EEG-based Emotion Recognition Using Discriminative Graph Regularized Extreme Learning Machine

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Abstract—**This study aims at finding the relationship between EEG signals and human emotional states. Movie clips are used as stimuli to evoke positive, neutral and negative emotions of subjects. We introduce a new effective classifier named discriminative graph regularized extreme learning machine (GELM) for EEG-based emotion recognition. The average classification accuracy of GELM using differential entropy (DE) features on the whole five frequency bands is 80.25%, while the accuracy of SVM is 76.62%. These results indicate that GELM is more suitable for emotion recognition than SVM. Additionally, the accuracies of GELM using DE features on Beta and Gamma bands are 79.07%, 79.93% respectively. This suggests that these two bands are more relevant to emotion. The experimental results indicate that the EEG patterns for emotion are generally stable among different experiments and subjects. By using minimal-redundancy-maximal-relevance (MRMR) algorithm and correlation coefficients to select effective features, we get the distribution of top 20 subject-independent features and build a manifold model to monitor the trajectory of emotion changes with time.**

I. Introduction

Emotional states significantly affect the cognition and behaviors of people. In human-human interaction, besides words and gestures, emotion is one of the most important feedbacks for us to understand each other better. With the development of artificial intelligence and machine learning technology, human-machine interaction tends to be more and more intelligent. Therefore, how to detect and model users' emotional states becomes a key factor to make human-computer interface more natural and enjoyable. In the 1990s, Picard firstly proposed the definition of Affective Computing (AC) [1]. She introduced the emotion-related signals, the emotion modeling approaches, and the potential applications of AC. Nowadays, automatic emotion recognition, which plays a huge role of affective computing, has been one of the most popular research topics in the fields of computer vision, speech recognition, brain-machine interface, and computational neuroscience [2].

As the importance of emotion recognition increases, researchers from different fields have studied this topic and proposed various kinds of methods, including some basic prototype systems. Approaches to emotion recognition can be divided into two categories: one is based on non-physiological signals such as facial expression [3] and voice [4]; the other one is based on physiological signals [5] which refer to electroencephalography (EEG) [6], electromyogram (EMG) [7], electrocardiogram (ECG) [8], skin resistance (SR) [9] and pulse rate [9]. However, even if physiological signals need contact detection which seems not to be convenient, in some specific environments, especially when our emotional states remain internal rather than external, emotion recognition based on physiological signals would be more appropriate and effective than that based on non-physiological signals. As we all know, brain is the nerve center controlling most emotional activities of people. Recently, functional magnetic resonance imaging (fMRI) has been used to reveal how emotions are processed in the brain [10]. Unfortunately, it is too difficult for us to use fMRI to collect data from brain in practical application. By contrast, collecting data from EEG signals, which also contain useful information of brain activities, is much simpler [11].

So far, various approaches have been developed for EEG-based emotion recognition using machine learning approaches. In one kind of studies, the energy spectrum (ES) features and their combinations are chosen as emotion features. Also, the support vector machine (SVM) is a traditional effective classifier for emotion classification. Lin *et al.* [12] extracted ES features from EEG signals and used the SVM to classify four kinds of emotions, which got average performance of 82.29%. Nie *et al.* [13] also used SVM to classify positive and negative emotions based on ES features, and found that the right occipital lobe and parietal lobe for the alpha band, the central site for beta band, and the left frontal lobe and right temporal lobe for gamma band are most associated with positive and negative emotional states. Recently, the differential entropy (DE) features and their combinations were introduced to EEG-based emotion recognition [14], and their performance is better than that of ES features.

In this paper, we adopt DE as time-frequency domain features and introduce a new classifier called discriminative graph regularized extreme learning machine (GELM) to

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emotion recognition. We focus on relationship between EEG data patterns and three emotional states (positive, neutral and negative). To confirm the stable common pattern of EEG signals changing with emotional states, we invited six subjects to participate in the experiment for three times each and chose the training set and testing set from different experiments and different subjects. We also used minimal-redundancy-maximal-relevance (MRMR) algorithm and correlation coefficients to select effective features and find the key encephalic regions associated with emotion recognition. We finally got the distribution of top 20 subject-independent features. By putting these features into a manifold model, we achieved the trajectory of emotion changes with time.

