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Exploring Sex Differences in Key Frequency Bands and Channel Connections for EEG-based Emotion Recognition

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***Abstract*— Previous studies have demonstrated the existence of sex differences in emotion recognition by comparing the performance of same-sex and cross-sex training strategies. However, the EEG properties behind the sex differences have not been fully explored. To fill this research gap, we aim to investigate the sex differences in key frequency bands and channel connections of EEG signals. The single-modality attentive simple graph convolutional network (ASGC) is applied to three datasets SEED, SEED-IV and SEED-V under subject-dependence conditions. The classification rates are $90.86 \pm 4.84\%$, $83.14 \pm 8.84\%$ and $78.33 \pm 7.83\%$, respectively. The adjacency matrices learned by ASGC indicate that females and males have similar channel-connection patterns, but the degree of importance of channel connections varies by sex. Additionally, by comparing the classification results of 5 frequency bands, we find that males and females represent similar frequency band characteristics, i.e., high-frequency bands achieve better performance, indicating that these frequency bands are more related to emotion processing. Finally, we conduct the cross-subject experiment using ASGC and find that the same-sex strategy outperforms the cross-sex strategy, which is consistent with previous studies. The results also imply that males may be more suitable for sex generalization. However, this finding needs the support of more samples and advanced algorithms.**

I. INTRODUCTION

It has been a long conviction that there exists some extent of sex differences in emotion processing and emotion experience [1]. Notable sex differences in the clinical manifestation of many affective disorders are also observed [2]. Women tend to exhibit a higher incidence of affective disorders and often report more depressive symptoms than men [3], [4]. However, investigations on the neural bases of sex differences in emotional experience have been relatively limited.

In recent years, electroencephalography (EEG) signals have been used as important indicators for emotion detection. Zheng and Lu [5] applied deep belief networks (DBNs) to EEG-based emotion recognition and identified stable EEG patterns under different emotions. Zhao *et al.* [6] proposed a plug-and-play domain adaptation method. Employing a short calibration time, the performance of their approach is comparable to that of domain generalization methods.

Taking advantage of these experiences, some researchers endeavor to demonstrate the existence of sex differences in emotion recognition by comparing the performance of same-sex training strategy and cross-sex training strategy [7], [8]. The same-sex strategy means that the sexes of subjects in the training and test sets are the same, while the cross-sex strategy means that the sexes are different. If a higher accuracy rate of the same-sex strategy is observed, a sex-specific pattern does exist. Yan *et al.* [9] extracted the shared representation of EEG and eye movement features by the bimodal deep autoencoder (BDAE) algorithm. The shared representation was then conveyed to the support vector machine (SVM) classifier. The results showed that the same-sex strategy achieved better performance. Bao *et al.* [10] utilized a similar strategy but focused more on eye movements. They found that the average blink frequency and the average blink duration of females are higher and shorter than those of males.

Nevertheless, the studies mentioned above either ignored the investigations of EEG properties such as key frequency bands and EEG channel connections or merely utilized one dataset. To fill this research gap, we aimed to investigate the sex differences in key frequency bands and channel connections of EEG signals under conditions of emotion induction. We applied the single-modality algorithm ASGC [11] on three datasets SEED [5], SEED-IV [12] and SEED-V [13]. The subject-dependence experiment was conducted to determine the mentioned issues, while the subject-independence experiment was utilized to illustrate the different performances of the same-sex training strategy and cross-sex training strategy.

II. EXPERIMENTAL DESIGN

A. Datasets

We chose three public representative EEG datasets for our experiments, SEED[1], SEED-IV[1], and SEED-V[1], of which the categories of emotion labels are three (negative, neutral, positive), four (neutral, sad, fear, happy), and five (disgust, fear, sad, neutral, happy), respectively. All datasets recorded 62-channel EEG signals and eye movement signals from right-handed subjects aged between 19 to 24. The information of the subjects of each dataset is shown in Table I. Each subject

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[1]https://bcmi.sjtu.edu.cn/home/seed/

was required to watch video clips with different emotion labels and participate in the experiments for three sessions on different days. All the experiments have been approved by the Ethics Committee of Shanghai Jiao Tong University.

TABLE I
DATASETS' INFORMATION

Dataset	Subject	Male	Female	Classes
SEED	15	7	8	3
SEED-IV	15	6	9	4
SEED-V	16	6	10	5

B. Experimental Setup

The sex differences in EEG-based emotion recognition were analyzed under two circumstances. 1) Subject-dependence. For SEED, the first 9 trials were set as training sets while the last 6 trials were set as test sets for each session. The final accuracy was the mean of three sessions. For SEED-IV, the training and test sets were the first 16 trials and the last 8 trials respectively. For SEED-V, we utilized a three-fold cross-validation, which was the same as in [14]. 2) Subject-independence. The same-sex and cross-sex strategies and the leave-one-out cross-validation were applied. It should be noted that to balance the number of female and male subjects, we removed the female subject '2' in SEED dataset.

