Identifying Gender Differences in Multimodal Emotion Recognition Using Bimodal Deep AutoEncoder

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Abstract. This paper mainly focuses on investigating the differences between males and females in emotion recognition using electroencephalography (EEG) and eye movement data. Four basic emotions are considered, namely happy, sad, fearful and neutral. The Bimodal Deep AutoEncoder (BDAE) and the fuzzy-integral-based method are applied to fuse EEG and eye movement data. Our experimental results indicate that gender differences do exist in neural patterns for emotion recognition; eye movement data is not as good as EEG data for examining gender differences in emotion recognition; the activation of the brains for females is generally lower than that for males in most bands and brain areas especially for fearful emotions. According to the confusion matrix, we observe that the fearful emotion is more diverse among women compared with men, and men behave more diversely on the sad emotion compared with women. Additionally, individual differences in fear are more pronounced than other three emotions for females.

Keywords: EEG · Eye movement data · Emotion · BDAE · Gender differences

1 Introduction

Gender differences in many aspects such as temperaments, cognition and social behavior have been widely studied. Whether sexes are different or not has been systematically considered in a wide range of psychological aspects. However, gender differences are continually attracting people's interests because many observations should be verified.

One of the observations, that females are more emotional than males, is a prevailing acknowledgment among gender differences. In this paper, we intend to

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study gender differences in emotion recognition using EEG and eye movement data. Our previous work has found that the fusion on both the feature level and the decision level of EEG data and eye movement data can improve the accuracy of the emotion recognition model [10]. Moreover, the complementarity of EEG and eye movement data to the emotion recognition model indicates that using the combination of both data is a more appropriate method for emotion recognition [4].

Weiss *et al*. pointed out that in the neuropsychological processes, men showed significantly more activation in parietal areas, while women showed significantly stronger right frontal activation [9]. Therefore, different responses in emotion processes are supposed to occur in males and females' brain areas. In our previous work, we have indicated that neural patterns are distinct in different emotions [11], there exist some gender differences in three emotions (happy, sad and neutral) in EEG patterns [12]. However, whether there is difference in fear, a very important emotional state explored in animals in neuroscience field, between women and men in EEG and eye movement data is an open question. The goal of this paper is to investigate the gender differences of EEG data, eye movement data and their combination in emotion recognition using BDAE, and whether there are different brain responses between males and females to EEG patterns of four emotions. Moreover, individual differences in males and females for recognizing four emotions are also discussed.

2 Methodology

2.1 Feature Extraction and Feature Smoothing

In this paper, several eye movement parameters are applied according to our previous study [4]. Differential Entropy (DE) features of the pupil diameter using short-term Fourier transform (STFT) in four frequency bands (0–0.2 Hz, 0.2–0.4 Hz, 0.4–0.6 Hz and 0.6–1 Hz), as well as the mean and standard deviation features in X and Y axes are computed. Moreover, the mean and standard deviation of the pupil dispersion in X and Y axes, eye saccade in duration and amplitude and fixation are used as well. Besides, nine event statistics are also included. The total dimension of eye movement features is 31.

For preprocessing, EEG data is filtered between 1 Hz and 75 Hz and sampled down to 200 Hz to remove artifacts and to reduce computation. STFT with a 4-s-long window and no overlapping Hanning window is employed to calculate the DE features of EEG data. EEG data in each channel are filtered into five frequency bands (δ: 1–3 Hz, θ: 4–7 Hz, α: 8–13 Hz, β: 14–30 Hz and γ: 31–50 Hz) [1]. There are 62 channels used in the electrode cap, which means the dimension of EEG features is 310. To filter rapid fluctuations, the linear dynamic system is employed for feature smoothing [8].

2.2 Feature Fusion and Model Combination

In this paper, we apply two modality fuision strategies to combine EEG and eye movement data: the fuzzy-integral-based method [6] and the Bimodal Deep

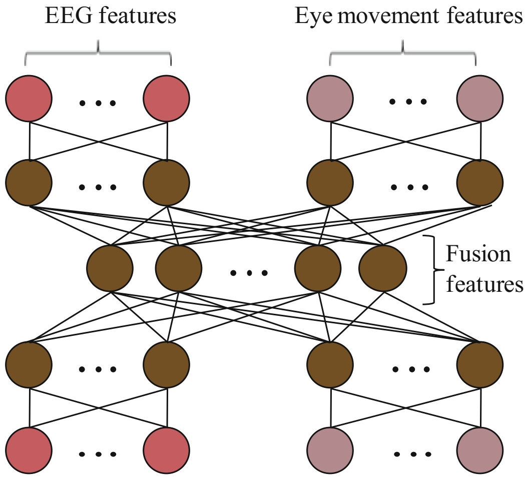

Fig. 1. The architecture of BDAE for fusing EEG and eye movement features. The high-level shared features of BDAE are used finally as the input of SVM.

