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Emotion Recognition and Dynamic Functional Connectivity Analysis Based on EEG

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ABSTRACT Although emotion recognition techniques have been well developed, the understanding of the neural mechanism remains rudimentary. The traditional static network approach cannot reflect the entire brain activity at the time scale. Instead, a newly introduced temporal brain network is an optimal approach which can be used to investigate the dynamic functional connectivity (FC) of the human brain in different emotion states considering the time-varying brain regional interaction. In this study, we focused on emotion recognition and dynamic FC analysis with SEED dataset. First, multiband static networks were computed by the phase lag index (PLI). Then, subject-independent discriminative connection features of such static networks were selected to recognize the positive, neutral, and negative emotion types. In addition, we constructed the temporal brain network by sorting the static network according to time sequence. The experimental results show that the beta band is the most suitable for emotion recognition due to the best accuracy of 87.03%. And, the frontal and the temporal lobes are more sensitive to brain emotion-related activities. Moreover, we find the spatio-temporal topology of dynamic FC shows the small-world structure. Notably, the positive emotion is more distinguishable in the temporal global efficiency, especially between positive and neutral emotion states. Our findings provide new insight into the emotion-related brain regional coordination evolution and show the potential of dynamic FC for the investigation of the emotion-related brain mechanism.

INDEX TERMS Emotion recognition, electroencephalogram, dynamic functional connectivity, temporal efficiency.

I. INTRODUCTION

The emotional expression is one of the most critical communication approaches of a human being. And individual can transmit different messages to another efficiently with different emotional types (sadness, fear, calmness, joy, and others). Technically, it is an excellent challenge for computers to recognize others' emotion. With growing techniques in pattern recognition, machines can understand users' words, behaviors, and facial expression and in consequence make proper judgments. However, such interactions disregard human affective states and fail to respond correctly to the order under different emotional conditions [1]. All these human-computer interactions will be perceived as stiff, dull, and unintelligent. Therefore, researchers are encouraged to reveal the neural mechanism of the emotion and establish a feasible emotion recognition system that has a desirable recognition accuracy for an individual's real intention.

The emotion can be primarily recognized with various modalities like facial images [2], speech [3], and gestures [4]. Nevertheless, such recognition approaches are susceptible to the individual's age, culture, language, appearance, and habit, and thus they are not universal and lack recognition accuracy [5]. Recently, emotion recognition with physiological features has attracted much interest, such as Electrocardiograph (ECG), skin conductance (SC),

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electromyography (EMG), and electroencephalograph (EEG) [6], [7]. These inherent attributes are superior to non-physiological features due to emotional performances are controllable by human consciousness.

EEG has been proved to advantageously reflect the activities of the central nervous system (CNS) in different fields, such as driving fatigue detection [8], [9], motor imagery tasks [10]–[12], and emotional states [13]. With the development of EEG processing methods, researchers have focused on EEG based emotion recognition and attempt to decode the emotion-related neural activity [14], [15]. Due to the excellent temporal resolution as well as the sensitivity to cognitive and mental states, EEG signals are widely employed in various experimental studies [16]. Moreover, researchers believe that EEG would be robust enough to suppress artifacts of human social cognition [17].

In the past few years, many EEG-based studies tried to find the proper methods for emotion recognition. Aydin *et al.* [18] proposed that high-frequency bands (beta and gamma) activities were susceptible to emotional activations. Bong *et al.* [19] induced six emotions (sadness, disgust, fear, anger, happiness, and surprise) of the stroke patient, and extracted Hurst Exponent to assess the persistence of EEG signals. The accuracy of the classification for sad emotion was as high as 83.32% in the beta band. Zheng and Lu [20] investigated the classification performances with differential entropy (DE), differential asymmetry (DASM), rational asymmetry (RASM), differential causality (DCAU), and power spectral density (PSD) in different bands and electrodes. These methods are well established for emotion recognition while the mechanism of brain regional interactions in different emotional states lacks adequate attention.

