Revealing Critical Channels and Frequency Bands for Emotion Recognition from EEG with Deep Belief Network

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Abstract— For EEG-based emotion recognition tasks, there are many irrelevant channel signals contained in multichannel EEG data, which may cause noise and degrade the performance of emotion recognition systems. In order to tackle this problem, we propose a novel deep belief network (DBN) based method for examining critical channels and frequency bands in this paper. First, we design an emotion experiment and collect EEG data while subjects are watching emotional film clips. Then we train DBN for recognizing three emotions (positive, neutral, and negative) with extracted differential entropy features as input and compare DBN with other shallow models such as KNN, LR, and SVM. The experiment results show that DBN achieves the best average accuracy of 86.08%. We further explore critical channels and frequency bands by examining the weight distribution learned by DBN, which is different from the existing work. We identify four profiles with 4, 6, 9 and 12 channels, which achieve recognition accuracies of 82.88%, 85.03%, 84.02%, 86.65%, respectively, using SVM.

I. INTRODUCTION

Affective computing (AC) aims to develop the computational models of emotions and advance the affective intelligence of computers [1]. One of the key elements of AC is automatic emotion recognition that estimates the emotional states from behavioral and physiological responses [2]. Among various emotion recognition approaches, the methods based on electroencephalogram (EEG) are more reliable because of its high accuracy and objective evaluation compared to other external appearance clues such as expression and gesture. However, EEG signals often cause much noise during acquiring. In addition, many channels are irrelevant to emotion processing tasks, which may degrade the performance of emotion recognition systems. It is also important to investigate critical channels and frequency bands for emotion processing, which can fundamentally help us deeply understand emotion processing mechanisms and find neural signatures associated with different emotions in the human brains.

In the past several years, many studies have examined the neutral correlates of emotion and tried to find the critical

channels and frequency bands associated with emotion processing. Li and Lu [3] proposed a frequency band searching method to choose an optimal band and their results indicated that the gamma band was suitable for EEG-based emotion classification. Lin and his colleagues identified 30 subject-independent features that were most relevant to emotional processing across subjects according to F-score criterion. They also explored the feasibility of using fewer electrodes to characterize the EEG dynamics during music listening [4]. The identified features were primarily derived from electrodes placed near the frontal and the parietal lobes. Kang *et al.* [5] presented a DBN based critical channel selection method with the observation that data in irrelevant channels randomly update the parameters in the DBN, and data in critical channels update the parameters in the DBN according to the related patterns. However, they did not investigated the performance of the selected pools of channels. Duan *et al.* [6] demonstrated that minimal-redundancy-maximal-relevance (MRMR) algorithm could help to improve the performance of classifiers. Their results indicated that some features are irrelevant or redundant for emotion recognition.

However, the critical channels and frequency bands for EEG-based emotion recognition are not fully determined and need further investigation. For example, the emotional stimuli used in [3] are still images and the category of emotions are only positive and negative emotions in [6]. In this paper, we use emotional film clips as stimuli and propose a novel deep belief network (DBN) based method for revealing critical channels and frequency bands. By examining the weight distribution learned by DBNs, we determine the critical channels and bands and identify four profiles of relative electrode sets, which can achieve comparable performance for emotion recognition.

II. EXPERIMENTS

We first design an emotion experiment to record EEG signals of different emotional states. In this study, we used emotional film clips as elicitation stimuli for their reliability and efficiency in emotion experiments. We carefully chose fifteen clips from a preliminary study for three emotions: positive, neutral, and negative. Each film clips lasted for about 4 minutes and each emotions had five corresponding emotional clips. The clips we chose were from Chinese films such as Tangshan Earthquake, Lost in Thailand, Flirting Scholar, and World Heritage in China.

Fifteen subjects (7 males and 8 females; MEAN: 23.27, STD: 2.37) with self-reported normal or corrected-to-normal vision and normal hearing participated in the experiments.

