Investigating Sex Differences in Classification of Five Emotions from EEG and Eye Movement Signals

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Abstract— **People generally agree that emotion processing differs between male and female. However, current hypothesis of sex differences needs more objective evidence and quantitative assessment. In this paper, we investigate the sex difference in classifying five emotions from eletroencephalograph and eye movement signals. We adopt two neural-network-based classifiers to objectively investigate sex differences from different perspectives. From experimental results, we find the following three observations: (1) a general higher accuracy of same-sex strategy suggests sex-specific factors have influence on emotion classification; (2) both blink duration and frequency differ from female to male and they are negatively correlated under different emotional states; and (3) there are larger differences of brain activities in the Theta, Alpha, and Beta bands between male and female for disgust, sad, and neutral emotions.**

I. INTRODUCTION

Sex differences in emotion have long been well noted. Taking major depressive disorder as an example, as a prevalent malady closely related to emotions, there are well-documented sex differences in the reports of both frequency and pervasiveness of depression [1] [2]. However, current theories of sex differences in emotion are lack of quantitative assessment and largely based on subjective measures such as interviewing and self report [3]. While the advance in machine learning leads to great progresses in developing emotion recognition systems, we know very little yet about the sex difference in emotion recognition.

Given that affective brain-computer interfaces develop rapidly, the existing studies have conducted to examine sex stereotypes. Ruben *et al.* used fMRI to study cognitive processing differences in verbal and spatial tasks, reaching the conclusion that female has an advantage in these tasks [4]. Jausovec *et al.* measured EEG in resting activity and found out men and women differ in coding of information [5]. Yan *et al.* investigated key brain areas in recognition of three emotions (happy, neutral, and sad) through EEG and revealed that sex-based lateralization pertains in the human brain [6]. Whittle *et al.* have used neuroimaging and figured out that the biggest difference between female and male occurs in negative emotional states [7]. Nevertheless, not many studies using neuroimaging or electrophysiological monitoring method are concerned with specific negative emotions such as fear and disgust, which depression is closely related to. Therefore, we study five emotions in this paper, including three negative emotions in addition to happy and neutral. Our major goal is to examine sex differences through the sex-based classification of five emotional states as well as to compare brain regions and eye movement features in a more interpretable and comprehensive way.

Our previous study has shown that the combination of EEG and eye movement signals can achieve greater accuracy in classifying three emotional states (happy, neutral, and sad) compared to the single modality [8], which indicates that multiple modalities could enhance the robustness of emotion recognition. In this paper, we utilize both the EEG and eye movement signals to investigate sex differences in classifying five emotions: disgust, fear, sad, neutral, and happy. Deep Canonical Correlation Analysis (DCCA) [9] and Bimodal-Long Short-Term Memory (LSTM) [10] are introduced to combine two modalities as classifiers.

II. EXPERIMENT DESIGN

A. Data Collection

There are totally 12 subjects (6 females and 6 males) in our experiments. All subjects are volunteered college students between the age of 18 and 28, and right-handed in order to eliminate the handedness influence. All subjects are fully informed of the procedures before taking the experiments and required to sign a consent form after the instruction. The study is approved by the local ethics and the dataset utilized in this paper was developed in our previous study [11].

B. Device Setups

The electrode cap from Neuroscan embedded 62 channels as well as SMI EGT eye tracking glasses are utilized to collect the EEG and eye movement signals, respectively. 30 minutes are taken to inject EEG recording gel into each electrode of the cap and set up the tracking glasses. After putting on the devices, recording system would be initialized and starts to record EEG and eye movement data continually.

C. Stimuli

During the experiment, movie clips of 2 to 4 minutes duration are randomly shown to evoke the five emotions. Before each clip begins, information about which emotion

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the following clip intends to elicit is presented. Each subject is required to participate in the experiment 3 times with an interval of at least three days in order to mitigate the individual disturbance and each experiment contains 15 clips. The subject is given a rating form to report whether the clip can evoke the required emotion. After evaluating the feedbacks from the participants, we could indicate whether these movie clips are provocative and rearrange the clips in the following experiments.

