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Identifying Functional Brain Connectivity Patterns for EEG-Based Emotion Recognition

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***Abstract*— Previous studies on EEG-based emotion recognition mainly focus on single-channel analysis, which neglect the functional connectivity between different EEG channels. This paper aims to explore the emotion associated functional brain connectivity patterns among different subjects. We proposed a critical subnetwork selection approach and extracted three topological features (strength, clustering coefficient, and eigenvector centrality) based on the constructed brain connectivity networks. The experimental results of 5-fold cross validation on a public emotion EEG dataset called SEED indicate that the common connectivity patterns associated with different emotions do exist, where the coherence connectivity is significantly higher at frontal site in the alpha, beta and gamma bands for the happy emotion, at parietal and occipital sites in the delta band for the sad emotion, and at frontal site in the delta band for the neutral emotion. In addition, the results demonstrate that the topological features considerably outperform the conventional power spectral density feature, and the decision-level fusion strategy achieves the best classification accuracy of 87.04% and the corresponding improvement of 3.78% in comparison with the state-of-the-art using the differential entropy feature on the same dataset.**

I. INTRODUCTION

Emotion recognition plays a crucial role in pursuit of emotional intelligence, which is an interdisciplinary research involving many fields, such as neuroscience, psychiatry and artificial intelligence. To date, various modalities convey emotional information and are employed in emotion recognition. Among these modalities, the electroencephalography (EEG) signal with objective and effective evaluation has been widely utilized to develop affective brain-computer interaction systems.

However, previous studies on EEG-based emotion recognition rely heavily on single-channel analysis. Specifically, features are usually extracted independently from each EEG channel, such as the most commonly used power spectral density (PSD) and differential entropy (DE) [1][2]. These features simply reflect neural activities within single EEG channel, which neglect the functional connectivity between EEG channels in different brain regions. In contrast, Mauss and Robinson [3] have suggested that emotion processing should be considered as involving distributed circuits rather than specific brain regions in isolation. Besides, EEG has been pointed to decreased functional connectivity between cortical regions in various psychophysiological diseases with cognitive deficits, such as autism, schizophrenia and major depressive disorder [4]. Therefore, exploring emotion associated functional brain connectivity patterns is of great significance and has a high potential in revealing the neural mechanisms underlying emotion processing.

Among a few preliminary studies on EEG-based emotion recognition that attempted to exploit the connectivity between EEG channels, Song *et al.* [5] modeled the multichannel features based on the dynamical graph convolutional neural networks. However, neither did they explicitly use the connectivity nor analyze the connectivity patterns. While Chen *et al.* [6] and Lee *et al.* [7] directly used connectivity indices as features, including correlation, coherence, phase synchronization, and mutual information, they did not take the brain network topology into account. Therefore, we aim to identify emotion associated functional brain connectivity patterns and exploit the topological properties of the brain network to classify three emotions (happy, neutral, and sad).

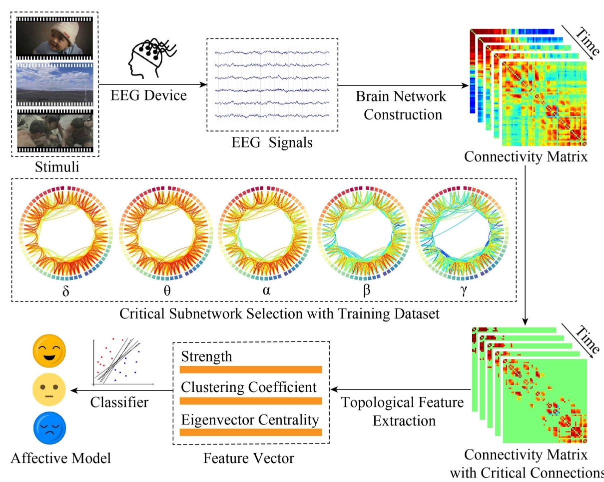

Fig. 1. The framework of our proposed approach

The framework of our proposed approach is depicted in Fig. 1. The working process of our framework consists of three main steps: 1) brain networks are constructed from the preprocessed EEG data; 2) critical subnetworks are selected using training dataset; and 3) brain connectivity matrices comprised of critical connections are employed to extract the topological features, which are further fed into the classifier to train the affective models.

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II. EXPERIMENT SETUP

The performance of our proposed approach is evaluated on a public emotion EEG dataset called SEED[1], which contains EEG signals of three emotional states (happy, neutral, and sad) from 15 subjects. During each experiment, while the subject was watching emotional movie clips, the EEG signals were simultaneously recorded with a 62-channel electrode cap at a sampling rate of 1000 Hz. Each subject was required to perform the experiment for three sessions on different days, and thus there are 45 experiments in total.

