Investigating Gender Differences of Brain Areas in Emotion Recognition Using LSTM Neural Network

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Abstract. In this paper, we investigate key brain areas of men and women using electroencephalography (EEG) data on recognising three emotions, namely happy, sad and neutral. Considering that emotion changes over time, Long Short-Term Memory (LSTM) neural network is adopted with its capacity of capturing time dependency. Our experimental results indicate that the neural patterns of different emotions have specific key brain areas for males and females, with females showing right lateralization and males being more left lateralized. Accordingly, two non-overlapping brain regions are selected for two genders. The classification accuracy for females (79.14%) using the right lateralized region is significantly higher than that for males (67.61%), and the left lateralized area educes a significantly higher classification accuracy for males (82.54%) than females (73.51%), especially for happy and sad emotions.

Keywords: Electroencephalography · Emotion · Long Short-Term Memory neural network · Gender differences · Brain areas

1 Introduction

Gender differences can be observed in both behaviour and character. In the field of emotion and psychopathology, gender differences are largely considered, since studying differences in gender of normal subjects, psychiatric or brain-damaged patients is instructive for clinical studies such as depression and obsessive-compulsive disorder [5]. On language processing and visuospatial tasks, gender differences are also widely discussed, with men outperform women on visuospatial tasks especially on mental rotation and spatial perception, and women perform better than men on language tasks particularly on verbal fluency [1]. In this paper, we intend to study gender differences of brain areas in EEG-based emotion recognition using Long Short-Term Memory (LSTM) neural network.

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The existing study in neuropsychological processes has found that men and women performed more activation in the parietal area and the right frontal region, respectively [11]. Accordingly, emotional processing in men and women is supposed to occur in different brain areas. Moreover, an overall observation that emotion is lateralized on the right hemisphere has been reported. However, there is evidence that the hemispheric asymmetry and lateralization of emotional activities are more complicated and region-specific than the previous observation [9]. Besides, differences on brain asymmetries are influenced not only by tasks but also by its details like stimuli and the presentation methods.

Therefore, in this paper, we focus on investigating the key brain areas for men and women while their emotions are evoked by using film clips as stimuli and analysing with EEG data. In the previous study, little work has been done on investigating gender-related differences of key brain areas on emotions using neural networks [5,7,9]. Since LSTM possesses a great characteristic on incorporating information over a long period of time, which accords with the fact that emotions are developed and changed over time, LSTM is an appropriate method for emotion recognition.

In our previous work, we have demonstrated that there are gender differences using EEG data to recognise three different emotions. We indicated that males are more individually different in emotions while females have more similar emotion patterns in EEG data [13]. In this study, we extend our previous study in two ways. First, we enlarge the dataset from 45 sets to 70 sets to confirm the efficiency of the experimental results, and apart from SVM, LSTM-based method is applied for emotion recognition. Second, we try to find out gender-related key brain areas for different emotions, which has not been investigated yet to our best knowledge. Besides, the influence of the key brain areas on each emotion is studied.

2 Methodology

2.1 Feature Extraction and Feature Smoothing

The EEG data is filtered between 0.05 Hz and 50 Hz and preprocessed by the notch filter to eliminate power-line interference. The Short-Term Fourier Transform (STFT) with a 1 s no overlapping Hanning window is employed to calculate the Differential Entropy (DE) features of EEG data [2]. 30 channels are used in the electrode cap, and the EEG data in each channel is 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), which means the total dimension of EEG features is 150.

There are some rapid fluctuations in EEG data that do not contribute to emotional states, so we further perform feature smoothing. The Linear dynamic system is an efficient method to remove noises and employed in this paper [8,10].

2.2 Feature Selection

In order to obtain the key regions of emotions for men and women, Minimal-Redundancy-Maximal-Relevance (MRMR) [6] is applied as feature selection method. We use selected features with different dimensions to classify emotions. The higher accuracy rates indicate that the more effective features are used, which suggests that areas where selected features are located are more likely to be key areas of emotion.

