Neural Patterns between Chinese and Germans for EEG-based Emotion Recognition

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***Abstract*— This paper aims to explore the neural patterns between Chinese and Germans for electroencephalogram (EEG)-based emotion recognition. Both Chinese and German subjects, wearing electrode caps, watched video stimuli that triggered positive, neutral, and negative emotions. Two emotion classifiers are trained on Chinese EEG data and German EEG data, respectively. The experiment results indicate that: a) German neural patterns are basically in accordance with Chinese ones; b) the main difference lies in the upper temporal region in Delta band which activates more when a German is in positive mood; and c) the Chinese positive emotion achieves the best accuracy while German emotions share the approximate accuracy. Moreover, Gamma band serves as the critical band for both German and Chinese emotion recognition.**

I. INTRODUCTION

Emotion plays a significant role in our daily life and it has been described as the 'driving force' behind motivation endowing meaning to all human interactions [1]. As we all know, various environment and culture influence human's physical peculiarity, the way human think, and many other aspects. Human race all over the world may have different emotion patterns or possess similar emotion characteristics. These years, multicultural research concerning emotion recognition has furnished evidence for cross-cultural differences as well as similarities.

In our previous work, Zheng *et al*. has investigated stable patterns of EEG over time for emotion recognition (positive, neutral, and negative) [2]. In other words, neural signatures for these three emotions exist and EEG patterns at critical frequency bands and brain regions are relatively stable within and between sessions. This result provides a good way to acquire the ground truth of human emotion and makes it less controversial using machine learning approaches on emotion recognition with EEG. Nonetheless, all the subjects participating in Zheng's experiments are Chinese. We tend to find out whether these neural signatures retain uniformity in different cultures.

II. RELATED WORK

The past decade has witnessed an upward trend in intercultural comparison on emotion. One of the popular experiment methods is through images or photographs. Beaupré *et al*. investigated cultural differences in recognition accuracy by arranging participants to view six basic expressions. They discovered that French Canadians did better in the decoding of ashamed and sad countenances, and sub-Saharan Africans recognized fear expressions best [3]. Hutchison *et al*. investigated the differences among American undergraduate college student's capability to recognize facial emotions and found that worldwide travel experience did not influence emotion recognition results [4].

Another kind of scheme is through sound. Sauter *et al*. studied the recognition of nonverbal emotional vocalizations like laughs and screams within two dissimilar cultural groups. The findings indicated that a quantity of primarily negative emotions had vocalizations which could be distinguished across cultures, however most positive emotions possessed culture-specific signals [5]. In addition to the existing approaches, this paper serves as a first attempt to compare intercultural neural patterns for EEG-based emotion recognition starting with Germans and Chinese.

III. EXPERIMENTS AND MATERIALS

Many different ways to induce emotions have already been used in emotion recognition experiments. Among these materials, movies have the desirable properties of being readily standardized, involving no deception and being dynamic rather static. The peculiarities of dynamic visual and audio stimuli make movies seem to be one of the most effectual ways to provoke emotions [6]. The Chinese EEG emotion data are from SEED[1] (SJTU Emotion EEG Dataset). We obtain the German EEG emotion data in the same way [7].

A. Stimuli Material

Schaefer *et al*. developed a new effective and comprehensive set of emotional film excerpts [8]. They selected the excerpts by asking 55 film experts about specific scenes they had in mind that would elicit strong emotions of different kinds. The set of film clips was then rated by 364 subjects individually on multiple dimensions. They computed positive affect and negative affect ranks based on the PANAS scales of the clips as well as the alternative positive and negative composite score (APCS and ANCS). The APCS is composed of amused, happy, joyful; elated, gleeful, warm hearted; friendly, loving, affectionate; pleased, satisfied, moved and the ANCS is composed of blue, downhearted, sad; angry, irritated, mad; anxious, tense, nervous; repulsed, disgusted;

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[1] http://bcmi.sjtu.edu.cn/∼seed/