III. Methodology

A. EEG and Eye Movement Features

For EEG signals, we extract the differential entropy (DE) feature [12], which is proved to be more stable in distinguishing negative emotions from the positive ones [13]. The EEG signals are firstly downsampled to 200 Hz, and then transformed to frequency domain using STFT (short-time Fourier transform), which is defined as:

$$\begin{aligned} STFT\{x[n]\}(m,\omega) &\equiv X(m,\omega) \\ &= \sum_{n=0}^{N-1} x[n]w[n-m]e^{-j\omega n}, \end{aligned} \tag{1}$$

where $x[n]$ denotes the EEG signals, $w[n]$ is the Hanning window, $X(m,\omega)$ denotes the fast Fourier transform algorithm, and $n = 0, 1, 2, ..., N-1$ is the sampling number. The squared value of STFT divided by bandwidth yields the power spectral density (PSD) of the EEG signals. The EEG data are then filtered into 5 frequency bands (Delta: 1-4 Hz, Theta: 4-8 Hz, Alpha: 8-14 Hz, Beta: 14-31 Hz, and Gamma: 31-50 Hz). For each frequency band, we calculate the DE feature as the logarithm of PSD [6].

For eye movement signals, we extract 12-dimension DE features for pupil diameters in addition to the statistical features of dispersion, fixation duration, blink duration, saccade, and 9 event statistics [8].

We preprocessed the signal with baseline correction and a bandpass filter of 1-50HZ. Both features are smoothed using the linear dynamic system (LDS). The feature selection approach, minimum redundancy maximum relevance (mRMR), is introduced to select emotion-related EEG features. Multiple models are introduced to ensure universality and stability of the result. We adopt Long Short-Term Memory (LSTM) [10] and Deep Canonical Correlation Analysis (DCCA).

B. Long Short-Term Memory

LSTM network is a recurrent neural network with LSTM blocks capable of taking temporal information, which achieved competitive performance in classifying emotions [15].

In LSTM model, complicated resulting units called memory cell and gate units including input gate, forget gate and output gate are introduced to preclude perturbation [10]. Gate units command the error flow for memorizing, forgetting and overriding the information during update, which precludes input as well as output weight conflicts and also circumvents other gates to be perturbed. By cutting back the gradient problem, LSTM network can minimize learning time of establishing bridges, whose time complexity is only $O(1)$ per step [10].

For i-th time step, states of cells c_i acquire input from the previous step's output out_{i-1} and the input in_i of the current time step. We have

$$c_i = c_{i-1} f_{g_i} + i_{g_i} e_i \tag{2}$$

$$o_i = S(W_o[out_{i-1}, in_i] + b_o) \tag{3}$$

$$out_i = o_i tanh(c_i) \tag{4}$$

where

$$\begin{aligned} f_{g_i} &= S(W_f[out_{i-1}, in_i] + b_o) \\ i_{g_i} &= S(W_i[out_{i-1}, in_i] + b_i) \\ e_i &= tanh(W_g[out_{i-1}, in_i] + b_g) \end{aligned}$$

in which f_g and i_g denote forget gate and input gate, respectively, S denotes sigmoid function, W denotes weight matrices, g_i denotes the i-th step's candidates of cell states and b denotes the bias. EEG and eye movement signals are encoded by LSTM network, and linear support vector machines (SVM) is applied in classification layer.

C. Deep Canonical Correlation Analysis

The DCCA model can establish a strong coordination between modalities on account of deep learning, which is favorable for emotion classification task [16].

The procedures of DCCA can be described as follows. Firstly, EEG and eye movement features are transformed nonlinearly in neural networks. Then features are calculated based on the canonical correlation analysis. Assuming the output features of nonlinear transformation are A_1 and A_2, the correlated result can be defined as:

$$\begin{aligned} corr(A1, A2) &= corr(f_1(X_1), f_2(X_2)) \\ &= ||S||_{tr} = tr(S'S)^{1/2}, \end{aligned} \tag{5}$$

where:

$$\begin{aligned} S = (\frac{1}{m-1}\bar{A}_1 \bar{A_2}1' + r_1 I)^{-1/2} \frac{1}{m-1}\bar{A}_1\bar{A}_2' \\ (\frac{1}{m-1}\bar{A}_2\bar{A}_2' + r_2 I)^{-1/2}, \end{aligned}$$

$$\bar{A}_1 = A_1 - \frac{1}{m}A_1 I, \bar{A}_1 = A_1 - \frac{1}{m}A_1 I,$$

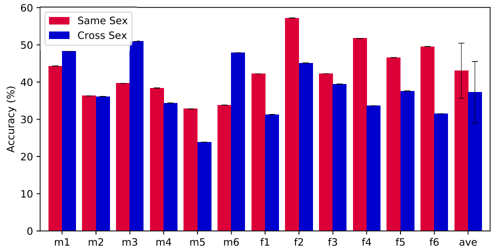
$\bar{A}_1$ and $\bar{A}_2$ denote the centered output, and r_1 and r_2 are the regularization constants. When updating the weight, the gradients are also calculated. After the transformed features are fused, SVM is utilized as the classifier.

