Discriminating Surprise and Anger from EEG and Eye Movements with a Graph Network

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***Abstract*—Emotion recognition based on EEG and eye movement signals has been studied extensively due to the reliability and stability of signals. The separability of four basic emotions, happy, sad, disgust and fear, has been systematically studied in the existing work. However, there is less research on the emotions of anger and surprise since they are more difficult to be elicited in lab settings. This paper investigates the discrimination ability of EEG and eye movement signals for surprise and anger. To this end, we design a stimulus paradigm that can effectively elicit surprise and anger. We propose a novel Graph Convolutional Network with Channel Attention (GCNCA) to classify three emotions, anger, surprise and neutrality. Experimental results indicate that: a) the proposed GCNCA model has an excellent classification accuracy of 86.47% using EEG and 84.22% using eye movement signals, which are better than other baseline methods; b) EEG and eye movements have a good ability to discriminate surprise and anger, while EEG performs better than eye movements; c) the high-frequency bands of EEG are more distinguishable on classifying surprise and anger than the low-frequency bands; d) there are some differences in neural patterns between surprise and anger, meanwhile critical channels and channel connections of EEG are found.**

***Index Terms*—EEG, eye movements, surprise, anger, graph convolutional network**

I. Introduction

Nowadays, the role of emotions in human-computer interactions is becoming more and more important. The emotion models can be divided into two main types: discrete models and dimensional models. Ekman *et al*. [1] proposed one of the famous discrete emotion models including six basic emotions, happiness, fear, disgust, anger, surprise, and sadness. Whereas, a dimensional model defines emotions in a coordinate system composed of multiple dimensions. In this paper, we mainly concentrate on the discrete model.

There are many studies on the discrimination ability of EEG and eye movements on the four of the six basic emotions. Zheng *et al*. [2] studied the stable neural patterns of happy, sad, and neutral emotions. Furthermore, they explored the discrimination ability of EEG and eye movement signals for happy, sad, fear, and neutral emotions [3]. After those findings, Li *et al*. [4] and Liu *et al*. [5] investigated the differentiation ability of EEG and eye movement signals for five emotions including happy, sad, fear, disgust, and neutral. Nevertheless, neither the discrimination ability of EEG and eye movement signals for surprise and anger nor the neural patterns have been fully investigated yet in the existing work. Thus, we study EEG and eye movement signals of surprise, anger, and neutrality in this paper.

The main contributions of this paper can be summarized as follows:

1) We conduct experiments to elicit subjects' surprise and anger in multiple ways. Additionally, we select neutral emotion as the anchor to compare with surprise and anger. EEG and eye movement signals are recorded during the experiment.
2) We propose a novel Graph Convolutional Network with Channel Attention (GCNCA) for classification. The GCNCA models EEG and eye movement signals as a graph taking advantage of the relationships among different channels and the channel attention mechanism automatically learns the importance of the channels.
3) We do classification tasks using the individual band and total band and explore the critical bands for discriminating surprise and anger. Furthermore, We study the neural patterns and find the significant difference between the three emotions. For eye movements, we investigate the distributions of some statistical features.

II. Experiment Setup

A. Stimuli Material

1) Surprise: For surprise, we choose magic videos as the stimuli materials. Each video contains several infectious fragments intercepted from various magic shows. The most important advantage of this approach is stability. Subjects can always get surprised while watching these magic videos. Moreover, watching videos evades the influence of limb movement on EEG signals.

2) Anger: Anger can hardly appear by only watching videos. To overcome this hurdle, we design and utilize three electronic games. Before the experiments, subjects are told that their remuneration is tied to their performance of playing the game. The purpose of doing this is to make sure that they play the games seriously for better effects.