TABLE I

SELECTED CLIPS FROM THE STUDY OF SCHAEFER ET AL. [8] FOR EMOTION STIMULI

Title	Emotion	Description	APCS	ANCS	Postive	Negative
Life is beautiful (4)	Positive	A father fabricates a translation to prevent his son.	4.18	1.45	3.12	1.77
Life is beautiful (3)	Positive	Mother and son get reunited.	3.75	1.51	3.73	1.35
Benny and Joone	Positive	A man plays the fool in a coffee shop.	3.80	1.04	3.54	1.27
The dinner game	Positive	A complex humouristic scene.	3.89	1.11	3.73	1.35
When Harry met Sally	Positive	A woman imitates an orgasm in a restaurant.	3.51	1.43	3.92	1.04
The visitors	Positive	Two men wearing armours attack a postman's car.	3.42	1.06	3.42	1.35
Highlands 2	Neutral	The history of Scottish skirts.	/	/	1.96	1.00
Stonehenge 1	Neutral	About the analysis of the area around Stonehenge.	/	/	1.58	1.04
Stonehenge 2	Neutral	The tools being used to build immense walls over 5000 years ago.	/	/	1.38	1.42
Unsere Erde 1	Neutral	Forest and life in the area of the taiga.	/	/	2.31	1.04
Unsere Erde 2	Neutral	The environmental cycle of our world.	/	/	1.73	1.08
Unsere Erde 4	Neutral	Journey and dinner of the humpback whale. Winter in Antarctic	/	/	1.73	1.19
Schindler's List (1)	Negative	Corpses get carried away in a concentration camp.	1.20	4.11	1.00	4.19
Dead Man Walking	Negative	A man is put to death by lethal injection.	1.39	3.54	1.12	4.19
The Piano	Negative	One of the characters gets her hand cut off.	1.36	3.35	1.00	4.15
Saving Private Ryan	Negative	A graphic war scene: fighting on the beaches.	1.17	3.31	1.00	4.54
Misery	Negative	A women breaks someone else's legs.	1.24	3.21	1.15	4.08
A perfect world	Negative	A man gets gunned down at the end of the movie.	2.19	2.91	1.19	3.65

afraid, scared, fearful; ashamed, embarrassed; disdainful, scornful; guilty, remorseful. The DES ranking of the clips and the alternative positive and negative composite score derived from the scale fit the purpose of the paper to find film clips eliciting emotions to viewing subjects.

Table I lists all the information about the selected clips. While Schaefer only has two videos marked as neutral, which sum up to about one minute, another way has been used to select neutral film clips. As with the Chinese clip selection, videos about natural scenery were used as neutral emotion clips. The evaluation forms, on which the subjects marked the clips during the experiments, verify the emotion of the neutral film clips. The scores are listed in the back of the table which range from 1 to 5.

B. Subjects

The experiments were completed by eight healthy subjects, one female and seven males, in the age between 20 and 26 years. The range of age matched the one in SEED data. All subjects were all exchange students at Shanghai Jiao Tong University and came from Germany.

C. Experiment Procedure

For the sake of investigating stable patterns across sessions, each subject was required to perform the experiments for 3 times with a time interval between one week or longer. Before the experiments, we prepared subjects by injecting conductive gel between their scalps and the electrodes to make sure the impendence of each electrode was lower than 5 kΩ. During the experiments, subjects watched the forthcoming movie clips attentively focusing their attention on the screen, and refrained as much as possible from needless facial or head movements. EEG data was recorded by an ESI NeuroScan System at a designed sampling rate of 1000 Hz from 62-channel active AgCl electrode cap based on the international 10-20 system. There was a 30-second interval between two clips for subjects to pacify their mood and to fill in a feedback form.

IV. METHOLOGY

A. Feature Extracting

The raw data, consisting of discrete time values for each of the 62 channels of the EEG cap, is first downsampled from 1000 Hz to 200 Hz to diminish the computation. After that, the processed data is low-pass filtered to 75 Hz aiming to dislodge the artifacts and then transformed into the frequency domain, where differential entropy (DE) features are extracted for frequency ranges from 0-4 Hz (Delta), 4-8 Hz (Theta), 8-14 Hz (Alpha), 14-31 Hz (Beta) and 31-50 Hz (Gamma). This feature extraction process is carried out on non-overlapping hanning windows with the size of 1 second each.