IV. Experiment and Result

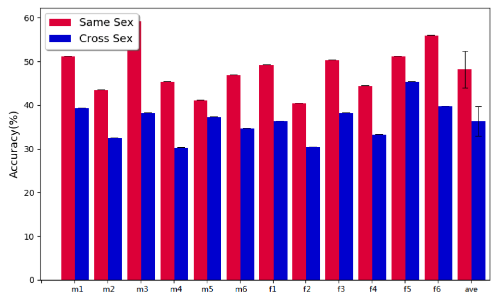
A. Dataset Division

In our dataset division, for each subject, the rest subjects' data are divided into same-sex dataset and cross-sex dataset according to their sex. We utilizes the single subject's data as test data.

We use ss_i and cs_i to represent the same-sex dataset and the cross-sex dataset, respectively, and $s_i (i = 1, 2.....12)$

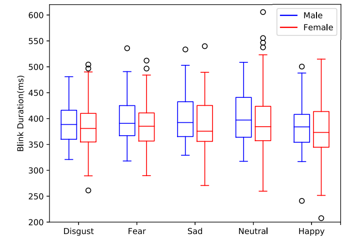


(a) using LSTM

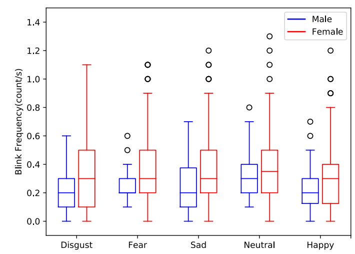


(b) using DCCA

Fig. 1. The same sex and cross sex accuracies using (a) LSTM and (b) DCCA of 6 male subjects, 6 female subjects, and the average of female, male and all subjects, respectively.



(a) blink duration



(b) blink frequency

Fig. 2. Boxplots of (a) blink duration and (b) blink frequency for each sex in five emotional states.

denotes a subject from 6 male subjects and 6 female subjects. Take male subject as example. In same-sex experiment, each male data $s_i (i = 1, 2, ..., 6)$ is taken as test set, and training set ss_i^m will be $\bigcup_{j \neq i} s_j (j = 1, 2, ..., 6)$. This procedure is repeated among all male subjects. In cross-sex experiment, the test set is same while the training set cs_i^m will be $\bigcup s_j (j = 7, 8, ..., 12)$. We obtain the same-sex accuracy when models are trained on same-sex dataset ss_i, while the cross-sex accuracy is obtained when models are trained on cross-sex dataset cs_i.

B. Sex Differences in Classification

The accuracy of LSTM model is $43.05\% \, (SD = 6.61\%)$ for same sex and $37.29\% \, (SD = 7.84\%)$ for cross sex and the accuracy of DCCA model is $46.89\% \, (SD = 5.34\%)$ for same sex and $36.48\% \, (SD = 3.78\%)$ for cross sex. A higher overall accuracy is achieved by DCCA, which correlates to previous study on non-related to sex [9], suggesting that DCCA's competitiveness is consistent in sex-based study. To specify the overall difference between cross sex and same sex accuracies, two types of accuracies from each subject and each model are illustrated in Fig. 1.

Though the accuracy is not competitive, it's still higher than random guesses (20%), which could illustrate sex difference. The performance gap between same sex and cross sex indicates that there exist sex differences for EEG and eye movements. All subjects display higher same sex accuracy in DCCA. So do 9 out of 12 in LSTM. It is to say that models without considering sex differences perform worse, and using same sex strategy could enhance the classification accuracy. It is also consistent with the finding that people in different sex share far less unified features in neuroimaging [3], which could be expanded into EEG and eye movement signals, suggesting that sex-based factors should be taken into consideration.