III. METHODS

A. Preprocessing

The raw EEG data were first downsampled to 200 Hz. In order to investigate the frequency-specific connectivity patterns, the EEG data were then processed with five bandpass filters corresponding to the five frequency bands (δ: 1-4 Hz, θ: 4-8 Hz, α: 8-14 Hz, β: 14-31 Hz, and γ: 31-50 Hz).

B. Feature Extraction

1) Functional Brain Network Construction: In EEG-based functional brain network, nodes are represented by EEG channels and links are the connections between pairs of channels [8]. In this paper, there are totally 62 nodes, and two connectivity indices are adopted, Pearson's correlation coefficient and spectral coherence [7], which can measure the connectivity between EEG channels in temporal domain and frequency domain, respectively.

For further comparison with the performance achieved by the conventional PSD and DE features which were extracted within a time window of 1 second [9], we constructed the brain network using the same window. As a result, each sample consists of 1-second EEG segment of 62 channels. After EEG signals were preprocessed with the five bandpass filters, the connectivity between pairs of EEG signals was calculated in each frequency band for each sample. Therefore, each brain network can be represented by a 62×62 symmetric connectivity matrix, and five networks were obtained for each sample corresponding to the five frequency bands.

2) Critical Subnetwork Selection: Since many weak connections may obscure the profile for the network topology, the conventional procedure directly discarded these connections based on an absolute or a proportional threshold [10]. However, considering that not all of the preserved connections are emotion relevant, we proposed an approach called critical subnetwork selection to identify the common emotion associated connectivity patterns among different subjects. In this paper, the training datasets from all the 45 experiments were exploited together to select the five critical subnetworks corresponding to the five frequency bands.

Assume that the connectivity matrices X and the corresponding labels Y in the training dataset of one frequency band are defined as follows:

$$X = \{x^i\}_{i=1}^{M} \ (x^i \in \mathbb{R}^{N\times N}), \ Y = \{y^i\}_{i=1}^{M} \ (y^i \in L), \quad (1)$$

[1]`http://bcmi.sjtu.edu.cn/~seed/`

where M and N denote the number of samples and nodes, respectively, and L is the set of emotion labels. The critical subnetwork selection for one frequency band is described in Algorithm 1 and presented in Fig. 2.

Algorithm 1 The proposed critical subnetwork selection approach for one frequency band

Input: The connectivity matrices X, the labels Y, the threshold t, and the nodes of the original network V

Output: The critical subnetwork G^*

for each $c \in L$ **do**
  Average the matrices with the same emotion label c:
  $$x_c = mean_{y^i==c}(x^i)$$
  Sort the upper triangular entries of the matrix x_c based on the absolute value of the connection weights:
  $$x_c^* = sort(abs(triu(x_c)))$$
  Preserve the indices of the strong connections according to the proportional threshold t:
  $$E_c = index(x_c^*(1 : t * N * (N-1)/2))$$
end for
Derive the critical connections, which are defined as the union set of the preserved connections in all classes:
$$E^* = union_{c\in L}(E_c)$$
Construct the critical subnetwork: $G^* = (V, E^*)$
return G^*

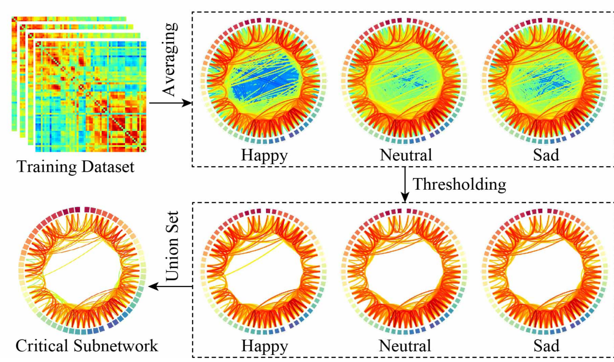

Fig. 2. Critical subnetwork selection for one frequency band

3) Topological Feature Extraction: Based on the five critical subnetworks, we can derive the connectivity matrices comprised of critical connections for each sample in the whole dataset. Then, we employed these matrices to extract three topological features (strength, clustering coefficient, and eigenvector centrality) by using the Brain Connectivity Toolbox [10]. As aforementioned that we adopted two connectivity indices (correlation and coherence), there are totally six different connectivity features evaluated in this paper.

C. Classification

Before feeding features into the classifier, a feature smoothing approach, linear dynamic system (LDS) [2], and a feature selection approach, minimal redundancy maximal relevance (mRMR) [9], were applied to filter out unrelated features and diminish the curse of dimensionality, respectively. The support vector machine (SVM) with linear kernel was used as a classifier to train the affective model for each experiment. The 5-fold cross validation strategy and the grid search method were adopted to tune the threshold value, the dimension of features, and the learning rate of SVMs.