Differential entropy is a concept in computer science. It is based on the idea of entropy and as such gives a measure of the information content, carried by a random variable or in our case a timespan of EEG data. The DE $h(X)$ of a random variable X, with density function f is defined as follows,

$$h(X) = -\int_X f(x) log f(x) dx. \tag{1}$$

If a random variable subjects to the Gaussian distribution $N(\mu, \sigma^2)$, the DE can be simplified to the following formulation:

$$\begin{aligned} h(X) = -\int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi\sigma^2}} exp\frac{(x-\mu)^2}{2\sigma^2} \log \frac{1}{\sqrt{2\pi\sigma^2}} \\ exp\frac{(x-\mu)^2}{2\sigma^2} dx = \frac{1}{2}\log 2\pi e\sigma^2 \end{aligned} \tag{2}$$

The DE feature is taken as the primary feature for the classification for it results in the best accuracy compared to other features. Duan *et al.* firstly introduced DE to EEG-based emotion recognition [7].

B. Feature Smoothing

Assumptions are made that human emotion states change in a fluid and sluggish way, so the features ought to be smoothed to get rid of the zag part in the feature graph. This paper uses a linear dynamic system (LDS) approach to smooth the features as it has shown splendid effect in smoothing EEG signals [7].

C. Classification

Several approaches have been made to get higher accuracy on emotion recognition so far [9], [10]. However, this paper focus on investigating neural patterns between Germans and Chinese instead of higher classification accuracy.

In this paper, the classification is achieved by using a support vector machine (SVM). Basically, SVM constructs a separating hyperplane between two classes in such a way that the distance from each sample of the two classes to the hyperplane is maximized. For the problem of separating the set of training vectors belonging to two classes $G = \{(X_i, y_i), i = 1, 2, ..., n\}$, here $x_i \in \mathbb{R}^m$ is the i-th input vector and $y_i \in \{-1, 1\}$ is the binary target. The equation of the hyperplane separating two different classes is given by the following equation:

$$y(x) = W^T \varphi(x) + b = 0 \quad (3)$$

where $\varphi : \mathbb{R}^m \to \mathbb{R}^r$ is the feature map mapping the input space to a higher feature space, where the instance points become linearly separable. All operations in training and testing modes are proceeded in SVM using kernel functions, defined as:

$$k(X_i, X_j) = \varphi^T(X_i) \cdot \varphi(X_j) \quad (4)$$

The problem of learning SVM, formulated as the task of separating learning vector x_i into two classes of the destination values with maximal separation margin, is reduced to the dual maximization problem of the function $Q(\alpha)$ defined as follows:

$$Q(\alpha) = \sum_{i=1}^{n} \alpha_i - \frac{1}{2} \sum_{i=1}^{n} \sum_{j=1}^{n} \alpha_i \alpha_j y_i y_j k(X_i, X_j) \quad (5)$$

$$\sum_{i=1}^{n} \alpha_i y_i = 0 \quad 0 \leq \alpha_i \leq C \quad (6)$$

where C is constant. It is a regulation parameter and determines the balance between the complexity of the network, characterized by the weight vector w and the error of classification of data.

V. DISCUSSION

For each frequency band, we use SVM to classify the emotion in a 6-fold cross validation. Figure 1 displays the comparison of Chinese and German EEG emotion classification result. Chinese EEG emotion recognition accuracy of total bands is 78.47% (SD=11.56%) while German one is 65.03% (SD=13.33%). The accuracy disparity between these two data results from several reasons. First of all, the stimuli in Chinese SEED data arouse emotion better than German one to some extent. In addition, there are more than one kind of positive emotions in German experiments such as warm-hearted and gleeful emotions instead of the only one happy emotion in SEED. This difference holds in negative emotions as well. Furthermore, there is probability that German emotions are not so easily aroused as Chinese ones.