The cerebral cortex will express the specific interactions of whole brain regions when people carry out the cognitive and vigilance task [21], [22]. EEG signal has a high temporal resolution and a low spatial resolution due to the limitation of recording [23]. Therefore, estimating the spatial functional structures of the brain is a crucial issue for EEG based emotional investigation. The static network is a method that describes the brain regional coordination by computing the statistical coupling between paired nodes [24], [25]. Such a method was widely used to investigate emotion-related network topologies and information communications [26]. The static brain network is a small-worldness which allows performing both local segregation and global integration for information processing [27].

The traditional static network research focuses on underlying topology without brain regional interactions in the time scale [28]. Such a method considers the network in separate time windows as independent components for emotional mechanism analysis and ignores that the brain regional interactions evolve with time. Particularly, brain interregional interactions are highly dynamic and non-stationary [29]. The most real-world system structures developed and changed over time [30], [31]. Thus, Sun *et al.* [32] proposed a dynamic FC for neural mechanism analysis. The dynamic FC method

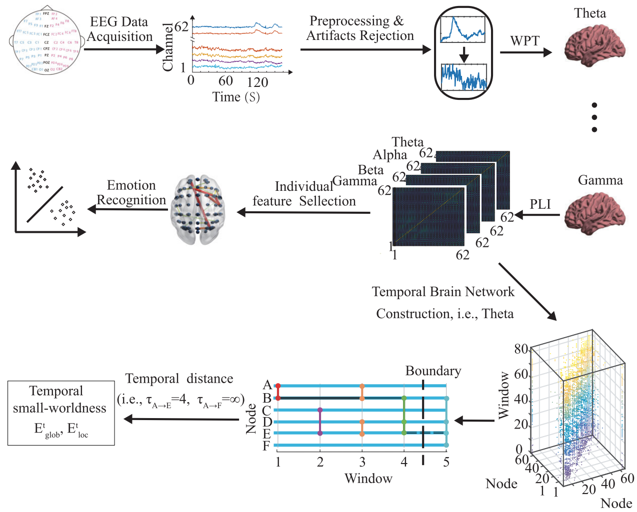

FIGURE 1. A flowchart of the emotion recognition and dynamic FC analysis procedure. After acquiring the 62 channel EEG data, raw EEG under different emotion types (positive, neutral, and negative) were preprocessed by ICA and WPT. Then, the static network was established by PLI with the optimal window length and step. For emotion recognition, we extracted individual connection features from the static network and classified the different emotion types. For temporal brain network analysis, we constructed the temporal brain network with the sequence of the time-ordered static network within the lifetime to measure the temporal small-worldness. The temporal brain network analysis was based on the temporal distance, which is defined as the minimum number of time window from a node to another one. Notably, two nodes do not connect with each other within the lifetime that the temporal distance between them is infinite. For instance, the lifetime of an example temporal network is defined to be 4 and thus the temporal distance between *A* at time 1 to *E* at time 4 is 4. Meanwhile, the temporal distance between *A* at time 1 to *F* at time 5 is infinite without connection within the entire lifetime.

added a time factor into static networks to compose full properties of the brain regional interactions within the lifetime. Dai *et al.* [33] proposed the overall temporal global efficiency and overall temporal local efficiency to measure the small-worldness in dynamic FC.

Dynamic FC is a newly developed method for neural mechanism analysis. We realized the emotion recognition based on the static network and investigated the spaito-temporal reorganization of the brain temporal network under positive, neutral, and negative emotion types. The EEG signals were restricted to theta, alpha, beta, gamma bands. The Phase lag index (PLI) was employed to construct the static network of each time window [34]. The emotion recognition performed by support vector machine (SVM) with subject-independent connection features [35]. Finally, the small-worldness of dynamic FC was measured by temporal global efficiency and temporal local efficiency. The investigation of the dynamic FC may provide a deeper insight into the neural mechanism of emotion.

II. METHOD AND MATERIALS

In this section, we will introduce the material and method adopted in this study. Fig. 1 shows a brief flowchart of the emotion recognition and temporal brain network analysis.

TABLE 1. The grouped index of wavelet coefficients of four sub-bands(theta, alpha, beta, and gamma).