II. METHODS

A. Feature extraction

In this paper, we used time-frequency domain features to extract emotion information from EEG signals. Duan *et al.* had applied DE features and their combinations on symmetrical electrodes as EEG features to classify positive and negative emotional states [14]. They found that the average accuracy using DE features was 84.22%, while the accuracy using ES features was only 76.56%. Therefore, we chose DE instead of ES as features for emotion recognition. We extracted features on the five common frequency bands of EEG, which are Delta (1-3Hz), Theta (4-7Hz), Alpha (8-13Hz), Beta (14-30Hz) and Gamma (31-50Hz). A short-time Fourier transform (STFT) with a 1s non-overlapped Hanning window had been used to calculate the average DE features of each channel on five frequency bands. Differential entropy is originally defined as

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

Here, the time series X obeys the Gaussian distribution $N(\mu, \sigma^2)$, and the length of EEG sequence is fixed. Thus, differential entropy can be calculated by

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

And also, it has been proven that DE described above is equivalent to the logarithm of ES [15].

The EEG signals at each frequency band had 62 channels, so we totally extracted DE features of 310 dimensions for one sample. As the effective experiment time lasted about 57 minutes, we finally got about 3400 samples for each experiment.

B. Feature smoothing

In this paper, we assumed that the trends of emotion changes with time were smooth and continuous. So, severe concussions and rapid changes of EEG features are less relevant to emotional states. Previous researches have also found that, the feature smoothing methods, such as moving average (MA) and linear dynamical system (LDS) [16], help to improve the performance of classifiers during emotion classification, and the LDS method performs more stable than the MA method [6] [14]. Therefore, we applied the LDS method to smoothing EEG features, in order to remove noises effectively and get more reliable data.

C. Classification

In this paper, we got about 3400 samples in one experiment and chose about 2000 samples to form a training set, and the rest 1400 samples from the same experiment were used as a testing set. In order to investigate the stable performance of the trained model, we also chose the data from one experiment as training set and the data from another experiment as testing set. Since we had collected data from the same subject for three times, training sets and testing sets would not only come from the same subject's different experiments, but also come from different subjects.

We introduced a new classifier called discriminative graph regularized extreme learning machine (GELM) [17] to classify emotional states based on EEG signals. To evaluate the performance of GELM, the traditional classifier, support vector machine (SVM), was used as a baseline classifier.

Extreme learning machine (ELM) is a single hidden layer neural network using a least square based training algorithm. Given a training data set, $L = \{(x_i, t_i) | x_i \in \mathbb{R}^d, t_i \in \mathbb{R}^m, i = 1, 2, ..., N\}$, where $x_i = (x_{i1}, x_{i2}, ..., x_{id})^T$ and $t_i = (t_{i1}, t_{i2}, ..., t_{id})^T$. An ELM with K hidden nodes and activation function g can be modeled as :

$$\beta^T H = T, \tag{3}$$

where

$$H = \begin{bmatrix} g(w_1 \cdot x_1 + b_1) & \dots & g(w_1 \cdot x_N + b_1) \\ \vdots & \ddots & \vdots \\ g(w_K \cdot x_1 + b_K) & \dots & g(w_K \cdot x_N + b_K) \end{bmatrix}_{K\times N}$$

$$\beta = \begin{bmatrix} \beta_1^T \\ \beta_2^T \\ \vdots \\ \beta_K^T \end{bmatrix}_{K\times m}, \; T = [t_1, t_2, ..., t_N]_{m\times N},$$

$w_j = (w_{j1}, w_{j2}, ..., w_{jd})$ is the input weight vector connecting the jth hidden node with input nodes, $\beta_j = (\beta_{j1}, \beta_{j2}, ..., \beta_{jm})^T$ is the weight vector connecting the jth hidden node with the output nodes, and b_j is the bias of the jth hidden node.

The output of (3) can be estimated by

$$\tilde{\beta} = \arg\min_{\beta} \left\|\beta^T H - T\right\| = H^{\dagger} T. \tag{4}$$

As the consistency property of data is not considered in ELM, GELM was proposed to balance the discriminative and consistency property of high dimension data, and to enforce the output of samples in the same class to be similar. In the GELM model, the labels of training samples are used to construct an adjacent graph and the graph regularization term is formulated to constrain the output weights. This constraint is added to the objective function of the basic ELM model, which also makes the output weights be solved analytically.