We selected the subjects using the Eysenck Personality Questionnaire (EQP). EQP is a questionnaire to assess the personality traits of a person as three dimensions of Extraversion/Introversion, Neuroticism/Stability and Psychoticism/Socialisation devised by Hans Eysenck *et al.* [7]. We tended to select subjects who are extraverted and have stable moods from the feedback of questionnaires. Subjects were informed about purposes and procedures before the experiments. Fig. 1 shows the experiment scene.

Fig. 1. The experiment scene. (One of our study motivations aims to enhance driving safety via recognizing and adapting to drivers' emotions. So we utilize a driving simulator in the lab, which has a relatively closed environment.)

While subjects were watching emotional film clips and elicited corresponding emotions, EEG signals were recorded with ESI NeuroScan System at a sampling rate of 1000 Hz from 62-channel electrode cap according to the international 10-20 system, simultaneously. There were fifteen trials for each experiments. There were a 5s hint before each trial, 45s for feedback, and 15s rest after each trials. For feedback, subjects were asked to rate the scores how they elicited the specific emotions. Each subjects performed the experiments twice at the interval of about one week and there were totally 30 experiments evaluated in this study.

III. METHODS

A. Feature Extraction

For preprocessing, the raw EEG data are first downsampled to 200Hz and then processed with a bandpass filter between 0.3Hz and 50Hz to filter out the noise and remove the artifacts. After that, we extract efficient EEG features associated with emotion processing. In this paper, we employ differential entropy (DE) features proposed in our previous work [6], [8]. For a fixed length EEG segment, differential entropy is equivalent to logarithmic energy spectrum in a certain frequency band. Our previous experiments showed that DE has the balance ability of discriminating EEG patterns between low and high frequency energy and outperforms other conventional EEG features. Therefore, we calculate DE features in five frequency bands (delta: 1-3Hz, theta: 4-7Hz, alpha: 8-13Hz, beta: 14-30Hz, gamma: 31-50Hz) with a 256-point Short-Time Fourier Transform. Features are normalized between 0 and 1 before training classifiers.

B. Deep Belief Networks

After extracting DE features from preprocessed EEG data, we adopt deep belief network (DBN) [9], [10] to build emotion recognition system. Deep Belief Network (DBN) is a probabilistic generative model with deep architecture, which is constructed by stacking a predefined number of RBMs on top of each other. The output from a lower-level RBM is the input to a higher-level RBM. For RBMs, there are no visible-visible and hidden-hidden connections.

In an RBM, the joint distribution $p(v, h; \theta)$ over the visible units v and hidden units h, given the model parameters θ, is defined in terms of an energy function $E(v, h; \theta)$ of

$$P(v, h; \theta) = \frac{exp(-E(v, h; \theta))}{Z}$$

where $Z = \sum_v \sum_h exp(-E(v, h; \theta))$ is a normalization factor. For a Gaussian (visible)-Bernoulli (hidden) RBM, the energy function is defined as

$$E(v, h; \theta) = -\sum_{i=1}^{I} \sum_{j=1}^{J} w_{ij} v_i h_j - \frac{1}{2} \sum_{i=1}^{I} (v_i - b_i)^2 - \sum_{j=1}^{J} a_j h_j$$

where w_{ij} is the symmetric interaction term between visible unit v_i and hidden unit h_j, b_i and a_j are the bias terms, and I and J are the numbers of visible and hidden units, respectively. The conditional probabilities can be efficiently calculated as

$$P(h_j = 1 | v; \theta) = \sigma(\sum_{i=1}^{I} w_{ij} v_i + a_j)$$

$$P(v_i = 1 | h; \theta) = N(\sum_{j=1}^{J} w_{ij} h_j + b_i, 1)$$

where $\sigma(x) = 1/(1 + exp(x))$ and v_i takes real values and follows a Gaussian distribution.

