indicates perfect synchronization and 0 is associated with the lack of synchrony. Therefore, a 16×16 connectivity matrix will be obtained corresponding to each epoch.

After checking for the required assumptions, repeated measure ANOVA is used for statistical analysis. The significance level was applied after a Bonferroni correction. Therefore, for $n = 16$ and $p - value < 0.01$, the actual p-value would be $\frac{0.01}{16} = 6.25 * 10^{-4}$. All statistical calculations are done using IBM SPSS Statistics 25. Other calculations are performed in MATLAB 2018b.

3 Results

This section is dedicated to the results. Figure 1 provides graphical representation of functional connectivity networks in 5 sub-bands and the whole band for three groups. In order to have better representation, graphs are pruned using a threshold which is selected as the mean + standard deviation value over all subjects. It should be mentioned that this is done just for visualization. Otherwise, the network would not be recognizable according to too many connections.

As Fig. 1 demonstrates graphs are different for three groups in the whole band and 5 sub-bands. However, to have a more reliable conclusion some statistical tests are essential to validate the existence of significant difference among groups.

Intergroup differences among each pair of groups are investigated in Figs. 2, 3 and 4. Topo-maps represent the average difference of calculated features (BC, ND and NE) for each channel. Figure 2 illustrates the differences of features calculated for the control and non-PTSD group. The first raw represents $BC_{control} - BC_{non-PTSD}$. The following rows show $NE_{control} - NE_{non-PTSD}$ and $ND_{control} - ND_{non-PTSD}$, respectively. As can be seen the $NE_{control} - NE_{non-PTSD}$ and $ND_{control} - ND_{non-PTSD}$ are negative values which indicates NE and ND are greater in the non-PTSD group comparing to the control group, in all channels. However, BC does not show a particular trend.

Figure 3 represents $BC_{non-PTSD} - BC_{PTSD}$ in the first row and $NE_{non-PTSD} - NE_{PTSD}$ and $ND_{non-PTSD} - ND_{PTSD}$ in the following rows, respectively. As can be seen ND and NE have values which are greater in non-PTSD group comparing to the PTSD group, except for gamma band. Therefore, the subtractions have positive values. BC, in contrast, does not show a particular trend in all channels.

As the next step three graph features including ND, NE and BC are extracted from connectivity networks. In the following, the intergroup statistical analysis is performed. Three aforementioned features are calculated corresponding to each of the 16 channels in 5 sub-bands as well as the whole band. Pairwise comparison between groups is reported in Table 2. As illustrated NE and ND have significant difference between each pair of groups (control and non-PTSD, non-PTSD and PTSD, and control and PTSD). This appropriate performance is observed in all of the sub-bands as well as the whole band with the $p - value < 0.0001$. As can be seen BC is not successful in revealing differences among pairwise groups.

Table 3 summarizes the pairwise comparison of control and non-PTSD group. P-values are reported for each of the 16 channels, corresponding to each of the three features (NE, BC and ND).

Similarly, Tables 4 and 5 express the comparison of control and non-PTSD, and non-PTSD and PTSD groups, respectively. As can be inferred NE shows significant difference between each pair of groups at the significance level of 0.01 with $p - value < 0.0001$.

This can be seen in almost all sub-bands, as well as the whole band and for almost all channels. Likely, ND reveals such a significant difference. However, BC was not successful in revealing such a difference.

Finally, we study channels. In this part channels which have significant difference with all other channels in three groups are extracted for each feature. As Table 6 demonstrated, NE and ND have much more channels with this characteristics compared to BC.

4 Discussion and Conclusion

In this study resting state eyes-closed EEG of combat related PTSD patients is investigated. The first characteristic of our work is studying patients who are suffering from PTSD symptoms more than 30 years (as the Iraq-Iran war had terminated 31 years ago). The second property of our study, is considering two control groups: trauma exposed non-PTSD and healthy controls who had not experienced any trauma. These features, in addition to considering higher frequencies (as recommended in [11]) make our work different from previous work.