For GELM, suppose that there is a data set with C classes and N samples. And the tth class has N_t samples. Then, the adjacent matrix W is defined as

$$W_{ij} = \begin{cases} 1/N_t, & \text{if both } h_i \text{ and } h_j \text{ belong to the } t\text{th class} \\ 0, & \text{otherwise} \end{cases} \tag{5}$$

where $h_i = (g_1(x_i), ..., g_K(x_i))^T$ and $h_j = (g_1(x_j), ..., g_K(x_j))^T$ are hidden layer representations for two input samples x_i and x_j, respectively. If we define a diagonal matrix D with column sums of W as its entries, the graph Laplacian can be calculated by $L = D - W$. We choose two vectors y_i and y_j from h_i and h_j, which are mapped by output weight matrix β.

According to the basic idea of GELM, when h_i and h_j are from the same class, y_i and y_j should share similar properties. Thus, we need to minimize the objective function as follows:

$$\min \sum_{i,j} \|y_i - y_j\|^2 W_{ij} = Tr(YLY^T), \tag{6}$$

where $Y = \beta^T H$. Therefore, the objective function of GELM is defined as follows:

$$min_\beta \left\|\beta^T H - T\right\|_2^2 + \lambda_1 Tr\left(\beta^T HLH^T \beta\right) + \lambda_2 \|\beta\|_2^2, \tag{7}$$

where $Tr\left(\beta^T HLH^T \beta\right)$ is the graph regularization term, $\|\beta\|^2$ is the l_2-norm regularization term, λ_1 and λ_2 are regularization parameters to balance the impact of these two terms. It can be calculated as follows:

$$\beta = \left(HH^T + \lambda_1 HLH^T + \lambda_2 I\right)^{-1} HT^T. \tag{8}$$

D. Feature selection

The 62-channel electrode cap provides 62 features for one frequency band. Thus, there are actually 310 features for one sample on total five bands. However, our training set only has over 2000 samples for one experiment, which implies that the 310 dimensions are too high for us to train a robust model using only 2000 samples. Therefore, minimal-redundancy-maximal-relevance (MRMR) algorithm [18] is used to select effective features and reduce the feature dimension for us. It would also help us investigate brain regions and frequency oscillations most related to emotional states and speed up computing procedure.

Furthermore, since cerebral cortices have different functions in different regions, we calculate correlation coefficients to find emotion-related features, emotion-related bands, and emotion-related encephalic regions.

E. Manifold learning

In order to find the trajectory of emotion changes intuitively, we reduced the feature dimension to 1, so that we could draw a curve of feature value changing with time during the whole experiment. In this paper, we first used correlation coefficients to select relevant features, and then put them into a manifold learning model so as to monitor the trajectory of emotion changes with time.

III. EXPERIMENTS

A. Stimuli

In order to evoke emotions of subjects, we chose movie clips which lasted about 4 minutes each as stimuli. These movie clips could be divided into three kinds of categories: positive, neutral and negative. There were 15 clips in one experiment, 5 clips for each emotional state. All the movies were in Chinese for native subjects to understand better. The stimuli were only made up of popular movies which are After Shock, Lost in Thailand, Just Another Pandora's Box, World Heritage in China, Back to 1942, and Flirting Scholar. Posters of these movies are showed in Figure 1. We also supposed that the 4-minute movie clip contained a vivid and relatively complete story, so that subjects were able to stay in the typical emotional state during this 4 minutes.

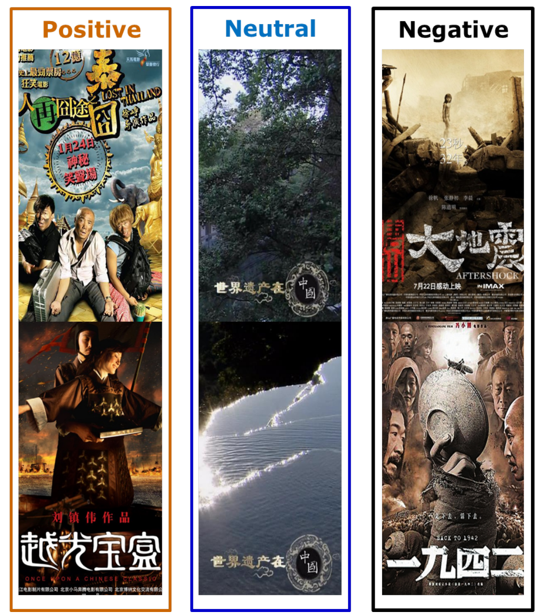


Fig. 1. Movie clips used as stimuli in this experiment.

Fig. 2. The actual scene of this experiment.