2.3 Classification

Linear Support Vector Machine (SVM) with soft margin and LSTM are applied as classifiers in the paper. LSTM neural networks provide a solution of vanishing gradient by replacing the summation units of a standard Recurrent Neural Networks (RNN) in the hidden layer with memory blocks [3]. Each block with one cell consists of the input gate, output gate and forget gate that can write, read and reset the information, which ensures the usage of data over a long period of time. The update rule of the block is shown below:
The input gate:

$$i_t = \sigma\left(W_{ix}X_t + W_{ih}h_{t-1} + b_i\right). \tag{1}$$

The forget gate:

$$f_t = \sigma\left(W_{fx}X_t + W_{fh}h_{t-1} + b_f\right). \tag{2}$$

The cell state:

$$\tilde{C}_t = tanh\left(W_{cx}X_t + W_{ch}h_{t-1} + b_c\right). \tag{3}$$

$$C_t = i_t * \tilde{C}_t + f_t * C_{t-1}. \tag{4}$$

The output gate:

$$o_t = \sigma\left(W_{ox}X_t + W_{oh}h_{t-1} + b_o\right). \tag{5}$$

$$h_t = o_t * tanh\left(C_t\right). \tag{6}$$

where σ is the logistic sigmoid function.

Before applying LSTM, EEG features are first normalised to zero mean and unit variance and then divided into 64-s data sequences, which is determined by the length of movie clips. The structure of LSTM model used in the paper is shown in Fig. 1. The processed EEG features are encoded by a single layer of LSTM and decoded by Multi-Layer Perception (MLP) using ReLU as the activation function. The encoder and decoder layer share the same number of neurons, and two dropout layers with a percentage of 0.5 are added between the LSTM decoder and the MLP decoder and before the output layer to improve the generalization ability.

The model is implemented based on Keras.[1] The weights of the linear transformation of the recurrent state and the inputs are initialised by a random orthogonal matrix and Glorot uniform initializer, respectively. The bias of the forget gate is initialised to one, and hyperparameters are determined by cross-validation. During training, the RMSProp method is employed to optimize the loss function and the early stopping strategy is adopted when there is no improvement on the validation set after 10 epochs.

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[1] https://keras.io/.

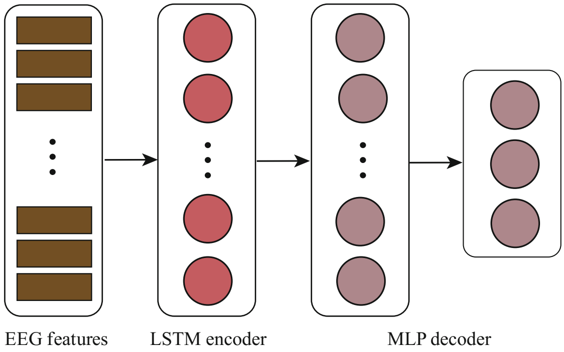

Fig. 1. The structure of LSTM nerual networks.

3 Experimental Results

3.1 Experiment Design

Each experiment consisted of 12 trials (4 trials per emotion). At the beginning of each trial, the textual guidance was presented on the screen for 20 s to ask subjects to relax and to calm their emotions. Then, the clip evoking one single emotion was presented for 1.5 to 4 min. During this time, subjects were asked to watch the film with emotional involvement. Finally, the self-assessment stage would last for 10 s for subjects to assess whether and what emotions were evoked and the extent to which their emotions were evoked.

Film clips used as stimuli were evaluated before experiments by 50 college students (25 females) aged from 19 to 26. They were asked to score the clips according to the degree their emotions were evoked and in the end, 60 clips (12 for each of the five experiments) were chosen based on ratings. In order to avoid effects of the former or similar clip, all clips were shuffled randomly and used only once during whole experiments for one subject.

During the experiment, the EEG data was recorded by the ESI NeuroScan System with a 32-channel electrode cap with 1000 Hz sampling rate.[2] The experiments were carried out in a clean and comfortable environment when subjects were in good mental states. Before each experiment, each subject was informed of details and precautions of the procedure, and feedback forms collected after experiments indicated that certain emotions were successfully evoked.

16 healthy subjects (8 females) aged between 18 and 28 were recruited from the university. Each of them participated the experiment for 5 times to avoid individual deviations, generating a total of 70 sets of valid data, half of which are from females. All the subjects were right-handed with normal or corrected-to-normal vision and were told the harmlessness and the goal of the experiment.