Functional connectivity graphs are generated by making benefits from a recent fast precise synchrony measure, ciPLV. As Fig. 1 indicates, graphs are considerably denser in non-PTSD group comparing to control and PTSD groups. Graphs associated with the PTSD group are less dens compared to the control group in parietal, pario-occipital and occipital regions in delta band. In addition, they are less dens in anterio-frontal and frontal regions in alpha band. On the other hand, PTSD graphs are denser in other regions and other sub-bands, as well as the whole band, compared to the control group. In gamma, theta and alpha band, there are links between frontal and parietal lobes which exist in PTSD graphs, but cannot be found in control graphs.

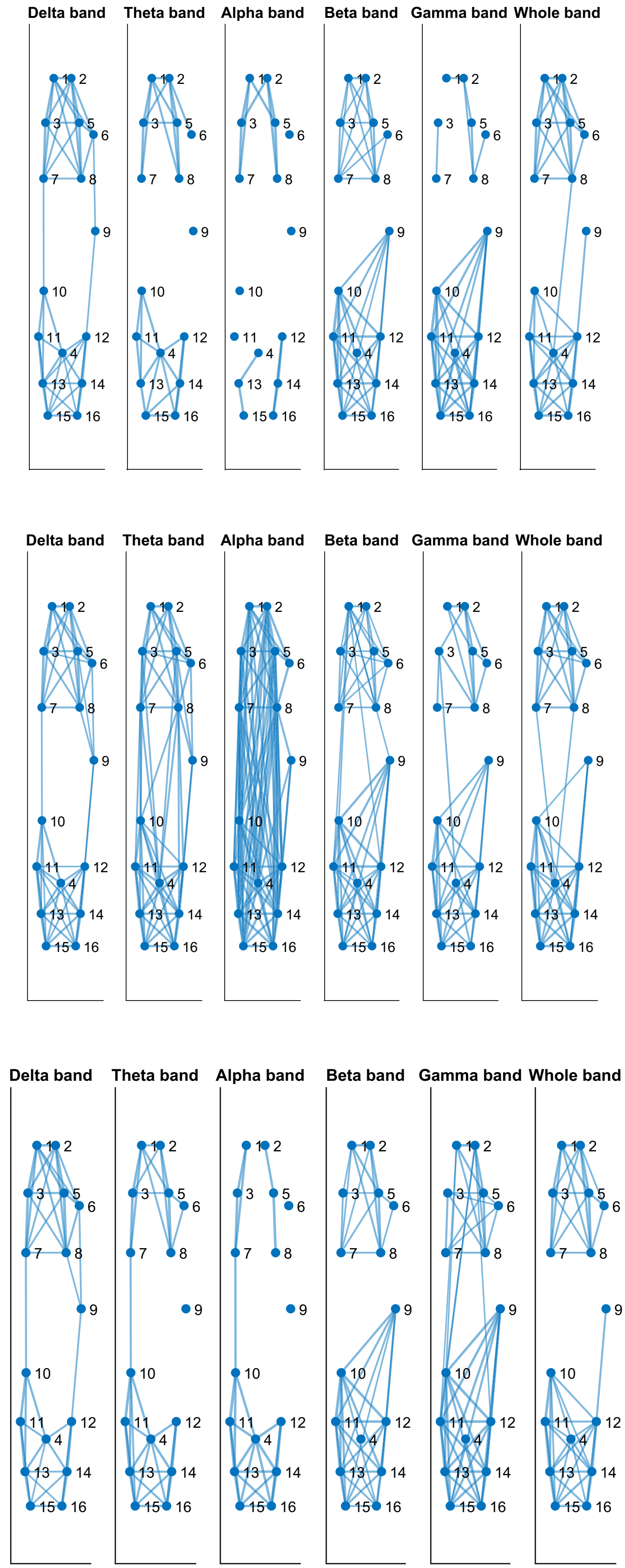

Fig. 1 Thresholded networks by mean + SD. Top to bottom: Control, non-PTSD and PTSD groups. Left to right: delta, theta, alpha, beta, gamma and whole band