B. Subjects

Three men and three women aged between 20 to 27 participated in the experiment for three times each, at the interval of about one week or longer. They were all right-handed and had no history of mental illness. The experiments

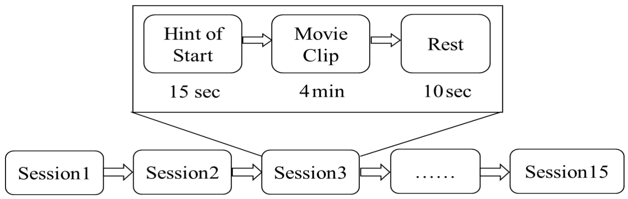


Fig. 3. Procedure of stimuli playing.

were performed in the day time and subjects were asked to have adequate sleep the day before experiment. Before the experiments, subjects were informed of the purpose and procedure of the experiment and also the harmlessness of the equipment.

C. Procedure

A 62-channel electrode cap according to the extended international 10-20 system and ESI NeuroScan System were used to record EEG data at a sampling rate of 1000Hz. Figure 2 shows the actual scene of the experiment. Fifteen movie clips were played with a 10s rest and a 15s hint between two clips. During the rest time, subjects were asked to fill a form as feedback to tell whether their emotions had been successfully evoked. Figure 3 shows the procedure of the experiment.

IV. RESULTS AND DISCUSSIONS

A. Classification

1) Using training sets and testing sets from the same experiment: Table I shows the classification accuracies of linear-SVM and GELM classifiers using differential entropy features on Delta, Theta, Alpha, Beta, and Gamma frequency bands as input. In this table, the training data and the testing data are from the same experiment. Cross-validation is used to determine parameters of classifiers. All data have been smoothed by LDS algorithm. From the results showed in Table I, we can find that, for the same training and testing data set on the same band, the classification accuracies of GELM are higher than accuracies of SVM in most cases. For the total 310 features on all bands, the classification accuracy of GELM on average is 80.25%, almost 4% higher than 76.62%, the result of SVM. We also compare the average accuracies of each frequency bands and find that all the results of GELM are over 3% higher than SVM. All of these results indicate that GELM classifier outperforms SVM classifier, so that GELM is more suitable for EEG-based emotion recognition than SVM.

Secondly, we compare the classification accuracies of each frequency bands and find that the accuracies of Beta and Gamma bands are much higher than Alpha, Theta and Delta bands. In some cases, the results of 62 features on Beta or Gamma bands are even better than the results of 310 features on the whole five bands. This consequence intuitively reflects that high frequency oscillations are more associated with emotion processing [21].

Thirdly, also from Table I, we see that the emotion recognition performance varies from person to person and experiment to experiment. For the results of 310 features classified by GELM, the highest accuracy reaches to 96.89%, while the lowest accuracy is just 59.25%. Moreover, in some cases, there are also big difference among classification results of the same subject's three experiments. Previous researches and theories suggest that two personality dimensions, extroversion and neuroticism, differentially influence people's reaction to emotional stimuli [19] and the ability for emotion recognition [20]. In these studies, persons with passible and stable characters are thought to perform better in emotion recognition experiment than those with phlegmatic or volatile characters.

Table II is the average confusion matrix of classifying 310 DE features by GELM and linear-SVM. The row index represents the actual labels of testing samples and the column index represents the estimated labels. Values here show proportions that certain kinds of samples are estimated to be negative, neutral or positive. Examining the results of GELM, we can see that on average, only 60.63% of negative samples have been predicted accurately, while 85.63% of neutral samples and 93.07% of positive samples have been correctly estimated. The results are similar in SVM matrix. This observation suggests that the negative emotion is the most difficult to be predicted, and the neutral emotion is less difficult, the positive emotion is the easiest to be estimated. We can also find that 24.01% of negative samples are predicted to be neutral, 8.65% higher than the proportion that the negative ones are predicted to be positive. And also, the proportion that the neutral samples are predicted to be negative is 0.95% higher than that they are predicted to be positive. These results imply that the negative emotion and the neutral emotion share much more similar DE features, yet the positive emotion has relatively large differences from the other two emotional states.

2) Using training sets and testing sets from different experiments: We use data from one experiment to train a model, and data from another experiment to test it. We choose training sets and testing sets in two ways. One way is that these two sets are both from the same subject but different experiments, such as the 1st and the 2nd experiments of subject A. The other way is that we choose data of the highest performance as training set (which is the 1st experiment of D in this paper), and data from other 5 subjects as testing sets (such as the 1st experiment of subject E). The results are described in Table III measured in percentage, where the row index of the table represents the training set, and the column index of the table represents the testing set. The EEG features used here are 310 DE features smoothed by LDS. We used both GELM and SVM to classify these features.