The first game is adapted from the traditional Stroop game. There is a large Chinese character representing color on the screen, whose font color is random and usually different from the color it means. Meanwhile, four options which are also

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Chinese character representing color with random font color are below the large character. Subjects are asked to choose the character whose meaning is consistent with the large character's font color. We set 150 problems which takes about 25 minutes to complete. The subjects have 5 seconds per problem. If they run out of time, it will straightly go for the next one. The higher the accuracy, the more rewards. In order to make subjects more angry, we deliberately set the following system bugs:

1) Random mouse click recognition error. The system recognizes the mouse click area incorrectly for a small probability.
2) Random mouse malfunction. The mouse randomly does not respond when the subjects click the option.
3) Random frozen. The system randomly freezes couple times for about half a minute each.
4) Setting up a fake leader board. We set up a fake leader board at the upper left corner of the screen. People on the leader board have extremely high scores that the subjects are impossible to achieve.
5) Game program crash. At the end of the game, the program automatically crashes and the subjects are required to play it again. To limit the gaming time, we only set 20 problems when the subjects replay the game.

The other two games are existing games on the Internet, named *Golfing Over It* [1] and *Boxman's Struggle*[2]. These two games require the players to control objects which are a golf and a box respectively to climb upwards. We set a goal for all the subjects. They can get all the remuneration only if they reach the target position in the game within 25 minutes. Otherwise, they can only get 30 percent of the remuneration. Once the time runs out, the game is over. There are many obstacles in these two games which make it difficult to achieve the goal. A small mistake may cause the objects falling to the ground which means all effort is wasted. The subjects are likely to be angry as the game unfolds.

Besides games, we also select some videos to elicit anger. These videos reflect injustices in the society and can make people feel angry to some extent. We find some people still feel angry when they think of something that made them angry recently. Inspired by this, we add a section when subjects are asked to recall annoying things to get angry in the experiment. Thus, we have diverse angry data from gaming, recalling and videos.

B. Subjects

Seventeen participants aging from 18 to 30 enroll in our experiments, including 9 males and 8 females. All have normal or correct-to-normal vision and normal hearing. We use questionnaires to understand the basic information of the participants including age, gender, background, etc. Through the questionnaire, we select 17 suitable candidates from the registered people to participate in our experiment. All subjects

[1]https://www.majorariatto.com/golfingoverit
[2]https://oneblock.itch.io/boxmans-struggle

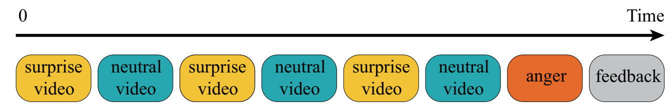


Fig. 1. The procedure of the experiment.

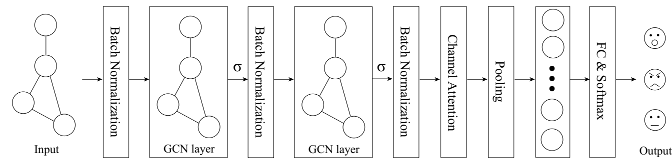


Fig. 2. The overall architecture of proposed GCNCA model.

are informed of the content of the experiment before start and sign an informed agreement. This experiment passed the review of the Ethics Committee of Shanghai Jiao Tong University.

C. Procedure

All of the subjects perform the experiment 3 times. The process of the experiment is shown in Figure 1. Each session of the experiment contains several trials. Each trial consists of two parts. The first part is video, recall or playing games, and after that is self-assessment which subjects score their emotional arousal from 1 to 10 points. Most videos are about 2 to 4 minutes long. The first six trials are alternate playbacks of surprise and neutral videos. The rest of trials are designed to elicit anger. The original intention of the design is based on the observation that people are more prone to continuous anger. The anger eliciting part contains 5 trials. The first one is "anger boost" that are some drag racing videos aiming to stimulate adrenaline secretion for better anger induction later. EEG and eye movement signals are not recorded for this trial. Subsequent two trials are anger videos followed by a trial that requests subjects to recall annoying things for about 2 minutes. The last trial is the game and the total 3 sections of experiments correspond to the 3 games mentioned above, respectively.

