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Anxious Mood Recognition Based on Electroencephalogram Pattern Recognition

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***Abstract*—This work recruited college students with anxious or non-anxious moods as subjects and collected their electroencephalogram (EEG) data. The scores of Generalized Anxiety Disorder scale (GAD) and Beck Anxiety Inventory (BAI) were applied to divide the subjects into the anxious group and non-anxious group. Then, EEG features were extracted and statistically tested, in order to find the the EEG parameters most related to anxious mood. We applied backward feature selection and classifier training to construct an EEG pattern recognition model of anxious mood. The results showed that anxious and non-anxious moods were distinguished with a test accuracy of 86.67% and a subject-independent validation accuracy of 63.04% by using delta-band power and alpha-band power of the FT7 channel.**

Keywords*—*anxious mood, EEG, pattern recognition, emotion recognition, physiological features

I. Introduction

Anxious mood is a kind of restless experience combined with continuous stress response without clear stimulation event. Individuals under stress state have excessive sympathetic activation and weak parasympathetic activity, and the two branches of the autonomic nervous system are in an unbalanced state [1]. Long-term continuous stress will seriously damage the normal functions of nervous, immune and endocrine systems [2]. People with anxious mood are also accompanied by certain behavioral withdrawal and cognitive impairment in stimulus evaluation, leading to excessive worrying [3,4]. Persistent anxious mood has the risk of becoming anxiety disorder. For people with anxiety disorder, they not only have pathologically lasted excessive worry and restless introspection experience, but also persist with the disorders of the nervous, immune and endocrine systems, which may cause other comorbidities, such as depression and sleep disorder [5]. Therefore, in order to reduce the risk of anxiety developing into anxiety disorder, detection and early warning of anxious mood is of great significance for the proactive regulation and timely intervention of anxiety.

The existing anxiety detection methods use Electrocardiograph (ECG), Electroencephalography (EEG), galvanic skin response and other physiological signals to identify anxiety [6-14], indicating that the physiological changes caused by anxiety can be measured by the physiological signals. However, these studies have applied specific task to induce transient anxiety state of certain age groups and used physiological data classification to distinguish different levels of anxiety. Task-induced transient anxiety is common and normal part of most people, and an appropriate level of anxiety can also promote task performance [4]. Therefore, if the aim is to promote individual health, identifying anxious mood is better than detecting task-induced anxiety states.

This work collected the EEG signals of two groups of people who were respectively in anxious and non-anxious moods and compared their neurophysiological responses under the same tasks. Besides, we constructed a recognition model of anxious mood by using low-dimensional EEG features.

II. Methods

A. Experimental Design

We selected subjects with Generalized Anxiety Disorder scale (GAD) [15] score greater than or equal to 10 points and Beck Anxiety Inventory (BAI) [16] score greater than or equal to 41 points as the experimental group (anxious mood group), and subjects with GAD score less than or equal to 4 points and BAI score less than or equal to 30 points were put in the control group (non-anxious mood group). A total of 125 subjects were recruited to participate in the experiment. The experiment required the subjects to open their eyes to recall yesterday's weather and then close their eyes to recall yesterday' dress color in a quiet environment. Each recall lasted 20 seconds, with a 20-second countdown reminder on the screen when recalling with eyes open, and an alarm clock to remind subjects to open their eyes when recalling with eyes closed. The subjects' EEG data were recorded at 1000 Hz throughout the recall process.

The conceptual framework of the experimental design is shown in Fig. 1 below.

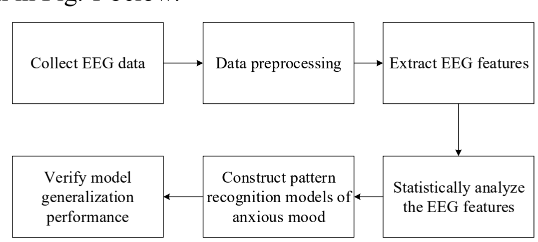

Fig. 1. Conceptual framework.

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B. EEG Data Preprocessing

The 64 EEG data channels were located according to the International 10-20 standard EEG positioning system. First, the EEG data were filtered by a band-pass filter of 0.5-60 Hz and a band-stop filter of 49-51 Hz. Then, the whole brain average potential was used for re-reference. In order to remove the interference caused by artifacts such as eye blinks, we used independent component analysis methods to manually remove artifact interference in the EEG data. Finally, we segmented the EEG data with eyes open as one part of a sample and those with eyes closed as the other part of a sample. After excluding data records with heavy noise, 106 EEG data samples were obtained, including 58 data records in the experimental group and 48 data records in the control group.