We also switch the training set and test set of our current strategy, taking one subject data as test set to validate if our strategy is more dependable, which acquires $32.05\% \, (SD = 4.06\%)$ in same sex and $30.34\% \, (SD = 4.46\%)$ in cross sex using LSTM. The result still correlates to the former accuracy's conclusion, but fails to achieve a competitive accuracy. Moreover, difference in emotional states and neural patterns are opaque through classification due to the fusing of features and qualified difference in accuracy among emotions. In order to give a deeper insight of how sexes differ in EEG and eye movements, specific patterns are compared in the following section.

C. Sex Differences in Eye and Neural Patterns

The momentary tension, i.e. anxiety level, is related to the human eyelid dynamics [17]. In order to identify how two sexes differ, we chose blink frequency (BF) and blink duration (BD). BF is founded to be effective in identifying cognitive processing that varies in emotional stimuli [17], which is expected to correlate with the tension level and could be crucial for classifying the negative emotions. BD can reveal the alertness of seeing unexpected things [18].

To study sex's statistical significance as a factor, one-way analysis of variance is conducted. For BF, $F - value$ is 37.57 and p is 1.44×10^{-9} and for BD, $F - value$ is 7.20 and p is 7.45×10^{-3}. Both $p < 0.01$ indicates sex's influence is significant. The average of BF over five states is $0.26 \, (SD = 0.15)$ for male and $0.37 \, (SD = 0.27)$ for female in count per second while male has an average BD of $395.88\,(SD = 45.30)$ and female's is $385.19\,(SD = 55.07)$ in millisecond. As the boxplots presented in Fig. 2, difference in BF is founded, in which average BF of female under five states are all higher than male's average BF. The negative correlation between BF and BD exists. Female has a shorter average BD as well as a higher average BF in all states and tends to be more fluctuating among emotions.

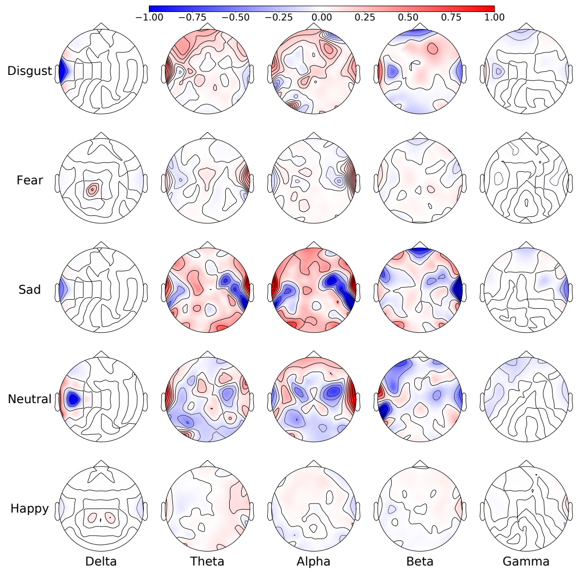


Fig. 3. The difference between the average normalized DE features of male and female from each emotion in five frequency bandwidths with contour lines.

The brain mapping shown in Fig. 3 can give direct insight to how neural patterns differentiate in frequency bands and emotional states. The brain topography shows that male tends to be more activated under disgust and sad states in Theta, Alpha and Beta bands. In Delta and Gamma bands, differences are invariably subtle. In detail, the frontal temporal lobe of male activates stronger than female under disgust state in Theta, Alpha and Beta band. Under sad state, differences are more significant especially in Alpha band, in which male's majority of brain area is far more activated while in the remain area, female's activity shows to be stronger possibly resulting from the divided approach of emotional process. Besides, the frontal lobe of male reacts more intense in theta band under sad and disgust states, and in alpha band under the disgust, sad and neutral, suggesting that a tendency to utilize frontal lobe in emotion processing exists in male under disgust and sad states. Though male performs mainly more intense brain activity under disgust and sad states, female's brain activation under neutral state outweighs male's.

V. Conclusion

In this paper, we have investigated sex differences through EEG and eye movement signals utilizing DCCA and Bimodal-LSTM model. Experimental results reveal that same-sex classification could acquire higher accuracy and the strategy of data division influences the accuracy. Moreover, the differences are proved existent not only in classification, but also in EEG and eye movement patterns. Significant sex differences in cerebral activity especially in sad emotion and sex differencesx in blink duration are found. Although happy and fear emotions seem to be more similar for male and female in present study, it could be resulted from other factors requiring further study. Present results suggest that sex-specific classification can perform better accuracy and sex-based factors should be taken into consideration in emotion classification.

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