There is a feedback session at the end of each experiment. Most importantly, the subjects are asked to find out the period when they are most angry through the gaming trial. It's necessary because people are unlikely to remain angry throughout the game. Also, from each section of the experiment, we will get 3 surprise data, 3 neutral data and 4 anger data. In order to keep the balance of the data, we select 3 out of 4 anger data according to feedback from the subjects.

III. Methods

A. Preprocessing

Raw EEG data may contain a lot of noise from environment. We preprocess the EEG signals with Curry 7. We carry out a baseline correction followed by a band pass filtering between 1 to 50 Hz. To remove the artifacts caused by blinking, we apply Principle Component Analysis (PCA) and use VEO channel to detect and remove artifacts.

TABLE I
EXTRACTED EYE MOVEMENT FEATURES

Eye movement parameters	Extracted features
Pupil diameter(X and Y)	Mean, standard deviation, DE in four bands (0-0.2 Hz, 0.2-0.4Hz, 0.4-0.6 Hz, 0.6-1 Hz)
Fixation duration(ms)	Mean, standard deviation, maximum
Saccade duration(ms)	Mean, standard deviation
Blink duration(ms)	Mean, standard deviation
Event statistics	Fixation frequency, Saccade frequency, Saccade latency, Blink frequency

For eye movement signals, we mainly concentrate on left pupil diameter, right pupil diameter, fixation duration, saccade duration and blink duration recorded by Tobii Pro X3120 eye tracker. The pupil diameter is affected by the intensity of the light, so we apply PCA to remove the influence of the light on pupil diameter under the fact that different subjects watch the same videos in an experiment [3].

B. Feature Extraction

In this paper, we choose differential entropy (DE) of EEG as features. We first downsample the EEG signals from 1000 Hz to 200 Hz in order to speed up the data processing procedure. Then, we extract DE feature in five frequency bands: delta (1-3 Hz), theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz) and gamma (31-50 Hz). The Short Time Fourier Transform (STFT) with a 1-second-time window and no overlapping Hanning window is used to extract the DE features. Finally, we use a linear dynamic system algorithm to smooth the features. As for eye movement signals, Table I shows the features we extracted. Overall, the eye movement features are 23-dimension.

C. Graph Convolutional Network with Channel Attention

Given a graph $G = (V, E)$, where V denotes the set of vertices and E denotes the set of edges. We can use an adjacency matrix $A \in \mathbb{R}^{n\times n}$ to represent E, where n is the number of vertices i.e. $n = |V|$.

Kipf *et al*. [6] proposed the GCN model as follows

$$H^{l+1} = \sigma(\hat{D}^{-\frac{1}{2}}\hat{A}\hat{D}^{-\frac{1}{2}}H^l W^l), \tag{1}$$

where $\hat{A} = A + I$, $\hat{D}_{ii} = \sum_j \hat{A_{ij}}$, W^l denotes the weight matrix of layer l, $H^0 = X$, and σ is the non-linear activation function.

We extend the original GCN and propose the GCNCA model. The architecture of the proposed GCNCA model is illustrated in Figure 2. We apply batch normalization after input and each GCN layer for better and faster convergence. We choose leaky ReLU as the non-linear activation function. For the GCN layer, the adjacency matrix is vital as it describes the topology of the input features. We define the adjacency matrix $A \in \mathbb{R}^{n\times n}$ as a symmetric matrix to avoid overfitting, where n is the number of channels in features. Each entry A_{ij} indicates the weight between channel i and j and we set it learnable since the connections between channels are unknown.