Comparing the accuracies of these two classifiers in Table III as well, GELM performs much better than linear-SVM, which is just the same conclusion as we have drawn from Table I. Then, for the same subject, we compare the classification accuracies using training and testing sets from the same experiment, to the accuracies using training and testing sets from different experiments. The average accuracy using GELM of the former is 80.25%, while the average accuracy of the latter is 70.19%. The decline of average accuracy by about 10% is partly because environmental disturbances,

TABLE I. CLASSIFICATION ACCURACIES OF TWO CLASSIFIERS USING TRAINING AND TESTING SETS FROM THE SAME EXPERIMENT

Subject	Experiment	Classifier	Frequency Band					
			Delta (%)	Theta (%)	Alpha (%)	Beta (%)	Gamma (%)	Total[1] (%)
A	1	GELM	54.84	61.20	70.01	85.19	**86.64**	84.39
		SVM	49.93	60.26	65.17	**84.10**	81.50	82.59
	2	GELM	46.10	49.78	55.35	66.18	**75.07**	70.09
		SVM	37.57	49.35	54.41	65.46	67.27	**75.65**
	3	GELM	50.14	59.54	54.26	**66.26**	61.92	63.95
		SVM	46.75	58.31	48.13	57.15	59.54	**59.90**
B	1	GELM	58.09	63.44	82.73	88.08	**90.90**	89.45
		SVM	53.47	57.59	72.83	**90.17**	89.52	88.15
	2	GELM	51.30	58.89	65.10	**69.65**	69.22	69.15
		SVM	38.73	55.92	65.75	69.44	**70.66**	65.82
	3	GELM	54.55	58.82	71.32	**82.30**	77.75	79.48
		SVM	52.02	52.38	65.10	**78.97**	77.24	71.82
C	1	GELM	58.45	67.05	61.34	79.19	80.92	**82.37**
		SVM	50.79	69.44	61.13	**77.24**	76.37	76.52
	2	GELM	40.97	50.58	52.89	90.75	89.96	**92.99**
		SVM	35.77	49.57	50.43	90.03	89.45	**91.11**
	3	GELM	46.97	40.75	45.07	54.62	58.45	**67.85**
		SVM	44.73	43.93	49.21	58.60	59.18	**61.20**
D	1	GELM	78.61	84.90	88.01	**96.89**	96.60	96.68
		SVM	75.87	73.92	70.16	92.99	90.68	**96.68**
	2	GELM	58.96	61.34	85.33	95.30	**96.89**	**96.89**
		SVM	60.33	56.00	80.56	88.09	**91.98**	91.04
	3	GELM	62.72	60.91	90.10	**96.82**	95.74	96.53
		SVM	58.09	55.78	80.27	97.18	96.32	**97.25**
E	1	GELM	56.50	65.17	58.02	74.64	**80.35**	73.19
		SVM	58.89	66.47	46.89	67.12	**76.89**	70.01
	2	GELM	58.45	43.61	51.30	**74.35**	73.92	73.19
		SVM	55.85	40.25	34.39	53.90	**70.66**	60.19
	3	GELM	53.18	43.71	63.58	73.77	66.98	**74.57**
		SVM	48.70	40.10	60.69	63.08	63.29	**73.99**
F	1	GELM	72.25	59.47	64.74	80.20	**85.98**	84.32
		SVM	69.65	58.24	60.48	**73.19**	69.80	**73.19**
	2	GELM	40.25	49.21	57.08	57.88	57.08	**59.25**
		SVM	45.16	46.82	53.11	**59.25**	58.82	56.50
	3	GELM	57.73	64.38	69.15	91.18	**94.29**	90.10
		SVM	55.85	63.44	66.84	88.29	**93.86**	87.50
Average		GELM	55.56	57.93	65.85	79.07	79.93	**80.25**
		SVM	52.12	55.43	60.31	75.24	**76.84**	76.62
Standard Deviation		GELM	±9.60	±10.49	±13.34	±12.94	±13.24	±**11.92**
		SVM	±10.46	±9.46	±12.10	±14.00	±12.76	±13.12

[1] The condition "Total" means that data on all the five frequency bands are used to train and test together.

random noise signals, and the position of the EEG cap would not remain the same during different experiments. However, 70.19% is well above chance level which is only 33.33% in this experiment. It implies that the patterns of EEG changing with emotions among different passages of time are stable for the same subject, which has also been mentioned by Duan *et al.* before [14].