AutoEncoder (BDAE) method which is shown in Fig. 1. There are three layers in BDAE model and the hyperparameters are determined by cross-validation.

BDAE is formed by stacking Restricted Boltzmann Machines (RBMs) and contrastive divergence (CD) algorithm [3] is used to train Bernoulli RBM in this paper. RBM consists of hidden nodes and visible nodes. The energy function of visible nodes and hidden nodes is defined as below:

$$E(v,h;\theta) = -\sum_{i=1}^{M}\sum_{j=1}^{N} W_{ij}v_ih_j - \sum_{i=1}^{M} b_iv_i - \sum_{j=1}^{N} a_jh_j \tag{1}$$

where visible nodes $v \in \{0,1\}^M$, hidden nodes $h \in \{0,1\}^N$ and $\theta = \{a,b,W\}$ are parameters, a_j and b_i are bias of visible nodes and hidden nodes, respectively, and W_{ij} is the weight between visible and hidden layers. Then, the joint distribution of visible nodes and hidden nodes can be calculated from the energy function:

$$p(v,h;\theta) = \frac{exp\left(E\left(v,h;\theta\right)\right)}{\sum_v\sum_h exp\left(E\left(v,h;\theta\right)\right)} \tag{2}$$

Next, the derivative of log-likelihood with respect to W can be computed:

$$\frac{1}{N}\sum_{i=1}^{N}\frac{\partial logp\left(v_n;\theta\right)}{\partial W_{ij}} = E_{P_{data}}\left[v_ih_j\right] - E_{P_{model}}\left[v_ih_j\right] \tag{3}$$

2.3 Classification

The classifier of all models after parameter regulation is linear SVM with soft margin. Two training strategies are developed: the *different-gender strategy* where the training data and the testing data come from different genders, and the *same-gender strategy* where both data come from the same gender. In both methods, the testing data holds only one subject's data and the training data is all the rest data with the same or the opposite gender.

3 Experiment Design

A total of 16 subjects (8 females) aged between 18 and 28 participated the experiments for three times. All the subjects were healthy, right-handed, had sufficient sleep with normal or corrected-to-normal vision and were told the harmlessness and the goal of the experiment.

At the start of each trial, the textual description of the following movie clip was presented for 5 s, the clip evoking a single emotion was presented for about 4 min and then the self-assessment stage lasted for 45 s for subjects to assess whether the corresponding emotions are evoked. In the end, 15 s were left for subjects to relax.

Movie clips used as stimuli were evaluated and selected for experiments. 20 persons were asked to score the clips according to the degree that emotions were evoked and finally, 72 clips (24 for one experiment) were chosen on the basis of scores. There are twenty-four movie clips (6 clips per emotion) for one experiment in total. In terms of avoiding the influence of the movie order and similar movies, the movie clips in each experiment were shuffled randomly and no two same clips were used.

During the experiment, the ESI NeuroScan System with a 62-channel electrode cap and the SMI ETG eye tracking glasses were used to collect EEG data with 1000 Hz sampling rate and eye movement data, respectively. Each subject conducted experiments for three times to avoid individual deviations. The experiments were carried out when subjects were in good mental states and they were familiar with the procedure. Feedback forms collected after the experiment indicated that certain emotions were successfully evoked.

4 Results and Discussions

4.1 Gender Differences in Different Data

Using single EEG data. Figure 2(a) illustrates two models using EEG data. The upper one is female models: a female's data is used as the testing and two strategies are employed to train the model. The lower one is male models. One way analysis of variance (ANOVA) is used in both models. Under female models $[F(1, 46) = 8.72, p = 0.0049]$ and male models $[F(1, 46) = 9.7, p = 0.004]$, gender differences have highly significant influence on the accuracy changes. Furthermore, the average accuracy is higher when using the model trained and tested by the same gender for both models. These experimental results indicate that there does exist some gender differences in neural patterns for emotion recognition.