To explore the significance of each channel in the input features, we propose a novel channel attention method which can adaptively learn the weights among all the channels. We use $H^l \in \mathbb{R}^{n\times d}$ as the output of the l-th GCN layer, where n is the number of channels and d is the dimension of each channel. The normalized weight matrix $\widetilde{W} \in \mathbb{R}^{n\times d}$ can be measured through a softmax function as:

$$\widetilde{W} = softmax(WH^l + B), \tag{2}$$

where $W \in \mathbb{R}^{n\times n}$, and $B \in \mathbb{R}^{n\times d}$. After that, the output of the channel attention can be calculated as follows:

$$\widetilde{H}^l = \widetilde{W} \odot H^l, \tag{3}$$

where $\widetilde{H}^l \in \mathbb{R}^{n\times d}$. The element in $\widetilde{W}$ denotes the importance of its corresponding dimension in H^l. The larger the value is, the more crucial the corresponding dimension will be. W and B are initialized randomly and updated through training.

After the channel attention, we apply sum pooling, fully-connected layer followed by a softmax layer to derive the classification results. The objective loss function we want to optimize is:

$$\mathcal{L} = -\sum_{i=1}^{N} \log(p(Y_i|X_i, \theta)) + \lambda \sum_{W_i\in\theta} \|W_i\|_2^2, \tag{4}$$

which is the cross-entropy loss with weight decay. Here, θ denotes the parameters of the model and λ is the strength of L2 regularization of all the weight including the adjacency matrix A.

For hyperparameter settings, we empirically set the number of convolutional layers $L = 2$, batch size of 32. We only tune the hidden dimension of channels d, learning rate η and the strength of weight decay λ. We select Adam as the optimizer to update the parameters of our model.

IV. RESULTS

To evaluate the classification performance of EEG and eye movement signals for the three emotions, we establish a model for each experiment of each subject. For each experiment, we divide the data into three folds and each fold contains one clip of surprise, anger and neutral data to perform a three-fold cross-validation.

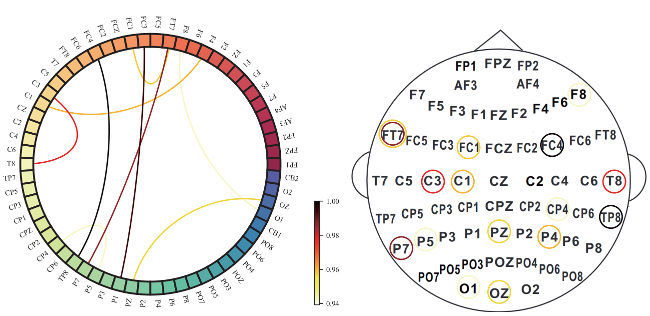
A. Discrimination Ability of EEG

For EEG, we conduct the classification task on individual bands (delta, theta, alpha, beta, gamma) as well as total bands to investigate the critical bands for surprise and anger. We compare our GCNCA model with several other methods including support vector machine (SVM), K-nearest neighbor (KNN), graph convolutional network without attention (GCN) and hierarchical convolutional neural network (HCNN) [7], which transforms the EEG features into image-like tensors and using convolutional neural networks (CNN) to conduct the classification. Table II shows the average classification accuracy results.

1) Discrimination of Different Frequency Bands: As shown in Table II, it's obvious that high frequency bands alpha, beta

TABLE II
EEG AND EYE MOVEMENTS CLASSIFICATION ACCURACY(MEAN/STD) % RESULTS

Model	EEG						eye movements
	Delta	Theta	Alpha	Beta	Gamma	Total	
KNN	45.03/19.49	48.11/21.24	54.73/23.16	58.14/23.68	53.37/22.03	57.91/23.21	47.38/31.66
SVM	50.82/20.36	56.40/21.98	61.90/23.79	65.91/21.72	59.62/23.92	68.83/21.97	58.52/25.75
HCNN [7]	59.72/18.68	70.02/17.68	75.03/19.30	77.44/20.52	75.03/19.30	74.86/17.56	-
GCN	72.26/**15.11**	77.50/**15.26**	81.25/16.20	82.95/16.62	80.99/15.37	84.51/14.58	81.42/16.48
GCNCA	**74.52**/15.15	**78.04**/15.71	**84.19/15.39**	**84.79/14.62**	**83.04/15.20**	**86.47/13.87**	**84.22/14.38**



(a) Connectivity (b) International 10/20 system

Fig. 3. Visualization of the adjacency matrix of the GCNCA.