Taking the gradient of the log likelihood $\log p(v; \theta)$, we can derive the update rule for the RBM weights as:

$$\Delta w_{ij} = E_{data}(v_i h_j) - E_{model}(v_i h_j)$$

where $E_{data}(v_i h_j)$ is the expectation observed in the training set and $E_{model}(v_i h_j)$ is the same expectation under the distribution defined by the model. But $E_{model}(v_i h_j)$ is intractable to compute so the contrastive divergence approximation to the gradient is used where $E_{model}(v_i h_j)$ is replaced by running the Gibbs sampler initialized at the data for one full step.

C. Classifier Training

Besides DBN, we compare the performance of different classifiers, KNN, $l2$-regularized logistic regression (LR) and SVM. Here, we describe the details of parameters used in different classifiers. For KNN, we set $K = 5$ for comparison. For LR-$l2$, we tune the regularization parameter in [1.5:10] with step of 0.5. For SVM, we use LIBLINEAR software [11] to implement the SVM classifier with linear kernel. We search the parameter space $2^{[-10:10]}$ with step of one for C to find the optimal value. For DBN, we use the DBNToolbox

Matlab code [12] to construct the DBN classifier with two hidden layers. We search the optimal neuron numbers of first and second hidden layers in the range of [200:500] and [150:500] with step of 50, respectively. The unsupervised learning rate and supervised learning rate are 0.5 and 0.6, respectively. The data of the first nine trials are used as training data, and the rest six trials from the same experiment are used as testing data for performance evaluation.

IV. RESULTS AND DISCUSSION

First we compare the performance of different classifiers. Using DE features from five frequency bands as input, the means and standard deviations of accuracies of KN-N, LR, SVM and DBN are 72.60/13.16%, 82.70/10.38%, 83.9/9.72%, 86.08/8.34%, respectively. From the results, we can see that the DBN classifier achieves highest mean accuracy and lowest standard deviation, which outperforms other shallow classifiers, KNN, LR and SVM.

Electrode set reduction can, not only reduce the computational complexity, but also filter irrelative noise. The optimal electrodes placement is usually defined according to some statistical factors like correlation coefficient and accuracy rate in the existing work. In this study, we examine the critical channels and frequency bands through analyzing the weight distributions of the trained deep belief networks. According to the training algorithms of neural networks, the weights of neurons that contribute more for the tasks to be learned will be updated to certain high values, while the weights of irrelevant neurons tend to be distributed randomly. So the weight could represent how important it is for emotion recognition models. Fig. 2 shows the mean absolute weight distribution of the trained DBNs in the first layers learned from total experiments. We can see from the plot that the high peaks are mostly located at beta and gamma bands, which indicates that the feature components of beta and gamma bands contain more important discriminative information.
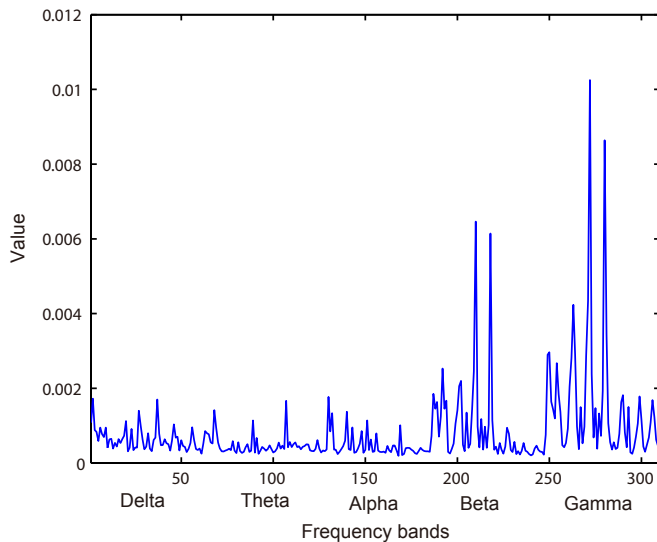