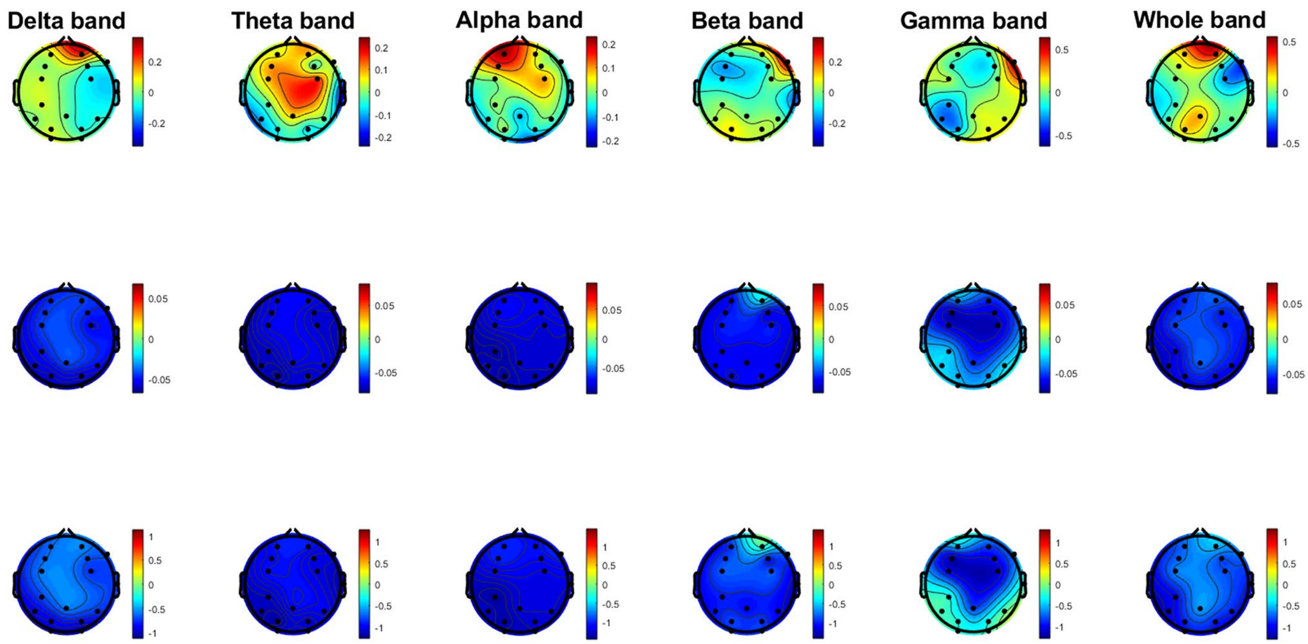

Fig. 2 Intergroup differences of control and non-PTSD groups in the whole band and 5 sub-bands. Based on BC (top), NE (middle) and ND (bottom)