Frequency Bands	Wavelet Coefficient	Frequency Range
Theta	$W_{6.2} - W_{6.5}$	3.13-7.81Hz
Alpha	$W_{6.5} - W_{6.9}$	7.81-14.06Hz
Beta	$W_{6.9} - W_{6.20}$	14.06-31.25Hz
Gamma	$W_{6.20} - W_{6.25}$	31.25-39.06Hz

A. DATABASE

In this study, the SJTU Emotion EEG Database (SEED) which is supplied by Brain-like Computing and Machine Intelligence Laboratory (BCMI) of Shanghai Jiao Tong University [20] is employed as both training and testing data for the emotion recognition. There are fifteen subjects (7 males and 8 females, and aged 23.27±2.37 (mean±std)) participated in the emotion-inducing experiment. Raw EEG data were recorded using an ESI NeuroScan System (Advanced Medical Equipment Ltd) according to the international 10-20 system with 62 electrodes at the sampling rate of 1000Hz. Each subject was required to watch selected Chinese film clips with positive, neutral, and negative content to conduct corresponding emotions. Moreover, to suppress the other cognitive activities of the brain, the duration of experiments was strictly limited to a short period: an experiment contained fifteen film clips and each of which was played within 4 minutes. Each subject needed to do the same experiments three times to guarantee the authenticity and universality of extracted EEG data. The feasibility of the database was validated by Zheng and Lu [20] research.

B. PREPROCESSING

In the preprocessing stage, the raw data were downsampled to 200Hz to reduce computing complexity. The statistical coupling method is significantly affected by various artifacts, especially eye blink which will lead to false connections. Then we used the independent component analysis (ICA) method to remove the noise which is mainly induced by electrooculogram (EOG) signals. The baseline of each trial was extracted and removed. After eliminating the physiological artifact, we decomposed the complete raw data into four standard frequency bands (theta, alpha, beta, and gamma) with wavelet packet transform (WPT). The Daubechies wavelet of db4 and decomposition level 6 were approved suitable for EEG frequency bands extraction [36]. Frequency ranges and wavelet coefficient are shown in Table. 1.

C. FUNCTIONAL CONNECTIVITY AND NETWORK CONSTRUCTION

For each sub-band, the EEG signals were divided by dividing the time window over step: window/step = 4/2 s. Then, the static networks (62 × 62) were estimated by the PLI method [34].

First, we calculated the instantaneous phase of each channel, which is expressed as a complex-value in the following equation:

$$\Phi_i(t) = x_i(t) + jHT(x_i(t)) \tag{1}$$

where $HT(x_i(t))$ is the corresponding Hilbert transform of time series $x_i(t)$ [37]:

$$HT(x_i(t)) = \frac{1}{\pi} P \cdot V \cdot \int_{-\infty}^{\infty} \frac{x_i(t)}{t-\tau} d\tau \tag{2}$$

In Eq. 2, $P \cdot V \cdot$ is based on Cauchy principal value. After computed phases of each time series, the phase locking between two nodes can be expressed as:

$$\varphi(t) = \left|\Phi_x(t) - \Phi_y(t)\right| \tag{3}$$

where $\Phi_x(t)$ and $\Phi_y(t)$ are unwrapped phases of time series x and y at time t.

Then, the PLI can be calculated as:

$$PLI = |\langle sign\varphi(t)\rangle| \tag{4}$$

The PLI value ranges between 0 and 1 where zero represents the no statistical coupling or coupling with a phase difference centered around 0 and π while 1 represents a perfect coupling between two time series.

D. EMOTION RECOGNITION

According to different emotion types, we mixed the connection features (the value of PLI between paired nodes in the static network) to three blocks (positive, neutral, and negative). The subject-independent discriminative connectivity features were extracted for each frequency band. Critical connections were selected by using the sequential floating forward selection (SFFS) [38]. The kernel of SFFS is to iteratively select features to maximize the objective function and to remove the unnecessary contents to avoid the local maxima. By the acceptance and rejection process, we obtain the optimal connection features. In this paper, we applied the difference of connection strength as the objective function. Fig. 2 shows the subject-independent connectivity networks under three emotion types in the beta band. After a critical connection selection, their connection strength among three emotion types is the feature for further SVM classification with 5-fold cross-validation.