Fig. 2. The mean absolute weight distribution of the trained DBNs in the first layers.
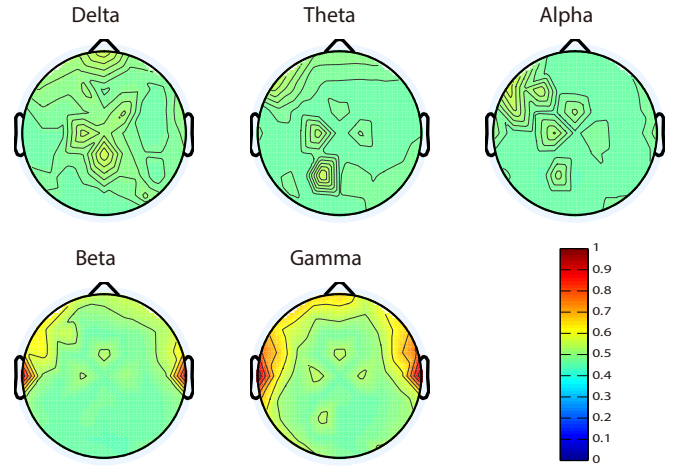

Fig. 3. We project the mean weight distribution to the brain scalp, which shows different activated brain regions in different frequency bands.

To clearly explore critical channels, we project the mean weight distribution to the brain scalp. Fig. 3 depicts the weight distribution of different brain regions in different frequency bands. From Fig. 3, we could extract the subject-independent critical channels for emotion recognition. The lateral temporal and prefrontal brain areas activate more than other brain areas in beta and gamma bands, which show that these brain areas are critical channels and contribute more than other areas in the deep neural networks. These results confirm the findings in the literature [3], [13].

We design four different profiles of electrodes placements according to features of high peaks in the weight distribution and asymmetric properties in emotion processing. Fig. 4 shows these four different profiles evaluated in this study: (a) 4 channels: $FT7$, $FT8$, $T7$ and $T8$; (b) 6 channels: $FT7$, $FT8$, $T7$, $T8$, $TP7$ and $TP8$; (c) 9 channels: $FP1$, FPZ, $FP2$, $FT7$, $FT8$, $T7$, $T8$, $TP7$ and $TP8$; and (d) 12 channels: $FT7$, $FT8$, $T7$, $T8$, $C5$, $C6$, $TP7$, $TP8$, $CP5$, $CP6$, $P7$ and $P8$. The electrodes of profiles (a), (b) and (d) are located in the lateral temporal areas, and profile (c) adds 3 extra prefrontal electrodes.

Considering that the selected pools of electrodes sets are reduced to comparably low dimensions as input and these critical channels are selected by deep neural networks when training, it is better to evaluate the performance of these critical channels for emotion recognition models with SVM, which has no explicit feature selection properties. Fig. 5 shows the mean accuracies of different profiles in different frequency bands. The best mean accuracies and standard deviations of 4 channels, 6 channels, 9 channels and 12 channels are 82.88/10.92%, 85.03/9.63%, 84.02/10.34%, and 86.65/8.62%, respectively, while the best mean accuracy and standard deviation of full 62 channels are 83.99/9.72%.