C. Feature Extraction

Although anxious mood tends to develop into anxiety disorders, it is difficult to directly observe the EEG differences between anxious and non-anxious mood with the naked eyes. Therefore, we extracted EEG parameters to measure the differences.

We extracted the average energy of EEG and its powers in five sub-bands called Delta, Theta, Alpha, Beta and Gamma as features. The detailed description of the features is shown in the Table 1.

For the raw EEG, 61-channel EEG data were obtained after removing two eyes channels and one reference channel. We extracted 6 features from each channel, and a total of 366 (61 $\times$6) EEG features were extracted for each part of a sample.

TABLE I. EEG FEATURE DESCRIPTION

ID	Feature	Description	Correlates with the central nervous system
1	AE	average energy	Time-domain measure of brain activity [10].
2	Delta	Power of 0.5-4 Hz	Frequency-domain measures of brain activity [17].
3	Theta	Power of 4-8 Hz	
4	Alpha	Power of 8-13 Hz	
5	Beta	Power of 13-30 Hz	
6	Gamma	Power of 30-60 Hz	

D. Feature Selection and Model Construction

Mann Whitney U test was performed to reveal the inter-group EEG difference between anxious mood and non-anxious mood groups. We found that there were three EEG features with eyes open and 18 EEG features with eyes closed that had significant inter-group difference, as shown in Table 2. We put the above-mentioned 18 EEG features with eyes closed into the initial features set, and then further decreased the dimension of the feature space to avoid overfitting of the mood recognition model. As to the dimension reduction of the feature space, we applied the sequential backward selection method to find the EEG feature subset most related to anxious mood recognition.

In each iteration of the backward feature selection, one feature were eliminated from the feature subset, so that the evaluation function value of the selected feature subset was the best among the feature subsets with the same dimension. The accuracy defined in equation (1) was used as the evaluation function of the feature subsets.

$$\text{Accuracy}=(TP+TN)/(TP+TN+FP+FN) \tag{1}$$

Where *TP, TN, FP* and *FN* respectively represented the number of true positive, true negative, false positive and false negative samples in the test or validation process. For 106 data samples, we selected 60 (30 from experimental group and 30 from control group) data samples for model training and test, and the remained 46 data samples were used to verify the generalization performance of the model. We trained four traditional classifiers, i.e. support vector machine with radial basis function (SVM-R), support vector machine with polynomial kernel (SVM-Q), k-nearest neighbor (KNN) and decision tree (DT), and we used the leave-one-subject-out (LOSO) method to test the performance of the classifiers. In each iteration of the LOSO test, one subject's data were used for classifier test, and the remained 59 subjects' data were used for classifier training. The training and test repeated until the 60 subjects' data were tested in turn.

TABLE II. INITIAL EEG FEATURE SET HAVING SIGNIFICANT INTER-GROUP DIFFERENCE

status	ID	X channel-Feature name	Sample number	Value (mean (std))	P
Eyes closed	1	FC4-mean energy	30 30	56.888 (28.297) 48.028 (39.316)	0.046
	2	Fz-delta	30 30	12.9713 (7.482) 9.338 (5.294)	0.029
	3	FC5-delta	30 30	15.870 (11.135) 9.608 (8.122)	0.008
	4	FT7-delta	30 30	23.439 (20.083) 16.377 (16.369)	0.018
	5	C5-delta	30 30	12.856 (8.479) 13.276 (33.776)	0.007
	6	FC6-delta	30 30	15.844 (12.016) 10.135 (8.627)	0.023
	7	C6-delta	30 30	11.364 (9.312) 7.006 (5.284)	0.023
	8	FC5-theta	30 30	4.255 (2.449) 2.909 (1.427)	0.014
	9	C5-theta	30 30	3.662 (2.104) 2.796 (1.601)	0.037
	10	F6-theta	30 30	5.616 (3.951) 3.981 (2.893)	0.044
	11	O2-theta	30 30	7.432 (5.273) 4.861 (4.372)	0.018
	12	FT7-alpha	30 30	14.864 (12.906) 7.794 (5.852)	0.021
	13	Cz-alpha	30 30	19.280 (18.101) 11.636 (13.993)	0.044
	14	TP9-alpha	30 30	21.267 (15.933) 13.790 (11.435)	0.049
	15	CPz-alpha	30 30	23.337 (23.012) 12.155 (19.433)	0.041
	16	TP8-alpha	30 30	19.016 (18.308) 11.003 (11.826)	0.049
	17	O2-alpha	30 30	40.685 (39.777) 23.108 (23.390)	0.048
	18	F3-beta	30 30	7.560 (4.894) 10.106 (7.187)	0.044