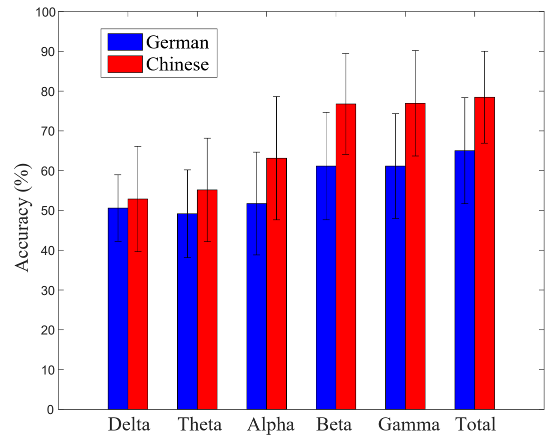


Fig. 1. Classification accuracy on each frequency band

Despite the accuracy disparity, we can find Gamma band outperforms other frequency bands in both cultures, thus it is still the critical band in emotion recognition, which reinforces the conclusion in our previous work [11], [12].

Table II shows the confusion matrices for German and Chinese emotion classification, respectively (PL: predicted label, TL: true label). Table II(a) reveals that German emotion arousal seems to be more stable with no relatively more identifiable emotion, while Table II(b) reflects Chinese positive emotion is the most distinguishable one. The classification accuracy of it reaches 92%.

TABLE II
THE CONFUSION MATRICES OF SVM CLASSIFIER

(a) German

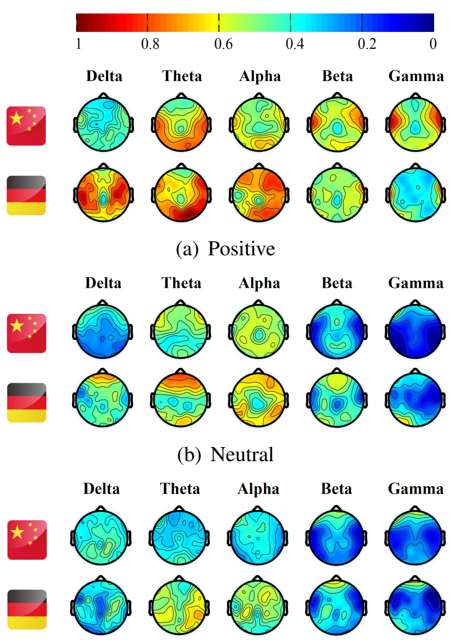
TL \ PL	Negative	Neutral	Positive
Negative	**0.61**	0.30	0.09
Neutral	0.24	**0.71**	0.05
Positive	0.22	0.12	**0.66**

(b) Chinese

TL \ PL	Negative	Neutral	Positive
Negative	**0.74**	0.18	0.18
Neutral	0.10	**0.86**	0.04
Positive	0.05	0.03	**0.92**

Figure 2 is a comparison of average topographical maps of brain regions in five frequency bands visualizing the DE features. Figure 2(a) indicates that German and Chinese neural patterns of positive emotion share the similarity in Gamma and Theta bands. Both German and Chinese EEG signals respond acutely in the temporal region in Gamma band and in the occiptal region in Theta band. On the other hand, there is an obvious distinction in the Delta band where German EEG signals activate much more. Eroglu *et al.* concluded that delta resoneses are chiefly invloved in signal matching, decision making and surprise [13], and it may signify that German subjects felt happy in a less spontaneous way. Moreover, the stimuli clips triggering positive emotion were not obvious and understandable in the beginning of them. As a result, the subjects kept thinking about whether the hint for positive emotion was wrong or not and trying to figure out the happiness in those clips. It echoes the relatively lower positive score in positive value than negative score in negative value in Table I.

Figures 2(b) and 2(c) display that temporal region activate much mildly in both neutral and nagetive emotions, which explains the reason why neutral and negative have a larger probability getting confused. However, EEG signals in Alpha band of both cultures activate more in neutral emotion than in negative emotion. This is consistent with Klimesch's finding that EEG Alpha activity reflects attentional processing [14] and the peaceful neutral emotion videoes cause subjects being drowsy and losing attention.



(a) Positive

(b) Neutral

(c) Negative

Fig. 2. Neural patterns comparsion between Chinese and Germans

VI. CONCLUSIONS

Overall, this paper compares the neural patterns between Chinese and Germans for EEG-based emotion classification from multiple perspectives. To acquire the German EEG data, we selected part of the clips from Schaefer's emotion excerpts and recruited 8 Germans, each performing 3 times, to participate in the experiments. After that, the feature extraction and smoothing procedure were the same as the ones in SEED, a Chinese emotion data set. The experimental results have indicated that the Gamma band serves as the critical band. Besides, the classification accuracy for Chinese positive emotion is highest, while German emotions are relatively stable and no emotion is obviously more identifiable. According to topographical maps of brain regions, the upper temporal region activates more in Delta band when a German is in positive mood, which is very likely due to the stimuli and a German's prudent personality. In spite of certain irrelevant-to-emotion factors, the tendency of German brain activities in positive, neutral and negative emotions is in accordance with Chinese one, which means these neural signatures retain uniformity.