[2] http://compumedicsneuroscan.com/product/32-channels-quik-cap/.

3.2 Key Features Selection for Two Genders

As mentioned in Sect. 2.2, we use MRMR to find the key brain areas of different emotions for males and females. Figure 2 illustrates the average accuracies of two genders under different feature dimensions using SVM. For males, the accuracy is highest when the feature dimension equals to 20, and for females, the model with 18 features acquires the best accuracy. Generally, when the feature dimension is around 20, the performance of emotion recognition is among the best for both men and women.

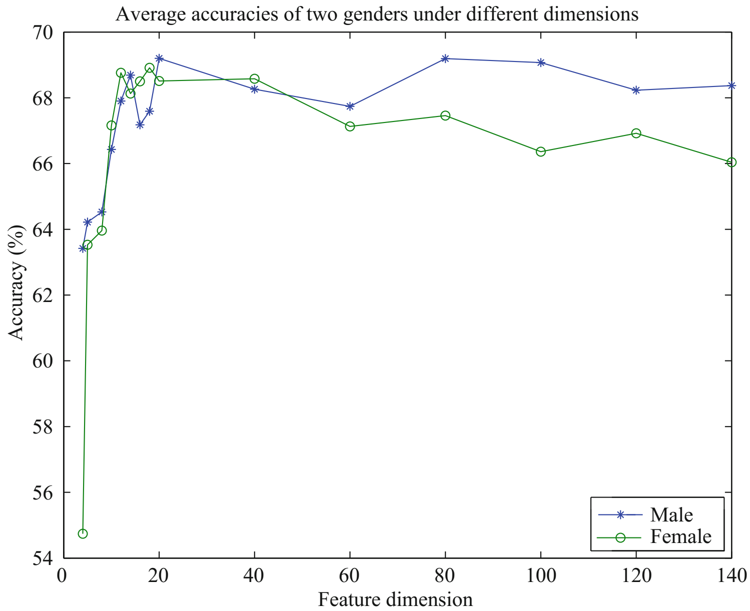

Fig. 2. The accuracy of emotion recognition using features selected by MRMR, with feature dimensions varying from 4 to 140.

To confirm the key brain areas, we investigate the discriminative neural patterns of three emotions using topography. Figure 3 shows the mean square deviation of average DE features across five frequency bands in each electrode for three emotions, and that the electrode location of 20 features based on the feature selection for females and males. The features selected from two methods are consistent with each other on the location, with key electrodes mainly concentrating on the right hemisphere in the α and β bands for females, and on the right part of the left hemisphere in the α and β band and the right temporal lobe in γ band for males. Therefore, the selected 20-dimension features are effective for emotion recognition.