III. METHODOLOGY

A. EEG Preprocessing and Feature Extraction

SEED, SEED-IV, and SEED-V followed the same data preprocessing and feature extraction strategies. For data preprocessing, a bandpass filter of 1-50 Hz was applied after the baseline correction to the raw EEG signals. The artifacts caused by blink were artificially removed in terms of the vertical electrooculogram (VEO) signal which was simultaneously acquired with EEG signals. Finally, the EEG signals were downsampled from 1000 Hz to 200 Hz.

For feature extraction, the short time fourier transform (STFT) with a 4 s nonoverlapping Hanning window was utilized to extract the differential entropy (DE) features in the five frequency bands (delta: 1-4 Hz, theta: 4-8 Hz, alpha: 8-14 Hz, beta: 14-31 Hz, and gamma: 31-50 Hz). DE features were smoothed by the linear dynamic system (LDS) method [10].

B. Attentive Simple Graph Convolutional Network

ASGC was proposed to distinguish the human decision confidence level [11]. It combines the attention mechanism with the simple graph convolutional network (SGC). The details of ASGC are as follows.

Let $\mathbf{X} \in \mathbb{R}^{n \times d}$ be the feature matrix, where n is the number of nodes, i.e., the number of channels and d is the number of features, i.e., the number of frequency bands. Let $\mathbf{Y}$ be the true labels with C classes. Let $\mathbf{A} \in \mathbb{R}^{n \times n}$ be the learnable adjacency matrix. $\mathbf{S}$ is defined as:

$$\mathbf{S} = \tilde{D}^{-\frac{1}{2}} \tilde{\mathbf{A}} \tilde{D}^{-\frac{1}{2}} \tag{1}$$

TABLE II
MEAN ACCURACY RATES (%) AND STANDARD DEVIATIONS (%) OF SVM AND ASGC ON SEED, SEED-IV AND SEED-V DATASETS.

		SEED	SEED-IV	SEED-V
SVM	M	77.01 ± 2.08	60.21 ± 18.61	55.67 ± 12.09
	F	76.49 ± 8.14	63.06 ± 10.32	61.01 ± 9.13
	All	76.73 ± 6.11	61.02 ± 14.3	59.08 ± 10.63
ASGC	M	$88.69 \pm \mathbf{2.47}$	79.72 ± 10.56	75.94 ± 10.67
	F	93.04 ± 5.92	$86.55 \pm \mathbf{6.09}$	$80.73 \pm \mathbf{4.59}$
	All	$\mathbf{90.86} \pm 4.84$	$\mathbf{83.14} \pm 8.84$	$\mathbf{78.33} \pm 7.83$

where $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I_n}$ and $\tilde{\mathbf{D}}_{ii} = \sum_j \tilde{\mathbf{A}}_{ij}$.

The K-step feature propagation of the SCG is:

$$\tilde{\mathbf{X}} = \mathbf{S}^K \mathbf{X} \tag{2}$$

where the conception of K is similar to the number of layers in the graph convolution network (GCN). It represents that each node can obtain the feature information from all nodes that are K-hop away. Then, we define $\mathbf{Z}$ as:

$$\mathbf{Z} = \tilde{\mathbf{X}} \mathbf{W} \tag{3}$$

Here, $\mathbf{W} \in \mathbb{R}^{d \times h_1}$ and h_1 is the number of nodes in the hidden layer.

The attention mechanism is utilized as follows:

$$\mathbf{M} = (m_{ij}) = softmax(\mathbf{Z}\mathbf{Z}^T) \tag{4}$$

$$\hat{\mathbf{X}} = \mathbf{M} \tilde{\mathbf{X}} \tag{5}$$

where $\mathbf{M} \in \mathbb{R}^{n \times n}$ is the attention matrix. Finally, the predicted label $\hat{\mathbf{Y}}$ can be calculated using a 2-layer multilayer perceptron (MLP).

$$\hat{\mathbf{Y}} = softmax(\hat{\mathbf{X}} \mathbf{W}^o) \tag{6}$$

where $\mathbf{W}^o \in \mathbb{R}^{h_2 \times C}$. h_2 is the number of nodes in the hidden layer of MLP.

C. Hyperparamter Tuning

The number of nodes h_1 is the hyperparameter. We tuned it from the set $\{10, 32, 36, 48, 64, 72, 128\}$ under the subject-dependence condition. For the subject-independence experiment, h_1 was set to 10 except for the situation of female features as training sets and male features as test sets, where h_1 was set to 32 and h_2 was 128. The activation functions were ReLU or LeakyReLU. K was set to 2. The batch size was 16, while the learning rate was 0.001. These settings were the same for both the subject-dependence and subject-independence conditions.