For 4 channels profiles, we can see that they can achieve comparably high and stable accuracies of 82.88/10.92% using DE features of total frequency bands, which is just slightly lower than the full 62 electrodes. Profiles of 6 channels, 9 channels and 12 channels with SVM achieve
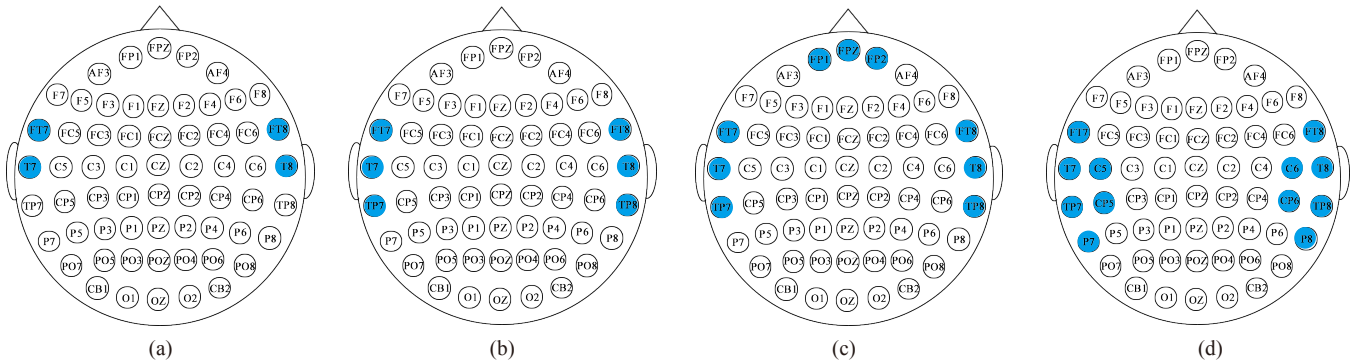
Fig. 4. Four different profiles of selected electrodes placements according to features of high peaks in the weight distribution and asymmetric properties in emotion processing: (a) 4 channels; (b) 6 channels; (c) 9 channels; (d) 12 channels
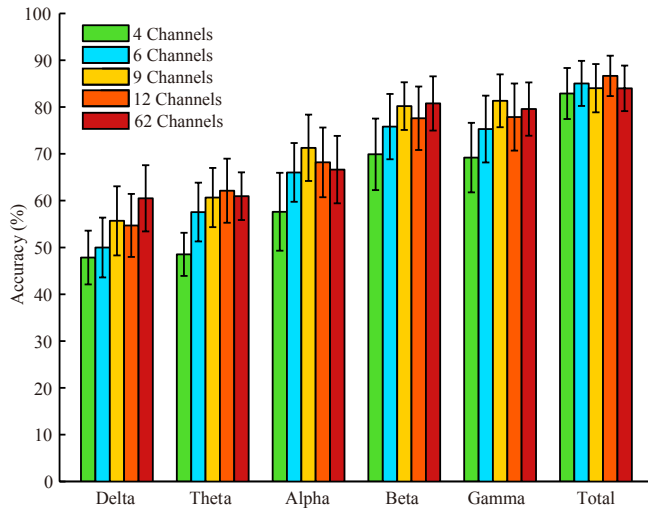

Fig. 5. The mean accuracies and standard deviations of different profiles of electrode sets in different frequency bands

better performance than 62 channels with SVM. These results indicate that the selected critical channels contain most discriminative information for emotion recognition and training with critical channels can enhance the performance. Moreover, 12 channels profile with SVM attains the highest accuracy and lowest standard deviation (86.65/8.62%), even better than the original full 62 channels with SVM (83.99/9.72%) and DBN (86.08/8.34%). We also investigate the performance of critical channels with leave-one-subject-out cross validation. For cross-subject scheme, the mean accuracies and standard deviations of 4, 6, 9, 12 and total 62 channels were 60.81/10.33%, 66.25/11.79%, 67.84/12.71%, 66.49/10.01%, and 63.91/14.77%, respectively. These results show that profiles of selected critical channels can also achieve better and more stable performance across subjects than whole channels. This further confirms the superiority and efficiency of the selected critical channels.

V. CONCLUSIONS

In this paper, we have proposed a novel DBN based method for revealing the critical channels and frequency bands for recognizing positive, neutral, and negative e-motions. Our experimental results indicate that the lateral temporal and prefrontal channels are critical channels and the beta and gamma bands are critical frequency bands. By examining the weight distribution learned by DBNs, we have identified four profiles of 4, 6, 9, and 12 channels, which achieve relatively stable performance with comparable accuracies in both subject-dependent and subject-independent experiments, even better than original whole 62 channels.

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