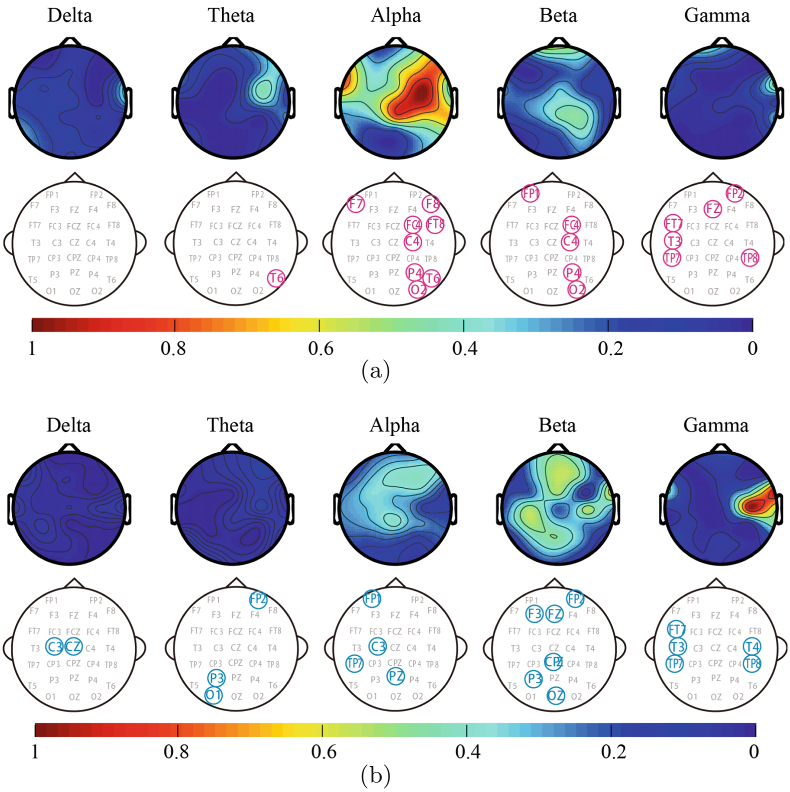

Fig. 3. The mean square deviation of the average energy of three emotions in brain topography, and features selected by MRMR: (a) females, and (b) males. From top to bottom and left to right, the electrodes selected are: (a) T6 in θ, F7, F8, FC4, FT8, C4, P4, T6 and O2 in α, FP1, FC4, C4, P4 and O2 in β, and FP2, FZ, FT7, T3, TP7 and TP8 in γ band; (b) C3 and CZ in δ, FP2, P3 and O1 in θ, FP1, C3, TP2 and PZ in α, FP2, F3, FZ, CPZ, P3 and OZ in β, and FT7, T3, T4, TP7 and TP8 in γ band.

3.3 Key Brain Areas for Two Genders

To investigate gender differences, the common electrode locations of females and males from the 20 features selected by MRMR are removed, and 11-dimension features that are critical only to females (FFs) and males (MFs) are left, respectively. The remaining features are T6 in θ band, F7, F8, FC4, P4, T6 and O2 in α band and FC4, C4, P4 and O2 in β band for females, and C3 and CZ in δ band, P3 and O1 in θ band, C3 and PZ in α band, F3, CPZ, P3 and OZ in β band and T4 in γ band for males. The detailed electrode location is presented in Fig. 4.

In order to explore the impact of FFs and MFs on men and women, respectively, four experiments named the cross-gender training are designed, with FFs and MFs classifying men and women's emotions. The result shown in Fig. 5 illustrates that with LSTM, accuracies of using FFs to recognise emotions of females and males are 79.14% and 67.61%, respectively, and accuracies of using MFs to recognise emotions of females and males are 73.51% and 82.54%, respectively, which are all higher than that of SVM. The one-way analysis of variance (ANOVA) shows that the performance of FFs for females is significantly better than that for males for both SVM ($p = 0.0024$) and LSTM ($p = 0.0022$) models. Also, the performance of using MFs to recognise emotions of males is significantly better than that of females for both SVM ($p = 0.0474$) and LSTM ($p = 0.0213$). Besides, the classification accuracy of the LSTM model is higher than that of the SVM model by 12.46% to 18.32% according to different training tasks. The experimental results indicate that the time-dependent property of LSTM make it perform better than SVM in terms of emotion recognition.

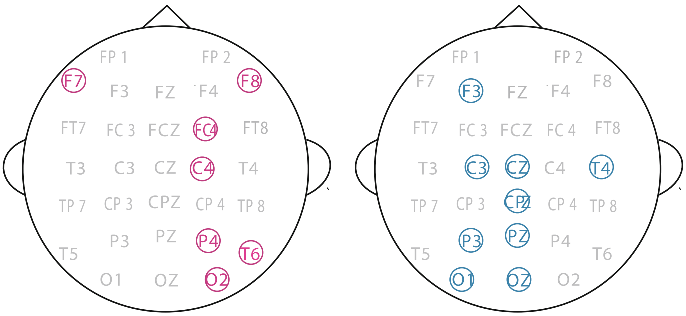

Fig. 4. The electrodes chosen for females and males after removing duplicate electrodes from the 20 features. The features chosen for females are shown on the left.