We investigate whether there are stable common patterns across subjects by choosing data set from one subject to train a model and data set from another subject to test this model. Here, we choose experiment D1 as training data set for its most stable performance among the total 18 experiments. The testing data sets are from the 15 experiments of the rest 5 subjects that are subject A, B, C, E, and F. Thus, the average accuracy of GELM using training and testing sets from different subjects' experiments is 62.20%, which is also well above chance level. This result implies that there are common patterns for EEG data changing with emotional states across subjects. However, since the average performance using training and testing sets from the same subject's different experiments reaches 70.19%, there must be some points differ from person to person which would reduce the stability and universality of the computational model. This should be studied in the further research.

TABLE II. AVERAGE CONFUSION MATRIX OF CLASSIFYING 310 DE FEATURES USING GELM AND SVM CLASSIFIERS

GELM	Negative (%)	Neutral (%)	Positive (%)
Negative	**60.63**±**29.23**	24.01±20.02	15.36±14.87
Neutral	7.66±12.08	**85.63**±**15.83**	6.71±7.95
Positive	3.93±6.26	3.00±3.88	**93.07**±**7.54**

SVM	Negative (%)	Neutral (%)	Positive (%)
Negative	**58.73**±**31.53**	24.16±22.28	17.11±15.91
Neutral	10.97±11.68	**79.17**±**16.24**	9.86±9.52
Positive	6.58±7.75	2.80±4.08	**90.62**±**10.15**

B. Feature selection

There are 310 DE features on the whole five frequency bands, which must contain some redundant information since the classification accuracies of features on Delta and Theta bands are much lower than other three bands. So we tried

TABLE III. CLASSIFICATION ACCURACIES OF TWO CLASSIFIERS USING TRAINING AND TESTING SETS FROM DIFFERENT EXPERIMENTS

Classifier	Train \ Test	A1*	A2	A3	Train \ Test	B1	B2	B3
GELM	A1	84.39	63.95	55.49	B1	89.45	61.56	77.67
SVM	A1	82.59	53.83	47.25	B1	88.15	37.21	61.05
GELM	A2	66.91	70.09	50.79	B2	72.90	69.15	73.70
SVM	A2	67.27	75.65	48.34	B2	51.95	65.82	64.52
GELM	A3	74.06	65.10	63.95	B3	69.65	65.46	79.48
SVM	A3	37.57	53.61	59.90	B3	68.42	52.24	71.82
GELM	D1	75.87	60.40	51.01	D1	67.27	49.21	59.47
SVM	D1	66.33	52.46	41.98	D1	49.71	58.02	57.66
Classifier	**Train \ Test**	**C1**	**C2**	**C3**	**Train \ Test**	**D1**	**D2**	**D3**
GELM	C1	82.37	89.02	67.05	D1	96.68	89.60	88.58
SVM	C1	76.52	82.88	67.63	D1	96.68	91.11	88.22
GELM	C2	67.77	92.99	74.71	D2	88.08	96.89	95.23
SVM	C2	55.92	91.11	61.71	D2	90.17	91.04	96.89
GELM	C3	75.29	80.42	67.85	D3	80.49	95.95	96.53
SVM	C3	76.52	75.29	61.20	D3	76.95	92.49	97.25
GELM	D1	65.82	71.75	73.41	D1	96.68	89.60	88.58
SVM	D1	58.89	57.15	53.76	D1	96.68	91.11	88.22
Classifier	**Train \ Test**	**E1**	**E2**	**E3**	**Train \ Test**	**F1**	**F2**	**F3**
GELM	E1	73.19	66.69	53.11	F1	84.32	42.34	59.54
SVM	E1	70.01	58.31	57.15	F1	73.19	44.65	51.45
GELM	E2	68.28	73.19	51.08	F2	77.60	59.25	64.38
SVM	E2	54.99	60.19	45.09	F2	59.03	56.50	44.51
GELM	E3	62.43	58.16	74.57	F3	74.35	59.47	90.10
SVM	E3	47.69	47.69	73.99	F3	60.69	58.89	87.50
GELM	D1	61.20	52.96	60.84	D1	52.82	59.25	71.75
SVM	D1	58.67	40.03	46.03	D1	48.19	48.98	70.89
Classifier	**Ave. / Train \ Test**	**1**	**2**	**3**	**Std. / Train \ Test**	**1**	**2**	**3**
GELM	1	85.07	68.86	66.91	1	±7.79	±18.01	±13.86
SVM	1	81.19	61.33	62.13	1	±10.01	±21.34	±14.65
GELM	2	73.59	76.93	68.32	2	±8.16	±14.77	±16.82
SVM	2	63.22	73.39	60.18	2	±14.20	±15.15	±19.91
GELM	3	72.71	70.76	78.75	3	±6.11	±14.66	±12.66
SVM	3	61.31	63.37	75.28	3	±15.97	±17.18	±14.70
GELM	D1	64.60	58.71	63.30	D1	±8.46	± 8.61	±9.29
SVM	D1	56.36	51.33	54.06	D1	±7.45	±7.30	±11.26