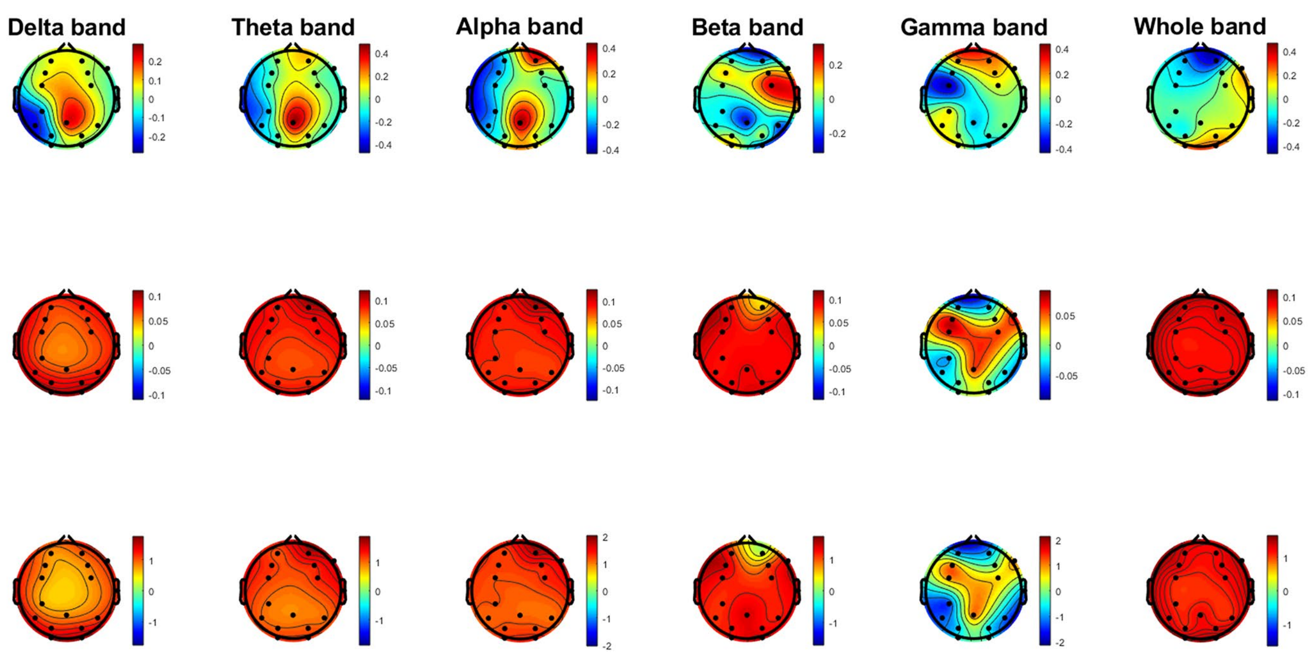

Fig. 3 Intergroup differences of non-PTSD and PTSD groups in the whole band and 5 sub-bands. Based on BC (top), NE (middle) and ND (bottom)

After showing that functional connectivity networks are different in three groups, some statistical analysis are used based on three graph features extracted from networks. Our statistical analysis supports that NE and ND, as graph features, are able to reveal significant differences between each pair of groups. Moreover, they detect significant differences between non-PTSD and control, and also PTSD and non-PTSD groups in all channels and all sub-bands, as well as the whole band. However, NE fails to detect significant difference between PTSD and control groups in a few channels