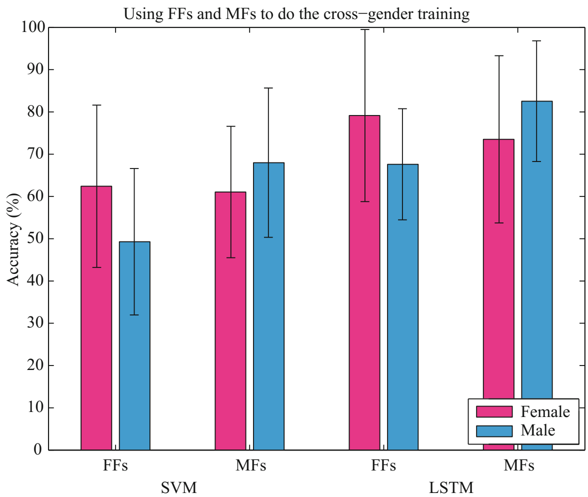

Fig. 5. The cross-gender training on emotion recognition by SVM and LSTM.

In conclusion, the right hemisphere where FFs are located is significantly important to females' emotions than males', and the left hemisphere where MFs are located is significantly critical to males' emotions than females'. The existing study [12] has shown that in terms of lateralisation, gender differences may be caused by using different cognitive strategies in the same task. Besides, in the functional magnetic neuroimaging (fMRI) study [1], males have been found to be more left lateralised in phonological processing tasks and females are more right lateralised in visuospatial processing tasks. These results imply that in our task, the lateralisation can be explained by men being more sensitive to phonological information while women being more sensitive to visuospatial information of movie clips during experiments.

3.4 Influence of Key Brain Areas on Each Emotion

The confusion graphs of cross-gender training strategy trained by LSTM are shown in Fig. 6, which gives insights into the influence of key brain areas on three emotions. Figure 6 demonstrates that as for the right hemisphere where FFs located, all three emotions are recognised with a higher accuracy and a lower misclassification probability for females than for males. Similar observation generally exists for the left hemisphere where MFs located, with which males are recognised with higher accuracy and lower misclassification probability than females, except for a few slight deviation such like the neutral emotion. Studies of attentional processes on EEG have shown that alpha activity can be found on overall parietal lobe when tasks not requiring attention [7]. In our experiment, subjects tended to be relaxed and pay less attention under neutral emotion, which evoked alpha activity. While for two key brain areas, FFs contain many features of the alpha band but MFs only contain few, which explains the

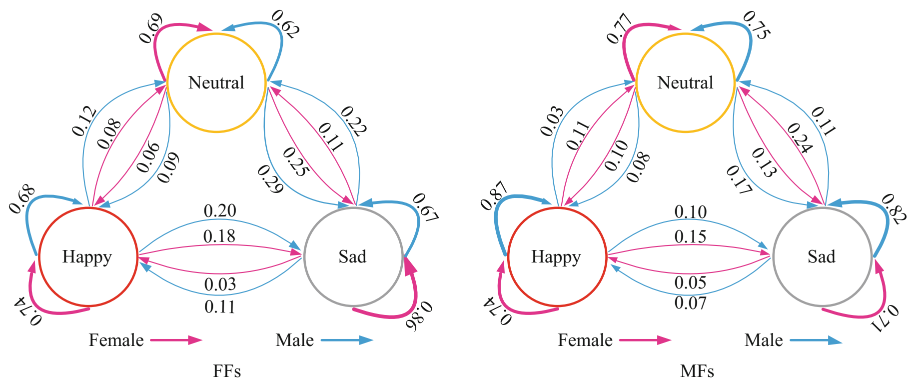

Fig. 6. The confusion graph of the cross-gender training strategy using LSTM models. The left one shows the confusion graph of using FFs to recognise emotions for females and males. The numbers are the proportion of samples in class (arrow tail) that is classified as class (arrow head), and the thickness of the line represents the value.

deviation result on neutral emotion. Furthermore, sad and neutral emotions are more confused with each other, which is consistent with our previous study [4].

In conclusion, key brain regions for females and males primarily have effects on happy and sad emotions. Due to the influence of alpha activity, the critical brain areas for two genders are affected in the neutral emotion.

4 Conclusions

In this paper, we have investigated the gender differences of key brain areas in emotion recognition from EEG data using LSTM neural network. From our experimental results, we have obtained the following observations: (1) Females and males have different key brain areas on emotions, with females showing the right lateralisation and males showing a trend of left lateralisation. (2) As for the overall emotion recognition, the performance of men's critical brain area on men significantly outperforms the performance on women, and the key brain area of women also performed significantly better for women than men. (3) The effect of two key brain areas is mainly on happy and sad emotions among three emotions.

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