* The experiment “A1” means the first experiment of subject A, and so on.

minimal-redundancy-maximal-relevance (MRMR) algorithm to select the effective features. Figure 4 demonstrates the performance of MRMR algorithm in feature selection. Each curve in the figure represents the average accuracies of the single subject’s three experiments. The training and testing data are from the same experiment and classified by the GELM. As the feature dimension is reduced from 310 to 40, the accuracies of these four subjects are generally staying stable with a very slight decline. But building a simpler model using 40 features is considerably faster than building a model using 310 features.

Besides MRMR approach, we also use correlation coefficients to find subject-independent features relevant to emotional states. These features are of highest correlation coefficients’ values and remain the same among different subjects. Figure 5 shows each subject’s average classification accuracy using subject-independent features. It is obvious that the results of top 10 features and the results of top 100 features remain almost the same. The top 20 subject-independent features are from FT7, FC4, FC6, FT8, T7, C5, T8, TP7, P7, PO8 of Beta band and FT7, FC6, FT8, T7, C5, TP7, CP5, TP8, P7, P8 of Gamma band. Figure 6 shows the positions of these subject-independent features. The regions of these two bands are almost overlap, which are called left temporal lobe and right temporal lobe biologically. The average classification accuracy of these 20 features using GELM is 76.89%, about 3.5% less than the result of 310 features. This result implies that EEG acquisition equipment for emotion recognition doesn’t need as many channels as 62. Fewer channels of EEG signals in left and right temporal lobes will also do good jobs.

Furthermore, comparing the results in Figure 4 and Figure 5, we find that when the feature dimension is below 100, the accuracies of features selected by correlation coefficients are higher than those selected by MRMR algorithm. It suggests that MRMR algorithm be less suitable for feature selection than computing correlation coefficients. This is partly because the MRMR algorithm removes features containing analogous information, but the most relevant features are in small fixed regions so that they share similar patterns. Under this circumstance, some effective features would be excluded by MRMR algorithm.

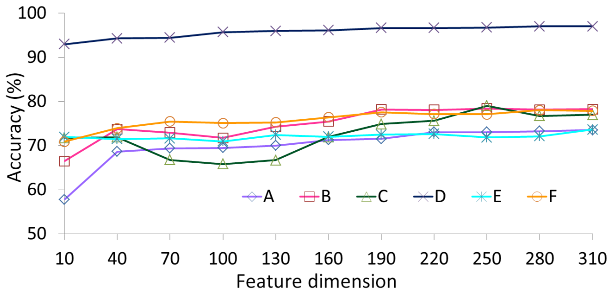


Fig. 4. Average classification accuracies of different feature dimensions for each subject using MRMR method.

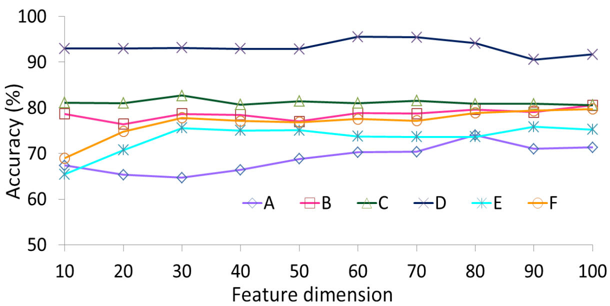
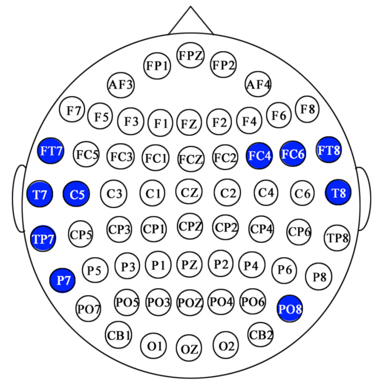
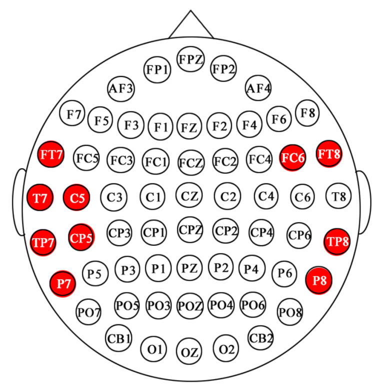