Support vector machine (SVM) is developed by statistical learning theory and has been applied to physiological signal processing due to their feasibility for substantial data classification or prediction [39]. The concept of SVM is to map extracted features onto higher-dimensional hyperplane by the selected kernel function. After that, a linear decision surface is computed in this hyperplane [40]. Based on the previous work of EEG signal pattern recognition [41], we employed SVM [35] for the emotion recognition.

The training data $(x_i, y_i), i = 1, \ldots, n, x \in R^d, y \in \{-1, 1\}$ were sent to the discrimination function which is defined as:

$$g(x) = w^T x + b \tag{5}$$

FIGURE 2. **The critical connectivity features for emotion recognition in the beta band. Features are presented on scalp maps under positive, neutral, and negative emotion types. The color bar represents the average connection strength under different emotion types. Electrodes follow the disposition of the international 10-20 system.**

and thus, its hyperplane is defined as:

$$w^T x + b = 0 \tag{6}$$

where w^T is the d-dimensional vector and b is a scalar. To acquire the optimal hyperplane, the maximized margin and the minimized train error are computed by:

$$\min \phi(\omega) = \frac{1}{2}\|\omega\|^2 + C\left(\sum_{i=1}^{n}\xi_i\right) \tag{7}$$

$$s.t : y_i\left[\left(\omega^T x_i + b\right)\right] - 1 + \xi_i \geq 0, \quad \xi_i \geq 0, \ i = 1, 2, \ldots, n \tag{8}$$

where C is the weight between the maximized margin and the minimized train error. The kernel function of SVM in this study is radial basis function (RBF) and the learning method is sequential minimal optimization (SMO).

The RBF is computed by:

$$K(x_i \cdot x) = \exp\left(-g\|x - x_i\|^2\right) \tag{9}$$

The classification function is:

$$f(x) = \mathrm{sgn}\sum_{i=1}^{n} a_i y_i K(x_i \cdot x) + b \tag{10}$$

We searched the best C and g from the interval $2^{[-10:10]}$ with the step of one based on cross-validation approach.

E. TEMPORAL BRAIN NETWORK

For each subject, EEG data corresponding to each film clips were extracted for 170 seconds for the construction of temporal brain network. Both the sliding window and the step length are set to be 2 seconds. The binarized static network G_t^w is acquired by the sparsity approach which is the threshold of connection strength (1% to 16%). And thus the temporal brain network $G^w = \{G_t^w\}_{t=1,2,3,\ldots,T}$ is computed, where T is the number of the corresponding static network in the lifetime [33]. Fig. 3 shows the sample of the temporal brain network.

The temporal distance ($\tau_{i\to j}(t)$) is defined as the minimum number of the time window of the time-varying path [42]. The temporal distance is the measurement of the interaction of two nodes in the time scale, and thus it is a positive integer ranged from 1 to T. However, if there is no connection between two nodes within the lifetime, their temporal distance is infinite. As shown in Fig. 1, the temporal distance from A to E at $t = 1$ is 4 while the temporal distance from A to F at $t = 1$ is infinite.

The overall temporal global efficiency is computed as [33]:

$$E_{glob}^t(G) = \frac{1}{T}\sum_{t\in 1,2,\ldots,T} E_{glob(t)}^t(G, t) \tag{11}$$

where $E_{glob(t)}^t(G, t)$ is the efficiency assessment at time t:

$$E_{glob(t)}^t(G, t) = \frac{1}{N(N-1)}\sum_{i\neq j\in 1,2,\ldots,N}\frac{1}{\tau_{ij}(t)} \tag{12}$$

where N is the number of channels in each static network and τ_{ij} is the temporal distance from node i to j at time t.

The overall temporal local efficiency is defined as:

$$E_{loc}^t(G) = \frac{1}{N}\sum_{i\in 1,2,\ldots,N}\left[\frac{1}{T}\sum_{t\in 1,2,\ldots,T} E_{glob(t)}^t(G(i,t), t)\right] \tag{13}$$

where $G(i, t)$ is the sub-temporal network that includes the nodes connected with node i at time t and preserves all contacts among these nodes over entire windows of the temporal brain network.