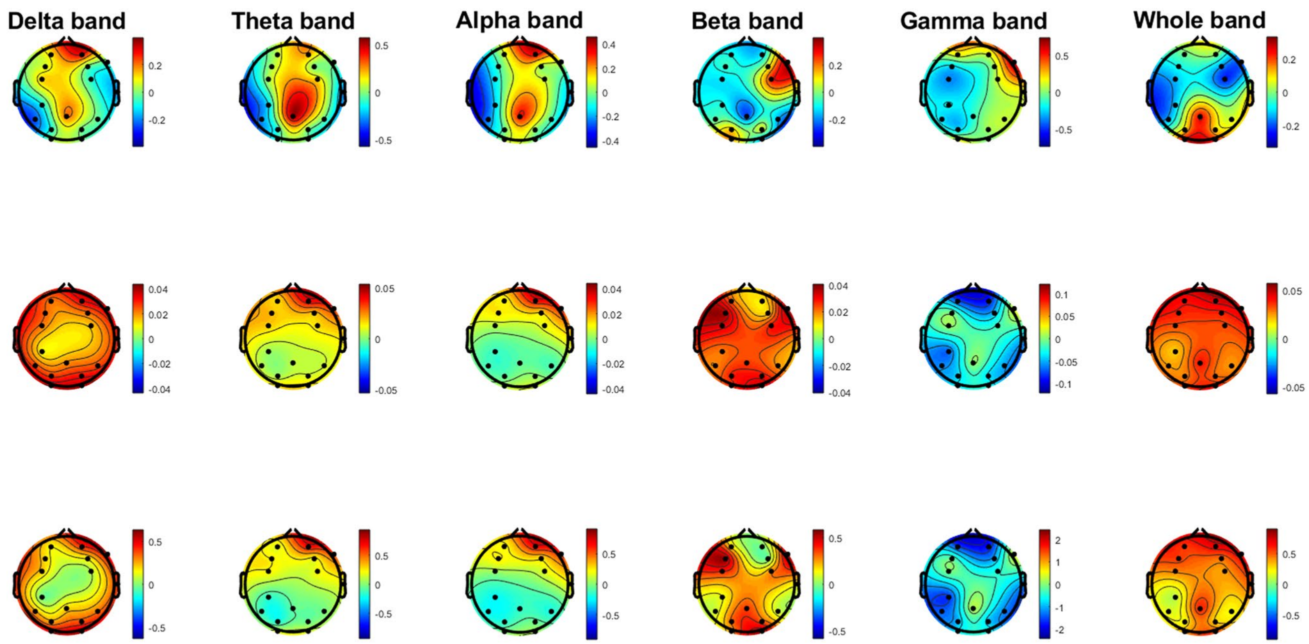

Fig. 4 Shows the differences between the control and PTSD groups. As can be seen, $NE_{control} - NE_{PTSD}$ and $ND_{control} - ND_{PTSD}$ have positive average values in all channels in delta and beta sub-bands as well as the whole band

Table 2 Pairwise comparison of groups based on three features (NE, BC and ND) in sub-bands and the whole band

Classes	Feature	Delta band	Theta band	Alpha band	Beta band	Gamma band	Whole band
Control-nonPTSD	**NE**	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
	BC	0.116	1	0.959	0.488	1	0.475
	ND	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Control-PTSD	**NE**	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
	BC	< 0.0001	1	1	0.959	0.959	0.220
	ND	< 0.0001	< 0.0001	**0.002**	< 0.0001	< 0.0001	< 0.0001
nonPTSD-PTSD	**NE**	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001
	BC	0.103	1	0.959	0.724	0.959	0.607
	ND	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001	< 0.0001

P-values are reported at 99% confidence interval for differences

in theta and alpha band. ND, also fails in a few channels in all sub-bands, and the whole band. Consequently, we propose that ND is the most powerful feature among these three. In addition, to have the best results it is better to investigate signals in delta, beta and also the whole band. Our final statistical analysis suggests that for each feature which electrodes has significant difference with all other electrodes in three groups. In summary, our study proposed which features and which recording sites can be used in machine learning classification analysis for automatically classifying aforementioned three groups.

To sum up, our findings demonstrate that in the whole band and delta sub-band of PTSD participants ND and NE show decrement compared to the control group. This can be found in all channels. In contrast, for non-PTSD participants these two features are greater than the control group in all channels. In other words, in lower and higher frequencies we have $ND_{non-PTSD} > ND_{control} > ND_{PTSD}$ in all channels. ND represents strength of connections to a node. Therefore, this finding means that for non-PTSD group strength of connections is higher than the control group. Moreover, this measure for the control group is higher compared to the PTSD group. Similarly, we have $NE_{non-PTSD} > NE_{control} > NE_{PTSD}$. In theta, alpha and beta sub-bands ND and NE in all channels are greater in non-PTSD participants compared to PTSD and control groups. However, there are some channels in which ND, or NE or both of them are lower in PTSD group comparing

Table 3 Abithe ability of NE, BC and ND features associated to each channel in making significant difference between control and non-PTSD groups

	Delta band			Theta band			Alpha band			Beta band			Gamma band			Whole band		
	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND
AF3	*	0.272	*	*	0.757	*	*	*	*	*	0.066	*	*	0.559	*	*	*	*
AF4	*	*	*	*	**0.002**	*	*	0.378	*	*	0.012	*	*	*	*	*	*	*
F3	*	0.876	*	*	0.027	*	*	*	*	*	*	*	*	1	*	*	0.143	*
Pz	*	1	*	*	0.344	*	*	**0.007**	*	*	0.044	*	*	0.024	*	*	*	*
F4	*	0.023	*	*	0.014	*	*	0.171	*	*	*	*	*	*	*	*	*	*
F8	*	0.076	*	*	1	*	*	0.814	*	*	*	*	*	*	*	*	*	*
FC3	*	1	*	*	**0.003**	*	*	1	*	*	*	*	*	**0.002**	*	*	1	*
FC4	*	0.078	*	*	*	*	*	0.013	*	*	*	*	*	0.087	*	*	*	*
T8	*	*	*	*	*	*	*	0.012	*	*	*	*	*	**0.001**	*	*	0.153	*
CP3	*	0.012	*	*	1	*	*	1	*	*	0.163	*	*	*	*	*	0.713	*
P5	*	0.278	*	*	0.538	*	*	1	*	*	0.041	*	*	*	*	*	0.715	*
P6	*	0.027	*	*	0.239	*	*	0.815	*	*	0.262	*	*	*	*	*	**0.005**	*
PO3	*	0.321	*	*	0.648	*	*	1	*	*	0.011	*	*	*	*	*	*	*
PO4	*	*	*	*	**0.001**	*	*	0.012	*	*	1	*	*	*	*	*	0.037	*
O1	*	0.278	*	*	0.045	*	*	1	*	*	0.089	*	*	1	*	*	**0.004**	*
O2	*	0.907	*	*	**0.002**	*	*	*	*	*	1	*	*	*	*	*	**1**	*