Fig. 5. Average classification accuracies of subject-independent features for each subject.



(a) Beta band



(b) Gamma band

Fig. 6. Distribution of the top 20 subject-independent features.

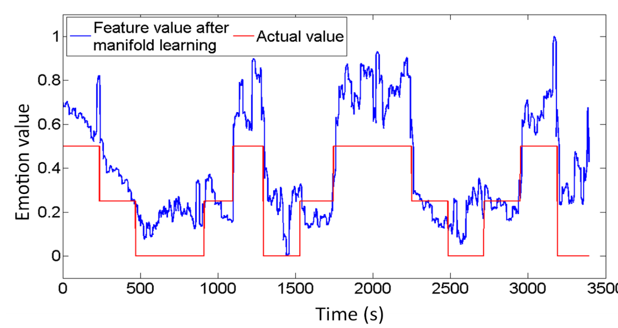


Fig. 7. The trajectory of emotion changes during the experiment 1 from subject D.

C. Manifold learning

From above, we finally reduce the feature dimension to 20. However, it is also unintuitive for us to find the relationship between the feature values and the emotional states. In order to visualize the trajectory of emotion changes with time, we try to put the top 20 subject-independent features into a manifold model so as to get one-dimension emotion values during the whole experiment, which is showed in Figure 7. A series of actual labels of the stimuli is also showed in this figure, where 0.5 represents positive emotion, 0.25 represents neutral emotion, and 0 represents negative emotion. It is implied that the value of positive emotion remains higher, while the value of neutral emotion becomes lower, and the value of negative emotion stays the lowest. We can also find that there are obvious step signals between the positive emotion and the other two kinds of emotions, These steps are coherent with the changes of actual labels entirely. On the contrary, the emotion values of neutral and negative states do not have such big difference. This result is consistent with the confusion matrix in Table II, which may be the reason why positive emotions can be classified most accurately, while neutral emotions and negative emotions are more easily confused with each other.

V. Conclusions and Future Work

In this paper, we tried to classify the three emotional states (positive, neutral and negative) using EEG signals collected during watching movies. A new classifier named discriminative graph regularized extreme learning machine (GELM) was introduced in this study to classify differential entropy (DE) features extracted from multichannel EEG data and smoothed by linear dynamical systems (LDS). According to the results, GELM classifier had a much better performance than linear SVM. We also calculated the average confusion matrix of classifying 310 differential entropy (DE) features using GELM and SVM, and found that the accuracy for classifying positive emotions was the highest, the accuracy for neutral emotions was lower and the accuracy for negative emotion was the lowest. We chose training set and testing set not only from the same experiment, but also from different experiments of different subjects. It was indicated that the relationship between emotional states and EEG signals remained stable among different experiments and different persons. In addition, minimal-redundancy-maximal-relevance (MRMR) algorithm and correlation coefficients were examined to select effective features and we got 20 subject-independent features which were most relevant to emotion changes. Mapping these features to the cerebral cortices and frequency bands, it was implied that EEG signals related to emotional states during watching movies were usually on Gamma band and Beta band, produced by left temporal lobe and right temporal lobe. Finally, manifold learning was used to visualize the changes of emotion values with time.

However, this study deserves more comprehensive and thorough researches. The three emotional states (positive, neutral and negative) seem to be too simple to express human's emotions. The number, age group, and nationality of subjects are also restricted in this paper. Furthermore, the stimuli used in experiments are only made up of one single series of movie clips. Thus, for our future work, it is quite essential to confirm the conclusions of this study in more complex situations to make them more convincing. Since there is no generally accepted theoretic foundation to explain the relationships between brain activities and emotional states, it is still an enormous challenge to find and prove these relationships.

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