We compared the differences of topology between the temporal brain network and the temporal random network to verify the small-worldness of the dynamic FC. Temporal random networks were computed by randomizing edges and contacts (Fig. 3). To extend the small-worldness in the static network [43], the temporal small-worldness should meet the following definition [32]: $E_{loc}^t/E_{loc\_rand}^t \gg 1$ and $E_{glob}^t/E_{glob\_rand}^t \approx 1$. The $E_{glob\_rand}^t$ and $E_{loc\_rand}^t$ are the means of the temporal global efficiency and temporal local efficiency of the generated temporal random network with 50 iterations.

F. STATISTICAL ANALYSIS

In order to investigate the brain efficiency alterations at different emotion types, we used the One-way repeated measures ANOVA for temporal global efficiency and temporal local efficiency. The value of $p < 0.05$ was considered significant. Corrections for multiple comparisons of regional characteristics were performed via false discovery rate (FDR) at $q = 0.05$. The statistical analysis was performed by SPSS software for Windows, version 23.0 (IBM, Armonk, New York).

III. EXPERIMENT AND RESULT

A. CLASSIFICATION PERFORMANCE

We used SVM for the recognition of emotion types with subject-independent connection features. Table. 2 shows the classification accuracies in the theta, alpha, beta, and gamma bands. In particular, across all the subjects, the best accuracies of 12 subjects were acquired in the beta band, and the remained 3 subjects achieved the best accuracies of emotion recognition in the gamma band. The highest classification accuracy (87.03%±4.73, mean±std) was obtained in the beta band. In addition, even the gamma band can also reflect the emotion activities of the human brain, which facilitate the accuracy of classification to 84.45%±3.95.

B. CONNECTIVITY PROPERTIES

We investigated the static network topologies in different emotion types. Even connection features of each subject are diverse, the significant connection in the specific brain region shows similar properties. Fig. 4 shows the proportion of regional activity level to all regions in the beta band across 15 subjects. The frontal and the temporal lobes show more active interactions in the emotional brain activities and the

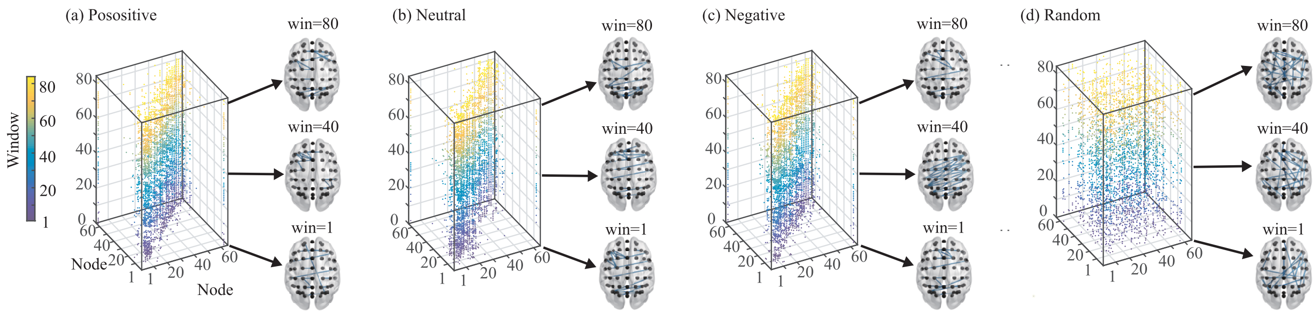

FIGURE 3. The example of temporal brain network of (a) positive, (b) neutral, (c) negative, and (d) random in theta bands. The performed networks are randomly selected from the data set. The networks were constructed by using the sparsity of 1% and the color bar shows the number of the corresponding static window. On the right side of the temporal network are the spatial distributions of the functional connectivity at 1, 40, 80 windows.

TABLE 2. The classification accuracies of emotion recognition across 15 subjects.