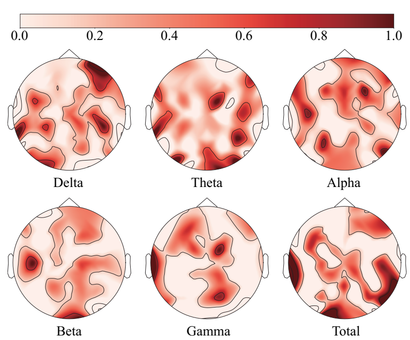
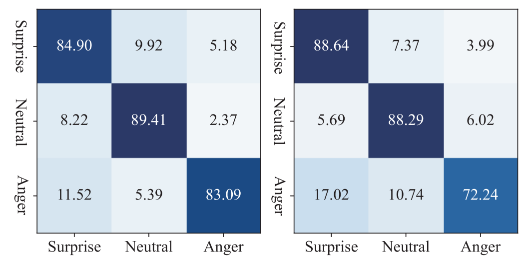


Fig. 4. Visualization of attention weight, obtained by calculating the mean of attention weight of each subject and normalized.

and gamma outperform low frequency bands. Furthermore, beta band acquires the best classification accuracy among other single bands which is consistent with the previous work of five emotions classification [4]. The total band achieves the best performance compared with single bands except the KNN and HCNN, which illustrates that there are complementary components between different frequency bands.

2) Discrimination of Different Models: Deep methods are significantly stronger than traditional machine learning methods such as SVM and KNN in discriminating three emotions. Compared with HCNN, GCN reaches better classification accuracy of 84.51% using total band, which demonstrates that the graph topology can better represent the relationship between the channels of EEG than simply modeling the EEG signals like an image according to the spatial relations. This also indicates that there are complex functional connections between different brain regions. The highest recognition accuracy is 86.47% acquired by the GCNCA model using total band.



(a) EEG (b) eye movements

Fig. 5. The confusion matrices of GCNCA using EEG and eye movements. The horizontal axis is the predicted labels and the vertical axis is the true labels.

Figure 3 shows the connectivity learned from the GCNCA model. Figure 3(a) shows the top 10 connections in the adjacency matrix using total band. For better visualizaion, those connections are circled in the same colors in Figure 3(b) which is the international 10/20 system depicting EEG electrode layout of 62 channels. It's clear that the main and strongest connections are between local brain areas mainly in temporal, occipital and parietal area, indicating that local inner-channel connections are essential for discriminating three emotions. Our GCNCA model achieves the best result in both single band and total band due to the channel attention module that takes the importance of different channels into consideration. We visualize the $\widetilde{W}$ in Equation 2 to identify the critical channels in EEG as depicted in Figure 4. It can be induced from the figure that there do exist differences in importance between the channels. In total band, the lateral temporal areas contribute the most to the emotion classification. Also, the parietal area is slightly stronger than other regions and the occipital area is an essential region as well. Note that the attention weight of total band just looks like what all single bands overlie with one another.

To further explore the discrimination ability of our model in different emotions, Figure 5(a) depict the confusion matrices of GCNCA. It can be seen that EEG can better distinguish neutral emotion compared with anger and surprise.