Furthermore, the feature-level fusion (FLF) strategy was utilized to concatenate the three topological features to train the model. In addition to the FLF, three decision-level fusion (DLF) strategies (max, sum, and fuzzy) were also employed to combine the best topological feature and the state-of-the-art DE feature to enhance the recognition performance.

IV. RESULTS AND DISCUSSION

A. *Classification Performance*

We first evaluated the three topological features and the FLF approach using two different connectivity indices. The mean classification accuracy and the standard deviation in percentage (%) are presented in Table I. We can observe that the strength feature performs the best in terms of mean accuracy regardless of the connectivity index, followed by clustering coefficient and eigenvector centrality. Moreover, features with correlation as the connectivity index achieve slightly better performance than those with coherence.

TABLE I

THE CLASSIFICATION PERFORMANCE OF THREE TOPOLOGICAL FEATURES WITH TWO DIFFERENT CONNECTIVITY INDICES

Features	Correlation	Coherence
Strength	**81.53 ± 7.61**	**81.04 ± 7.58**
Clustering Coefficient	80.11 ± 8.23	78.84 ± 8.38
Eigenvector Centrality	77.86 ± 8.24	76.83 ± 7.51
Feature-Level Fusion	79.16 ± 8.85	78.15 ± 8.45

The confusion matrices for the strength feature with two connectivity indices are depicted in Fig. 3. We can see that the happy emotion can be identified with a relatively higher accuracy and the sad emotion is the most difficult to be distinguished, which is consistent with our previous findings [2]. Besides, the result reveals that correlation outperforms coherence in quantifying the connectivity for all the three emotions. As shown in Fig. 4, the strength feature is also employed to evaluate the performance of different frequency bands. The results demonstrate that the gamma and beta bands are the critical frequency bands regardless of the connectivity index, which is in accordance with the results in our previous work [2].

Furthermore, we compared the topological features with two other categories of features. One is the most commonly used features, PSD and DE, which are based on the single-channel analysis; the other is using the connectivity indices directly as features, i.e. correlation and coherence. The mean accuracy (%) and the standard deviation (%) for the PSD, DE, correlation, and coherence features are 64.09 ± 15.24, 83.26 ± 9.08 [9], 76.60 ± 9.80, and 77.14 ± 9.69, respectively. These results indicate that the topological features

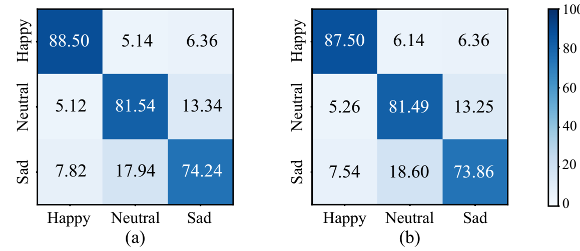

Fig. 3. The confusion matrices for the strength feature with two connectivity indices: (a) correlation and (b) coherence. Here, each row and each column represent the target class and the predicted class, respectively, and each element denotes the classification accuracy in percentage (%).

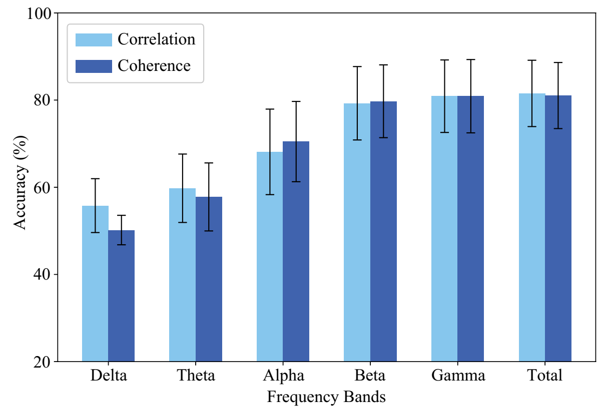

Fig. 4. The classification performance of different frequency bands using the strength feature with two different connectivity indices. Here, *Total* refers to the direct concatenation of the five frequency bands.

can achieve considerably better performance than that of the conventional PSD feature, and the best topological feature, the strength, is comparable to the state-of-the-art DE feature in terms of classification accuracy. Except for the eigenvector centrality with coherence connectivity, other topological features are also better than the correlation and coherence features, which implies the superiority of exploiting the topological properties of the brain network.

Table II presents the mean classification accuracy (%) and the standard deviation (%) of the four fusion strategies for combining the DE and strength features with two connectivity indices. The best classification accuracy of 87.04% is achieved by the decision-level fusion strategy with correlation connectivity, which improves 3.78% in comparison with the state-of-the-art DE feature on the same dataset [9].