Subject	*Theta*	*Alpha*	*Beta*	*Gamma*
Subject 1	71.43	74.07	**82.01**	81.48
Subject 2	81.88	83.86	**91.67**	86.51
Subject 3	70.63	75.26	**84.66**	81.88
Subject 4	86.64	86.51	**93.25**	89.42
Subject 5	80.29	80.69	**91.14**	88.89
Subject 6	68.92	71.03	**84.92**	78.97
Subject 7	62.17	67.72	78.44	**78.57**
Subject 8	82.54	83.99	**94.05**	90.61
Subject 9	80.82	84.92	**89.15**	87.30
Subject 10	74.87	78.31	**85.98**	78.84
Subject 11	67.72	77.12	80.69	**82.80**
Subject 12	68.78	82.14	**88.49**	85.45
Subject 13	76.59	82.28	**90.61**	87.30
Subject 14	77.25	80.69	82.94	**84.26**
Subject 15	72.09	80.42	**87.43**	84.52
mean ± *std*	74.84±6.77	79.27±5.35	**87.03±4.73**	84.45±3.95

Data were computed by SVM. The best classification accuracy across four frequency bands are highlighted in **bold**.

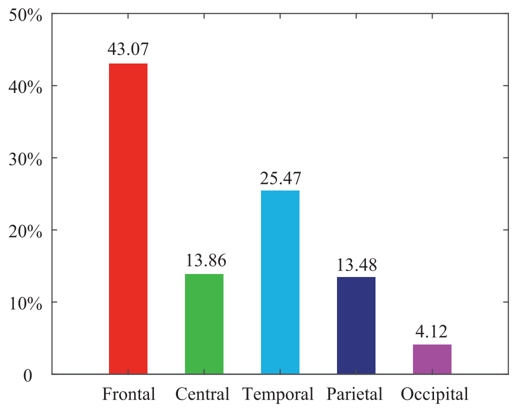

FIGURE 4. The proportion of emotion-related regional activity levels in the beta band across 15 subjects. It is computed by summarizing the active nodes in each region and then estimating their proportions to overall.

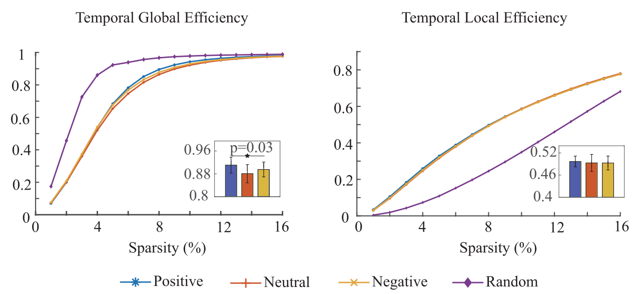

FIGURE 5. The temporal global efficiency and the temporal local efficiency of the temporal brain network in three emotion types (averaged over all subjects in each emotion type), and corresponding temporal random network. The sparsity ranged from 1% to 16%. The temporal efficiency at the sparsity of 8% is shown at the bottom of the corresponding plot (mean±std) of each emotion type. Meanwhile, the temporal global efficiency shows the great difference between the three emotion types.

proportion of emotion-related regional activity levels of the two regions reach 43.07% and 25.47%, respectively. Such a result demonstrates that the frontal and temporal areas are most sensitive to the emotional activities of the human brain.

C. TEMPORAL FUNCTIONAL NETWORK PROPERTIES

Fig. 5 shows the temporal global efficiency and the temporal local efficiency of three emotion types over 15 subjects in the beta band. Compared with temporal random efficiencies, the temporal functional network in different emotion types shows small-world architecture. The temporal efficiencies in different emotion types show a similar trend with the change of sparsity. However, at the sparsity of 8%, the higher temporal global efficiency ($F_{2,42} = 3.842$, $p = 0.030$, $\eta_p^2 = 0.165$) of positive is unmasked. The significant difference was computed between positive and neutral ($F_{1,28} = 7.035$, $p = 0.013$, $\eta_p^2 = 0.213$, FDR (false discovery rate)-corrected).