B. Discrimination Ability of Eye Movements

For eye movements, we also model the features as a graph using our GCNCA model since there might be potential relationships between different eye movement features and the channel attention mechanism can fully explore the significance

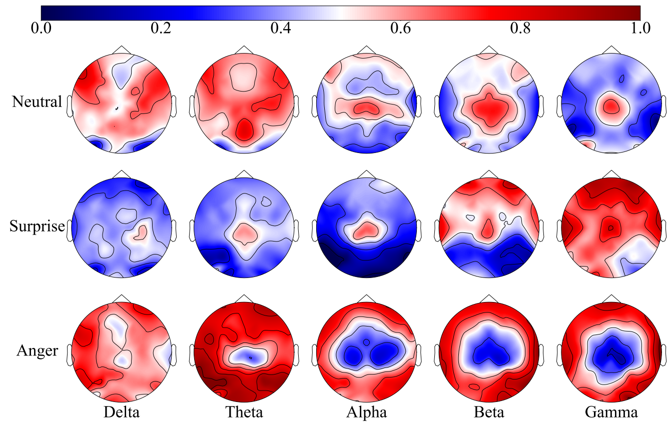


Fig. 6. Topographic maps of the three emotions in the five bands, obtained by averaging DE features over all subjects.

of different features to discriminate between surprise and anger. We compare our GCNCA model with SVM, KNN and GCN without attention. The results are shown in Table II. It can be seen from the table that our GCNCA model achieves the best accuracy of 83.74%, which is higher than GCN due to the accuracy gain of the channel attention mechanism. Compared with the same method using EEG, eye movement signals perform lower accuracy. This demonstrates that EEG has better discrimination ability for surprise and anger than eye movements.

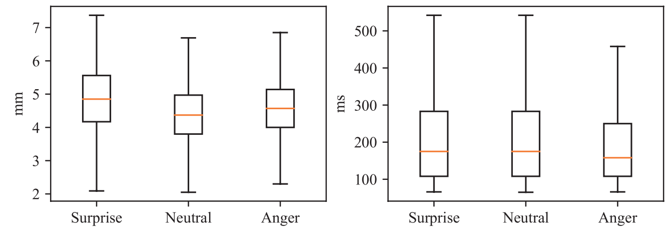
Figure 5(b) show the confusion matrices of GCNCA using eye movements. The proposed GCNCA model achives good accuracies among the three emotions. However, anger acquires the lowest accuracy which indicates eye movements are not good at distinguishing anger compared with EEG while the discrimination ability for the other two emotions is similar with EEG.

C. Neural Patterns and Statistics of Eye Movements

We investigate the neural topographic maps of EEG and some statistics of eye movements in order to further understand the characteristic of EEG and eye movements for surprise, neutrality and anger.

Figure 6 presents the topographic maps of three emotions in five bands, which is obtained by averaging the DE features of all subjects in five bands. The figure demonstrates that the energy is at a high level in the lateral temporal area, frontal area and occipital area for anger while the parietal area is of a low value on the whole. As for surprise, the lateral temporal area and frontal area usually has a strong activation in beta and gamma bands and the parietal area is at a high level relatively in all bands. Additionally, the energy of the neutral emotion is higher than surprise in delta, theta and alpha bands.

For eye movements, we study the data distribution of raw pupil diameter and fixation duration as depicted in Figure 7. It's obvious that the pupil diameter of neutrality is the smallest one compared with that of other emotions. Moreover, surprise emotion has the largest pupil diameter among the



(a) Pupil diameter (b) Fixation duration

Fig. 7. Box plots of two eye movement features. The red lines indicate the median.

three emotions. For fixation duration, anger emotion has a low value comparing with surprise and neutrality.

V. Conclusion

This paper has demonstrated that EEG and eye movements have good discrimination ability for surprise and anger, and EEG performs better than eye movements overall. Experimental results have shown that the proposed GCNCA model can reveal the relationships between channels and adaptively learn significance of channels through the channel attention mechanism. As for different bands, high frequency bands outperform lower ones. The neural patterns clearly show that parietal area is activated in surprise while the same region is at a low level in anger. Moreover, the discrimination ability of eye movements for anger is not as good as EEG. In conclusion, the discrimination of surprise, anger and neutrality from EEG and eye movements do exist.

Acknowledgment

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