ACKNOWLEDGMENT

This work was supported in part by the grants from the National Natural Science Foundation of China (Grant Nos.61272248 and 61673266), the National Basic Research Program of China (Grant No.2013CB329401), and the Major Basic Research Program of Shanghai Science and Technology Committee (Grant No.15JC1400103).

REFERENCES

[1] S. Ornstein and T. Nelson, "Incorporating emotional intelligence competency building into the preparation and delivery of international travel courses," *Innovations in Education and Teaching International*, vol. 43, no. 1, pp. 41–55, 2006.

[2] W.-L. Zheng, J.-Y. Zhu, and B.-L. Lu, "Identifying stable patterns over time for emotion recognition from EEG," *arXiv preprint arXiv:1601.02197*, 2016.

[3] M. G. Beaupr and U. Hess, "Cross-cultural emotion recognition among canadian ethnic groups," *Journal of Cross-Cultural Psychology*, vol. 36, no. 3, pp. 355–370, 2005.

[4] A. N. Hutchison and L. H. Gerstein, "The impact of gender and intercultural experiences on emotion recognition," *Revista De Cercetare Si Interventie Sociala*, vol. 54, pp. 125–141, 2016.

[5] D. Sauter, F. Eisner, P. Ekman, and S. K. Scott, "Cross-cultural recognition of basic emotions through nonverbal emotional vocalizations." *Proceedings of the National Academy of Sciences of the United States of America*, vol. 107, no. 6, pp. 2408–2412, 2010.

[6] X.-W. Wang, D. Nie, and B.-L. Lu, "Emotional state classification from EEG data using machine learning approach," *Neurocomputing*, vol. 129, no. 4, pp. 94–106, 2014.

[7] R.-N. Duan, J.-Y. Zhu, and B.-L. Lu, "Differential entropy feature for EEG-based emotion classification," in *6th International IEEE/EMBS Conference on Neural Engineering*. IEEE, 2013, pp. 81–84.

[8] A. Schaefer, F. Nils, X. Sanchez, and P. Philippot, "Assessing the effectiveness of a large database of emotion-eliciting films: A new tool for emotion researchers," *Cognition and Emotion*, vol. 24, no. 7, pp. 1153–1172, 2010.

[9] Y. Lu, W.-L. Zheng, B. Li, and B.-L. Lu, "Combining eye movements and EEG to enhance emotion recognition," in *International Conference on Artificial Intelligence*, 2015, pp. 1170–1176.

[10] W. Liu, W.-L. Zheng, and B.-L. Lu, "Emotion recognition using multimodal deep learning," in *International Conference on Neural Information Processing*. Springer, 2016, pp. 521–529.

[11] M. Li and B.-L. Lu, "Emotion classification based on gamma-band EEG." in *Engineering in Medicine and Biology Society. EMBC International Conference of the IEEE*, 2009, pp. 1323–1326.

[12] W.-L. Zheng and B.-L. Lu, "Investigating critical frequency bands and channels for EEG-based emotion recognition with deep neural networks," *IEEE Transactions on Autonomous Mental Development*, vol. 7, no. 3, pp. 162–175, 2015.

[13] C. Baar-Eroglu, E. Baar, T. Demiralp, and M. Schrmann, "P300-response: possible psychophysiological correlates in delta and theta frequency channels. a review." *International Journal of Psychophysiology Official Journal of the International Organization of Psychophysiology*, vol. 13, no. 2, pp. 161–179, 1992.

[14] W. Klimesch, M. Doppelmayr, H. Russegger, T. Pachinger, and J. Schwaiger, "Induced alpha band power changes in the human EEG and attention." *Neuroscience Letters*, vol. 244, no. 2, pp. 73–76, 1998.