P-values are reported Bolded values are below the significance level

*represents < 0.0001

Table 4 The ability of NE, BC and ND features associated to each channel in making significant difference between control and PTSD groups

	Delta band			Theta band			Alpha band			Beta band			Gamma band			Whole band		
	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND
AF3	*	**0.003**	*	*	0.567	**0.006**	*	**0.002**	*	*	*	*	*	*	*	*	0.064	*
AF4	*	*	*	*	*	*	*	*	*	*	*	0.115	*	*	*	*	0.086	*
F3	*	0.014	*	*	1	*	*	1	*	*	0.016	*	0.557	*	*	*	*	*
Pz	*	*	*	*	*	0.014	0.036	*	*	*	*	*	**0.008**	*	*	*	*	*
F4	*	0.130	*	*	**0.001**	*	*	0.103	*	*	*	0.012	*	1	*	*	*	*
F8	*	**0.005**	*	*	0.298	*	*	1	*	*	*	*	*	*	*	*	*	*
FC3	*	**0.002**	*	*	0.693	*	**0.003**	*	0.303	*	*	*	**0.002**	*	0.016	*	*	*
FC4	*	0.441	*	*	*	*	*	0.649	*	*	*	*	*	0.917	*	*	*	*
T8	*	*	*	*	*	0.137	*	*	*	*	0.855	*	*	*	*	*	0.047	*
CP3	*	0.036	1	1	*	*	*	*	*	*	0.011	*	*	*	*	*	0.013	0.604
P5	*	*	*	*	*	*	*	*	*	*	1	*	*	*	*	*	*	*
P6	*	0.963	*	*	0.019	0.020	*	0.013	*	*	*	*	*	*	*	*	1	*
PO3	*	*	*	0.960	**0.003**	*	*	1	*	*	*	*	*	*	*	*	*	*
PO4	*	0.096	*	*	0.693	**0.006**	0.697	1	*	*	1	*	*	**0.007**	*	*	*	*
O1	*	1	*	*	0.011	0.615	0.262	0.109	0.492	*	*	*	*	0.295	*	*	*	*
O2	*	0.372	*	*	0.033	0.618	**0.002**	1	1	*	*	*	*	0.406	*	*	*	*

P-values are reported. Bolded values are below the significance level

*represents < 0.0001

to the control group. In other words, our research demonstrates that functional connectivity decreases in the PTSD group comparing to the healthy controls. In contrast, it is increased in the non-PTSD trauma exposed group in comparison with the healthy controls. Considering the color bars in figures Figs. 2, 3, 4, it is found that although NE and ND both represents the pattern of $non-PTSD > control > PTSD$, the range of values in

Table 5 The ability of NE, BC and ND features associated to each channel in making significant difference between non-PTSD and PTSD groups