IV. DISCUSSION

In recent years, emotion recognition has achieved significant development while the neural mechanism about dynamic FC in different emotional states is beginning to be revealed. In this study, we investigated the emotion recognition by constructing the static network and the emotion-related neural mechanism of dynamic FC. First, we achieve a high classification accuracy in the beta band based on the subject-independent connection features of the static network. Then, for the overall connection features of 15 subject, we found that connections were concentrated on the frontal and the temporal lobes. Finally, we analyzed the temporal efficiencies of dynamic FC in different emotion types and found that the significant differences in temporal global efficiency were at the sparsity of 8%. These results are discussed in greater detail below.

A. EMOTION RECOGNITION PERFORMANCE IN DIFFERENT BANDS

For emotion classification, we employed SVM as the classifier. We have inspected the most discriminative connection features of each subject that will contribute to the high recognition accuracy. The best accuracy was obtained in the beta band (87.03%±4.73). This result confirms that the phase lag index (PLI) is a proper method to construct the brain functional connectivity networks for EEG based emotion recognition, and our classification procedures are feasible and efficient enough.

The specific response of brain cognitive, vigilance or emotion activities can be prominent in some frequency bands. Therefore, we restricted the EEG signals into the standard theta, alpha, beta, and gamma bands to search the most suitable frequency band for emotion recognition. From the empirical results, we found that the high-frequency bands, especially the beta band, are sensitive to emotion alteration. A number of literatures agree with our findings that the brain emotional activities are related to the beta band which possesses more reliable and obvious properties [44], [45]. Zhuang *et al.* [46] used the empirical mode decomposition (EMD) to recognize the emotion types, and their results indicated that the performance of beta and gamma bands is better than other bands. Murugappan and Murugappan [47] classified the happy, surprise, fear, disgust, and neutral emotion with Fast Fourier Transform (FFT) and implemented the K Nearest Neighbor (KNN) and Probabilistic Neural Network (PNN) to get the maximum accuracy of emotion recognition with the beta band.

We compared the other research based on the (SEED) database. Zheng and Lu [20] performed emotion recognition to search critical frequency bands and channels with deep neural networks. In their work, the differential entropy (DE) from 12 channels (FT7, FT8, T7, T8, C5, C6, TP7, TP8, CP5, CP6, P7, and P8) acquired the best emotion recognition accuracy 86.08%, which is lower than our empirical result 87.03%. Furthermore, they suggested that the high-frequency bands (beta and gamma) were more suitable for emotion recognition. Such a result demonstrated that the connection features are feasible enough for emotion recognition.

B. FUNCTIONAL CONNECTIVITY OF STATIC NETWORKS

The information spreading processing of neural activities involves multi-regional interactions and communications [48]. Investigating multiple correlations of emotional state will provide critical insights into the neuroscience research. In this study, we estimated the emotion-related brain interactions and computed the critical connections of three emotion types (positive, neutral, and negative). Specifically, we found the individual topological characteristics performed significant difference between different subjects, and thus we used the subject-independent feature selection for emotion recognition.

We tried to discover common interactions across 15 subjects. Therefore, we summarized overall connection features for more active regions. As shown in Fig. 4, we found significant active interactions in the frontal and the temporal regions. The intensive activities in the frontal and the temporal regions manifest they are sensitive to emotion alterations. These results suggested that the brain cooperation in the frontal and the temporal regions changed to react the emotion alteration. Li *et al.* [49] constructed emotion-related brain networks with phase locking value (PLV) and used a multiple feature fusion approach for emotion recognition. They found the frontal and the temporal lobes are more sensitive to emotion activities. Shahabi and Moghimi [50] investigated emotion recognition based on effective connectivity. Their research manifested that the perceived valence was positively correlated with the frontal inter-hemispheric flow. Various studies about emotion investigation have demonstrated that these regions are associated with emotion alterations, and these findings provide the evidence that the static network in this study is feasible for emotion-related investigation [51], [52].