IV. RESULTS AND DISCUSSION

A. Performance of ASGC

Table II presents the performance of SVM and ASGC for males and females on the SEED, SEED-IV and SEED-V datasets. ASGC achieves the highest accuracy rates on all datasets ($p < 0.001$ in the analysis of variance). With the increase in emotional categories, the recognition rates decrease in all situations.

TABLE III
COMPARING SEX DIFFERENCES IN MEAN ACCURACY RATES (ACC (%)) OF THE SVM CLASSIFIERS WITH THE DE FEATURES OF FIVE INDIVIDUAL FREQUENCY BANDS AND THEIR DIRECT CONCATENATION (TOTAL).

		Delta	Theta	Alpha	Beta	Gamma	Total
SEED	M	60.40	63.36	65.83	68.60	69.49	**77.01**
	F	59.23	56.67	62.40	70.65	71.63	**76.49**
SEED-IV	M	44.45	44.55	55.40	54.18	53.78	**60.20**
	F	46.63	49.23	47.39	58.14	49.91	**63.06**
SEED-V	M	44.52	44.91	44.21	51.62	45.17	**55.87**
	F	53.56	52.43	48.78	53.67	55.18	**61.01**

SEED-V has the most diverse emotion labels among the three datasets. Additionally, according to the instructions on the SEED website, the emotion labels in SEED-V cover them in SEED and SEED-IV. Hence, we choose the confusion matrices of SEED-V to investigate the gender differences in emotion recognition. From Figure 1, we can conclude that males and females follow a similar tendency, i.e, the accuracy rates descend in the order of fear, neutral, happy and disgust. The only exception is sad, indicating that for the ASGC model, female features are more distinguishable for sad emotions than male features.

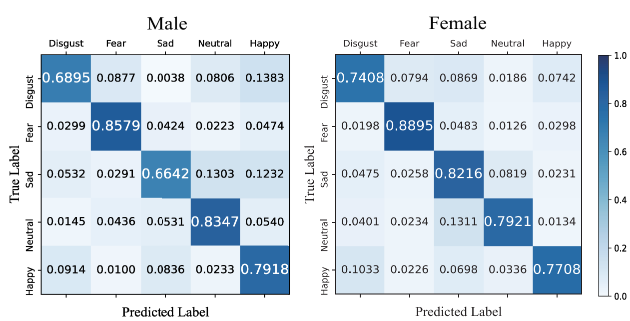

Fig. 1. The confusion matrices for males and females on SEED-V

B. Sex Differences in Key Frequency Bands

Table III displays the mean accuracy rates of five frequency bands. Due to the huge time consumption of ASGC, we only applied SVM to demonstrate the trend, as Zheng *et al.* did in [5]. For each dataset, we performed analysis of variance (ANOVA) to find if there are significant differences in the accruacy rates of five frequency band and found $p < 0.05$ for all datasets. Males and females represent similar frequency band characteristics. The direct concatenation achieves the best accuracy rate regardless of sex, which indicates that five frequency bands may complement each other. Beta and gamma show relatively higher emotion discrimination abilities compared with low-frequency bands. This result is consistent with the research [5] and indicates that high-frequency bands contain more emotion-related information and bear more responsibility in emotion recognition.

C. Sex Differences in Channel Connections

To investigate the sex differences in channel connections, the learned adjacency matrices $\mathbf{A}$ of subjects in all datasets were averaged and visualized. Figure 2 depicts the 30 strongest connections for males and females. The majority of the 30 strongest connections for males can also be found in those for females but in different order. The two connections between CPZ to C4 and CPZ to F7 are the strongest for both sexes, while the connection between CPZ to F6 for males is stronger than that for females. Generally, strong connections occur between the middle parietal lobe and the left frontal lobe and between the middle parietal lobe and the temporal lobe. Several relatively weak connections, such as C1 to FCZ and FPZ to OZ, are only found in females, while connections between FC6 to PF1 and C4 to AF4 only appear in males. These results suggest that channel-connection patterns for emotion are similar in both sexes but these connections have different degrees of importance for males and females.