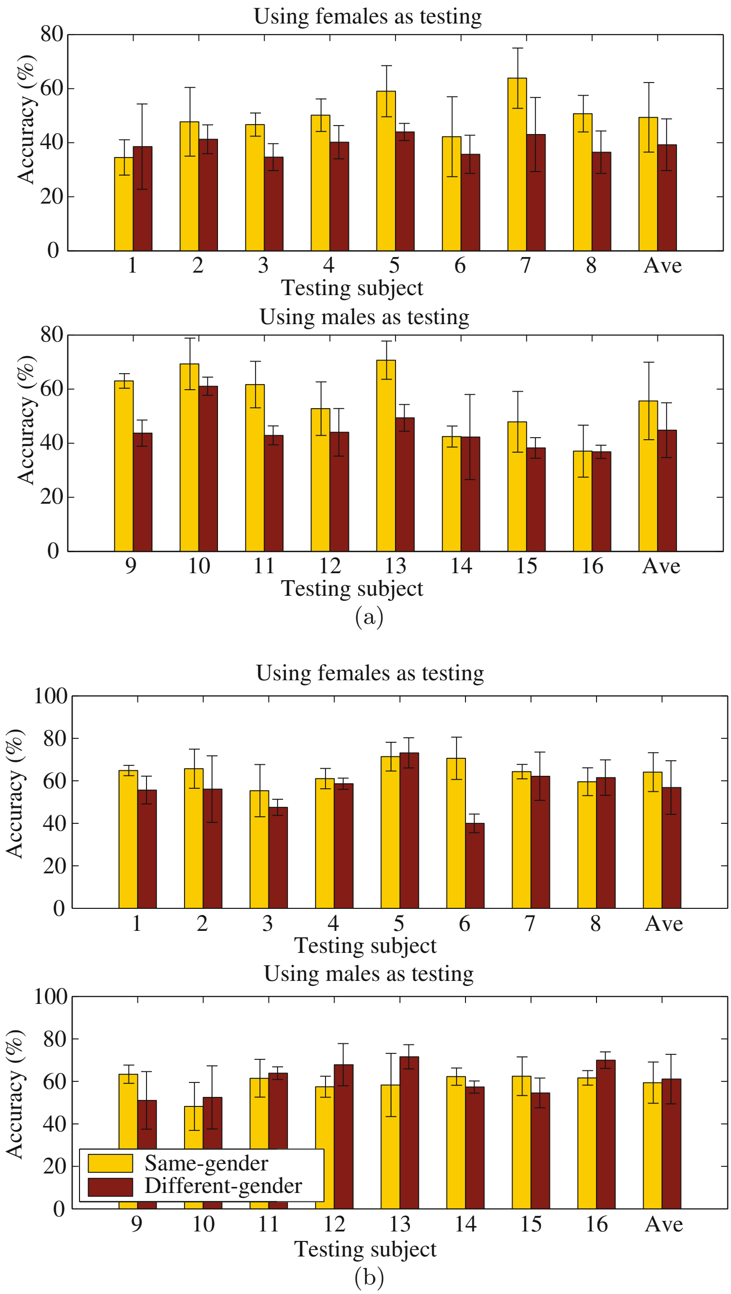

Fig. 2. The accuracies of female and male models: (a) using single EEG data, and (b) using single eye movement data. The upper figure represents female models using females as testing data. Two training strategies are applied for each model.

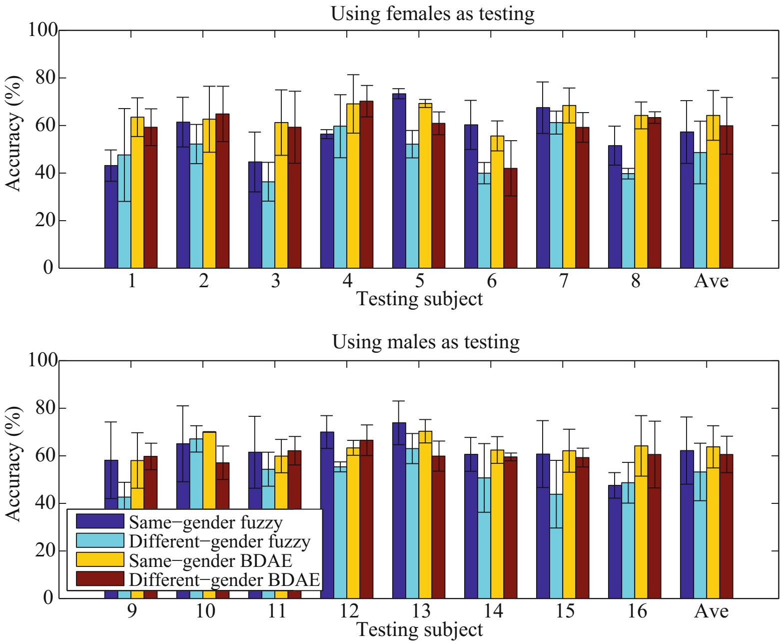

Fig. 3. The accuracies of female and male models using both EEG and eye movement data. The same-gender strategy and the different-gender strategy are used. Each strategy is separately used fuzzy integral and the BDAE algorithm to compare effects. The upper figure represents female models using females as testing data.