TABLE II

THE CLASSIFICATION PERFORMANCE OF THE DE AND STRENGTH FEATURES WITH TWO DIFFERENT CONNECTIVITY INDICES

Fusion Strategies	Correlation	Coherence
FLF	84.31 ± 8.32	84.28 ± 8.22
Max	85.73 ± 8.40	86.22 ± 7.67
Sum	**87.04 ± 7.41**	86.33 ± 7.79
Fuzzy	86.65 ± 7.70	**86.43 ± 8.14**

B. Functional Brain Connectivity Patterns

As aforementioned that only the training datasets were exploited in critical subnetwork selection and 5-fold cross validation manner was adopted in performance evaluation, we selected the critical subnetworks for five times in this paper. The results indicate that the critical subnetworks exhibit consistency during these five times of selection.

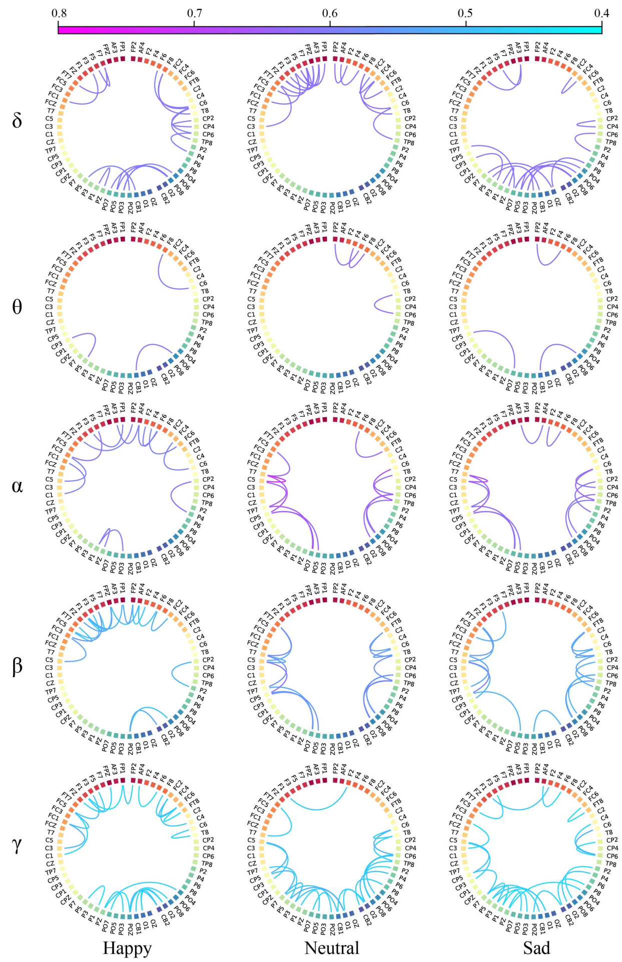

Fig. 5. The functional brain connectivity patterns for the three emotions in the five frequency bands with coherence as the connectivity index. In each subfigure, the nodes in the left and right represent EEG channels located in the left and right cortical regions, respectively; the nodes from top to bottom represent EEG channels located from the frontal, temporal, parietal to the occipital lobes. It should be noted that the intersections of the critical connections among these three emotions are not displayed in this figure.

The averaged critical subnetworks over five folds are depicted in Fig. 5, where 15 subfigures correspond to the functional connectivity patterns associated with the three emotions in the five frequency bands. Fig. 5 reveals that the sad and neutral emotions share relatively similar connectivity patterns in comparison with the happy emotion, which may account for the results depicted in Fig. 3. For the happy emotion, the coherence connectivity is significantly higher at frontal site in the alpha, beta, and gamma bands. In accordance with the previous findings that the neural patterns have significantly higher delta responses at parietal and occipital sites for the sad emotion [9], Fig. 5 shows significantly higher coherence connectivity at these sites in the delta band for the sad emotion. Whereas for the neutral emotion, significantly higher coherence connectivity is found at frontal site in the delta band. These results verify the conclusion accomplished by fMRI that the brain areas contributing to emotion processing predominate in the frontal and parietal structures [11]. Additionally, the coherence connectivity is significantly higher at temporal site in the alpha band for the sad emotion compared to the happy emotion, which is consistent with the existing work [7].

V. Conclusions

In this paper, we have proposed a critical subnetwork selection approach to identifying the functional connectivity patterns associated with three emotions (happy, neutral, and sad). The results have indicated that the emotion associated connectivity patterns do exist, where significantly higher coherence connectivity can be found in the alpha, beta, and gamma bands at frontal site for the happy emotion, in the delta band at frontal site for the neutral emotion, and in the delta band at parietal and occipital sites for the sad emotion. Furthermore, the topological features are considerably better than the conventional PSD feature, and the decision-level fusion strategy for the best topological feature (strength) and the state-of-the-art DE feature achieves the best classification accuracy of 87.04%, which is 3.78% higher than that of the DE feature on the same emotion EEG dataset.

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