	Delta band			Theta band			Alpha band			Beta band			Gamma band			Whole band		
	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND	NE	BC	ND
AF3	*	0.193	*	*	1	*	*	**0.001**	*	*	0.075	*	*	*	*	*	*	*
AF4	*	1	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*
F3	*	0.191	*	*	0.016	*	*	*	*	*	*	*	*	*	*	*	*	*
Pz	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	*	0.023	*
F4	*	0.756	*	*	1	*	*	1	*	*	*	*	*	*	1	*	0.026	*
F8	*	1	*	*	0.057	*	*	0.814	*	*	0.344	*	*	*	*	*	*	*
FC3	*	0.034	*	*	0.095	*	*	*	*	*	0.744	*	*	*	*	*	**0.001**	*
FC4	*	0.456	*	*	1	*	*	0.059	*	*	*	*	*	**0.001**	*	*	1	*
T8	*	0.077	*	*	0.017	*	*	*	*	*	*	*	*	1	*	*	*	*
CP3	*	*	*	*	*	*	*	**0.001**	*	*	*	*	*	*	*	*	0.172	*
P5	*	*	*	*	*	*	*	0	*	*	**0.004**	*	*	*	*	*	**0.002**	*
P6	*	0.238	*	*	1	*	*	0.262	*	*	*	*	*	0.280	*	*	**0.001**	*
PO3	*	*	*	*	0.278	*	*	1	*	*	1	*	*	1	*	*	0.011	*
PO4	*	**0.001**	*	*	**0.004**	*	*	0.069	*	*	1	*	**0.004**	0.027	*	*	*	*
O1	*	0.040	*	*	1	*	*	0.021	*	*	**0.003**	*	1	0.443	*	*	*	*
O2	*	1	*	*	0.395	*	*	0	*	*	*	*	*	**0.001**	*	*	*	*

P-values are reported. Bolded values are below the significance level

*represents < 0.0001

Table 6 Channels which have significant difference with all other channels, corresponding to each feature

	Delta band	Theta band	Alpha band	Beta band	Gamma band	Whole band
NE	4, 5, 6, 8, 9, 10, 11, 13, 15	4, 6, 9	4, 6, 9	1, 3, 6, 7, 8, 9, 10, 11, 12, 15	1–8, 10, 15	3,4,14
BC	4, 8, 14	-	6, 9	6, 9	5, 6, 9, 12	4
ND	4, 5, 8, 9, 11	4,6,9,12	4,6,9	2,3,5, 6,8,10,11,12,15	1–8	3,6,8,9,11

ND is greater than NE. This illustrates that ND is more powerful.

As the same graph features as [11] are used in our study, we can compare the results. Lee et al. investigated PTSD participants and a healthy control group, based on EEG signals recording in 62 channels. Their focus was on the severity of PTSD. Participants of their work had experienced different kind of traumas. Lee et al. reported that PTSD participants showed decreased functional connectivity in terms of ND and NE, which is confirmed in our study as well. They reported significant differences in NE, in FC4z and C1, in beta band. In addition, they reported significant differences in NE values in C1 and FC6 in gamma band. They also found significant differences in ND in FCz in beta band, in addition to AF3, FC1, FC2, FC4 and C1 in gamma band. In their study, as well as ours, BC did not provide a proper performance. Moreover, ND has superior performance comparing to NE in their study.

Lee et al. illustrated that differences were found in higher frequencies (beta and gamma in their study). In our study, however, it is found that ND and NE are higher in delta, beta and the whole band in control group compared to the PTSD group. In contrary to their results, our findings illustrate that in gamma band both ND and NE are higher in the PTSD group compared to the control group. The other difference of our results with the Lee et al. study, is that they reported such differences just in fronto-central electrodes, where as we find them in almost all electrodes. As discussed above, there are some similarities and some differences between our results and Lee et al. study. Differences between results could be due to different type of trauma, different period of being involved with PTSD symptoms, or even the synchrony measure used for generating functional connectivity graphs.

NE, as defined in method section, is communication efficiency. It can be used for assessment of the adaptive functional reorganization, based on the brain networks economical properties [36]. Therefore, decreased NE may be interpreted as adaptive reorganization of the resting-state functional connectivity network. Higher values of NE and ND in non-PTSD group may arise hypothesis of post-traumatic growth (PTG) for this group. PTG is defined as the experience of significant positive change arising from a struggle of a life crisis [38]. Actually, PTG refers to the experience of trauma exposed individuals who use such experience as an opportunity for further individual development. Those individuals overcome trauma with improved psychological functioning in specific domains [39, 40]. Further studies are essential for investigating this hypothesis.

Our last investigation (Table 6) determines which channels have significant difference with all other channels in three groups, corresponding to each feature. It proposes that channel 4 (Pz) have the highest rank among channels. Therefore, it could be a crucial position in detection/classification of these classes.

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