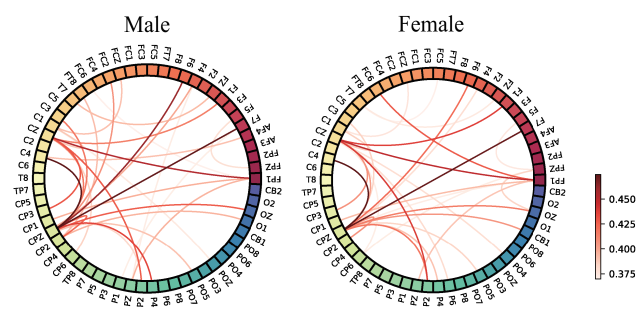

Fig. 2. The adjacency matrices visualization

D. Cross-subject Analyses

Table IV describes the accuracy rates of same-sex and cross-sex strategies of ASGC on the SEED dataset ($p = 0.07$). The same-sex strategy achieved higher accuracy rates. For males as the test set, the results of the same-sex and cross-sex strategies achieve 78.79% and 77.18%, respectively. For females, the same-sex strategy achieves a higher accuracy of 89.44%. This finding is consistent with a previous study [9], which proves the existence of sex differences in emotion recognition. In addition, using male features as the training set and female features as the test set outperforms the opposite, even under the condition that females perform better than males in both same-sex and subject-dependence situations, which may indicate that males are more suitable for sex generalization. However, these finding were not significant and still need more samples to support.

E. Sex Differences in Neural Patterns

In this section, brain topographic mapping is applied to study sex differences in neural patterns. The differences between the normalized DE features of males and females were calculated for each emotional state in each dataset. The mean of the differences under the same emotional states is utilized to construct Figure. 3.

TABLE IV
SAME-SEX AND CROSS-SEX ACCURACY RATE (%) AND STANDARD VARIATIONS (%) OF ASGC ON SEED DATASET

Train	Male	Female	Male	Female
Test	Male	Male	Female	Female
Mean	78.79	77.18	82.17	**89.44**
Std.	**5.71**	9.5	10.5	5.8

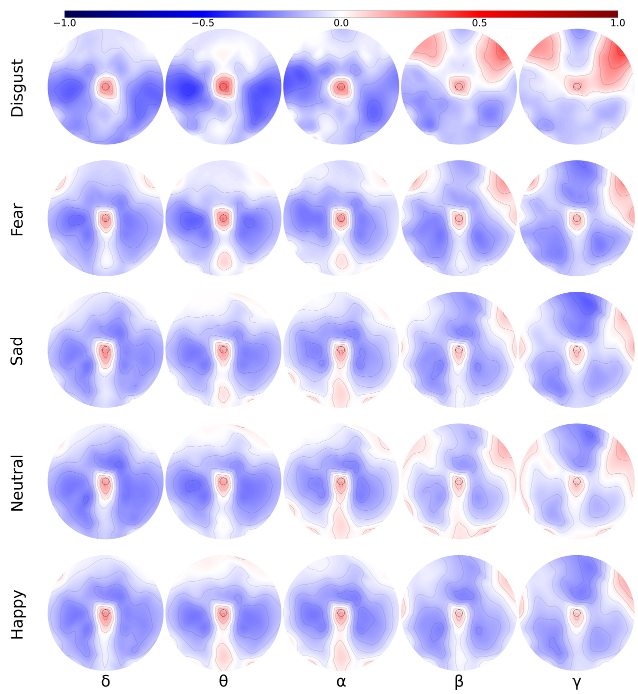

Fig. 3. Brain topographic mapping of the differences between the average normalized DE features of males and females

From the brain topographic mapping, we find that in the majority of regions, females have higher activation levels. Additionally, the delta, theta and alpha bands showed different sex patterns compared with the beta and gamma bands. In low-frequency bands, the only regions where males have higher energy are the middle parietal lobe and the middle occipital lobe. The energy of the female temporal lobe is much higher. In the beta and gamma bands, the energy of the middle occipital lobe of males is weaker than that of females, whereas the temporal lobe region of males has a higher activation level.

V. CONCLUSIONS

In this paper, we applied ASGC to the investigation of sex differences in EEG-based emotion recognition. ASGC can fully utilize the information of the networks constructed by the DE features of each channel, and the learnable adjacency matrices can provide evidence for analyzing key channel connections. The classification results of ASGC on SEED, SEED-IV and SEED-V are $90.86 \pm 4.84\%$, $83.14 \pm 8.84\%$ and $78.33 \pm 7.83\%$, respectively. The visualization of adjacency matrices indicates that females and males have similar channel-connection patterns. By analyzing the confusion matrices of SEED-V, we found that ASGC has a stronger ability to distinguish sadness in males than in females. The SVM was utilized to explore the crucial frequency bands for each sex. The results show that females and males have similar frequency band characteristics, i.e., high-frequency bands achieve higher performance. This finding is consistent with a previous study [5], where the analyses were conducted regardless of sex. These results imply that sex differences in EEG properties, such as frequency bands and channel connections, exist. Additionally, we conducted a cross-subject experiment and found that males may have better sex generalization abilities. However, these are merely preliminary findings. More samples and advanced algorithms are required to support this finding.

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