Using single eye movement data. As for female models [$F(1, 46) = 5.02, p = 0.0299$], the average performance in Fig. 2(b) shows that using the same gender's data to train can obtain higher accuracies than using different gender's data. On the other hand, gender has no significant effect on the accuracy of the subjects for male models [$F(1, 46) = 0.29, p = 0.5949$]. These indicate that when using single eye movement data, no significant gender differences were found when testing males' data, but differences were more pronounced in women, which implies that eye movement patterns are not as obvious as EEG patterns on gender differences in emotion recognition.

Combining EEG and eye movements. Two fusion methods and two training strategies are used in two models in this part. The fuzzy-integral-based method is to fuse the output of two classifiers on the decision level while the BDAE is to fuse EEG and eye movement features on the feature level.

The experimental results shown in Fig. 3 demonstrate that when using BDAE, average accuracies for females and males training are 64.26% and 59.88% in the female models, respectively, and as for the male models, average accuracies for males and females are 63.77% and 60.56%, respectively. These performances are all better than the fuzzy method. When using the fuzzy-integral-based method, genders have a significant influence on classification accuracies for both male models $[F(1,46) = 5.35, p = 0.0253]$ and female models $[F(1,46) = 4.97, p = 0.0308]$. However, no significant influences on the accuracy results have been shown when the BDAE method is applied to male models $[F(1,46) = 1.73, p = 0.1947]$ and female models $[F(1,46) = 1.75, p = 0.1928]$. These results indicate that when using two kinds of data, whether genders have influences on classification accuracies is affected by the fusion strategy.

On the content of our present discussion, EEG data is the most suitable data for studying the gender differences in emotions. To examine specific differences,

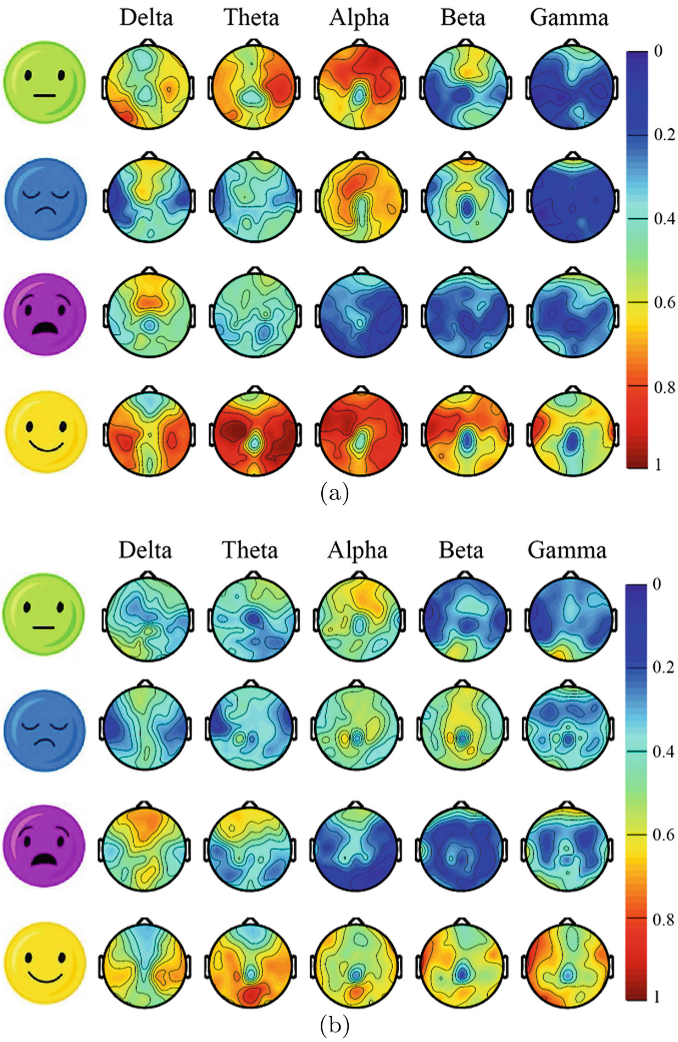

Fig. 4. The brain topographic mapping of females and males: (a) female's pattern, and (b) male's pattern.

we studied gender differences with respect to two cases using single EEG data: one is to focus on neural patterns, and another is to focus on different emotions.