C. TOPOLOGY OF TEMPORAL BRAIN NETWORK

The dynamic FC is an emerging method for brain activity analysis, few literatures revealed the essential time-respecting neural properties under different emotion types. The traditional static network analysis considers the connections of a separate time window as the feature for emotion-related investigation. However, the generated emotional activities are not a brief process, and the segmented static network cannot correctly reflect the entire brain activity within the lifetime. As shown in Fig. 3, the connections are different between the time window at 1, 40, and 80 of each emotion type. The brain activity has been suggested to be highly dynamic [53], and thus the static network cannot contain the full topology of the emotion-related brain regional interactions. The dynamic FC method sorts the separate static network into temporal brain network based on the time variation. Such method focuses on the interregional information spreading ability in the time scale and may provide a new insight for the brain functional organization investigation.

We compared the temporal efficiencies of the emotion-related temporal brain network and the generated temporal

TABLE 3. Summary of relevant research works in the field of emotion-related research using different method.

Research work	Channels	Method	Multi-regional connection features	Temporal features
Zheng et al. [20]	62	DE, DASM, RASM, DCAU, PSD	No	Yes
Zhuang et al. [46]	32	Empirical mode decomposition	No	Yes
Shahabi et al. [50]	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4	Effective connectivity	Yes	No
Yuvaraj et al. [52]	AF3, AF4, F7, F8, F3, F4, FC5, FC6, T7, T8, P7, P8, O1 and O2	Functional connectivity	Yes	No
Our work	62	Static network for emotion recognition, temporal brain network for emotion mechanism research	Yes	Yes

random network. The dynamic FC meets the criterion of small-worldness with a similar temporal global efficiency and significantly higher temporal local efficiency (Fig. 5). The previous literatures have suggested the small-world architecture in the static network [54], [55]. Few studies have focused on the small-world properties in the dynamic FC. These empirical results demonstrated the particular topology of the spatio-temporal architecture of the human brain in which the brain regional interaction evolved with the global integration and local segregation.

In term of the higher temporal global efficiency at the positive emotion type, especially between positive and neutral (Fig. 5), the human brain performs a more efficient information spreading ability at such emotions. It might demonstrate that positive emotion state is more suitable for brain workload task.

D. COMPARISON BETWEEN DIFFERENT EMOTION-RELATED RESEARCH

In this paper, we used the static network for emotion recognition and the temporal brain network for the emotion related mechanism analysis. Obviously, compared with other latest methods (Table. 3), there were few researchers achieved emotion recognition based on the connection features and investigated the spatio-temporal connection under different emotion types. Our temporal brain network framework could measure the brain regional interactions in the time scale, which provides the new insight for neural mechanism analysis.

E. EXPERIMENTAL LIMITATION AND FUTURE CONSIDERATIONS

First, the limitation lies in that the emotion data were limited to SEED database which can not reflect the overall situations. For example, the emotion types of fear, anger, and others are not included in the database. In the future, we will achieve emotion recognition with more emotion types. Second, we summarized the subject-independent connections features for emotion recognition which is not an efficient approach for practical application. The common emotion-related topological structures across all subjects are urgently need to be discovered. Third, we only measured the small-worldness of dynamic FC while the nodal properties are not paid attention. The nodal efficiency or temporal closeness centrality should be considered in the further research.

V. CONCLUSION

In the present work, we achieved emotion recognition based on the static network and investigated the small-worldness of dynamic FC of different emotion types. Experimental results revealed that the beta band is more sensitive for emotion alteration with the best recognition accuracy of $87.03\pm4.7\%$. Even the selected individual connections are different, interactions of the frontal and the temporal regions are considered to associate with brain emotional activities. Finally, the existence of small-world properties are proved in dynamic FC, and we discovered the higher temporal global efficiency at the positive emotion type, especially between the positive and neutral emotion types. This study provides new insight into affective computing, and manifests the dynamic FC is a feasible method to investigate the mechanism of emotion generation and alteration.

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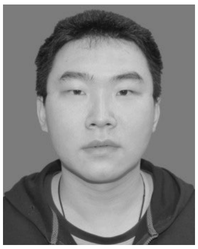

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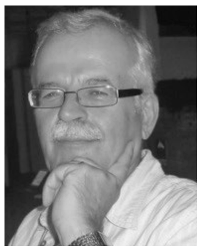

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