4.2 Gender Differences in Neural Patterns

To identify neural patterns of two genders, the brain topographic mapping of four emotions across five frequencies is given in Fig. 4. DE features are normalized between 0 and 1 to represent the neural patterns of subjects. Common patterns exist for two genders. The temporal lobe activates the most under happy emotions on gamma band, and there are lower responses in the occipital lobe under fearful emotions than neutral and sad emotions on the alpha band. Neutral patterns hold more activation on the parietal and frontal lobe in the alpha band than sad patterns.

Figure 5 illustrates the difference between females and males in neural patterns. Except for the temporal lobe in theta band under neutral emotion and the frontal lobe in alpha band under happy emotion, most brain areas under four emotions across five frequencies band activate more in males than in females, which is consistent with results of Imaizumi *et al.* who found that under emotional tasks, males show greatly stronger activation in certain areas [2]. This phenomenon is more obvious in fear. The whole brain of men response more under fear in all frequency band than women. Schienle *et al.* also observed that men emerge greater activation watching fearful pictures than women [7].

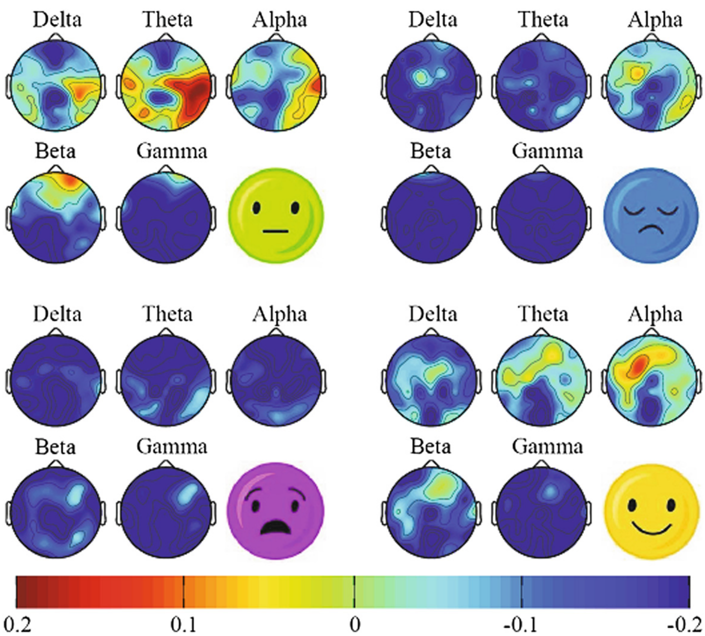

Fig. 5. The difference between the average neural pattern of females and males.

4.3 Gender Differences in Different Emotions

In this section, the same-gender training strategy is used to explore gender differences in emotion recognition for males and females. The confusion matrix of EEG data is calculated as listed in Table 1, where the first row and column of Table 1 mean true labels and predicted labels, respectively.

Table 1. The confusion matrix of EEG data for two models

Female models	Neutral	Sad	Fearful	Happy	Male models	Neutral	Sad	Fearful	Happy
Neutral	**0.53**	0.19	0.09	0.19	Neutral	**0.56**	0.14	0.16	0.14
Sad	0.20	**0.52**	0.17	0.11	Sad	0.18	**0.43**	0.20	0.19
Fearful	0.20	0.26	**0.38**	0.16	Fearful	0.15	0.16	**0.49**	0.20
Happy	0.26	0.12	0.12	**0.50**	Happy	0.19	0.14	0.17	**0.50**

On account of the use of the same-gender training strategy, bold numbers in Table 1 mean abilities to use existing data to predict new data, which indicates that as for neutral and happy emotions, the abilities are similar for males and females. The main difference lies in the other two emotions where women share less fearful emotion patterns among females compared with men and men share less sad emotion patterns among males compared with women. Other researches also point out that women perform more fearful emotions during their lifetimes than men [5].

Besides, a significantly low accuracy of the fear emotion in female models, with the number of 38%, means females share more individual differences in the fearful emotion compared with other emotions among women.

5 Conclusions

In this paper, we have investigated the gender differences in multimodal emotion recognition using Bimodal Deep AutoEncoder. From our experiment results, we have obtained the following observations: (1) Gender differences do exist in neural patterns and the same sex has more similar emotion patterns than the opposite sex. (2) Eye movement data is not as obvious as EEG data in discussing gender differences in emotion recognition. (3) Females' responses are generally lower than males' in most bands and brain areas for four emotion patterns, especially for the fearful emotion. (4) Females have more individual differences in the fear emotion among four emotions, and males differ more in sad emotions compared with females while females differ more in fearful emotions compared with males.

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