Eyes open	1	O2-theta	30	6.212 (3.623)	0.023
			30	4.628 (3.442)	
	2	F3-gamma	30	3.923 (2.873)	0.041
			30	5.759 (4.283)	
	3	P5-gamma	30	5.160 (4.326)	0.040
			30	6.212 (3.623)	

III. RESULTS

The LOSO-test and validation accuracies of the classifiers by using feature subsets with 1-18 dimensions obtained in each iteration of the feature selection process are shown in Fig. 2. We can see that the decision tree classifier has obtained the highest LOSO-test accuracy (86.67%) and a validation accuracy (63.04%) much higher than the accuracy of random guess, i.e. 50% guess accuracy for binary classification problems. The two-dimensional feature subset corresponding to the above LOSO-test and validation accuracies included the the delta-band power and alpha-band power of FT7 channel, and we show the scatter plots of the training and test samples in the feature plane of these two features in Fig. 3.

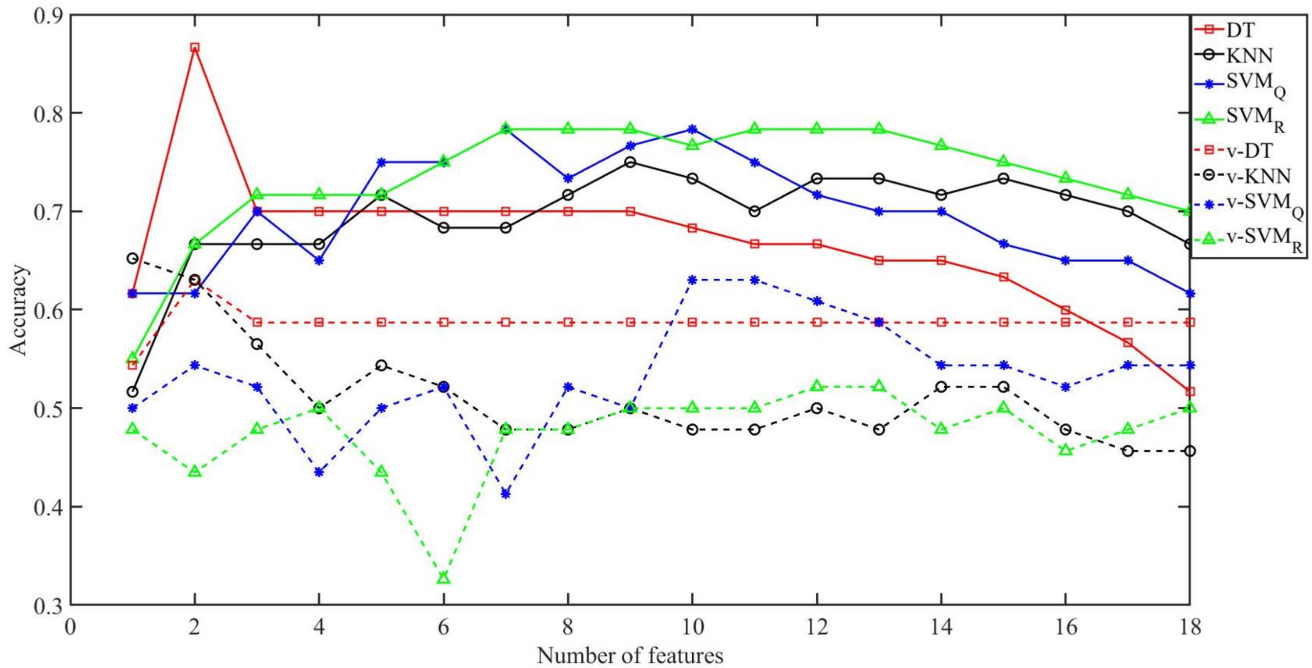

Fig. 2. Accuracies of the classifiers in the LOSO-test and validation processes with 18-dimensional initial feature set. The solid lines show the LOSO test accuracies, and the dashed lines show the validation accuracies.

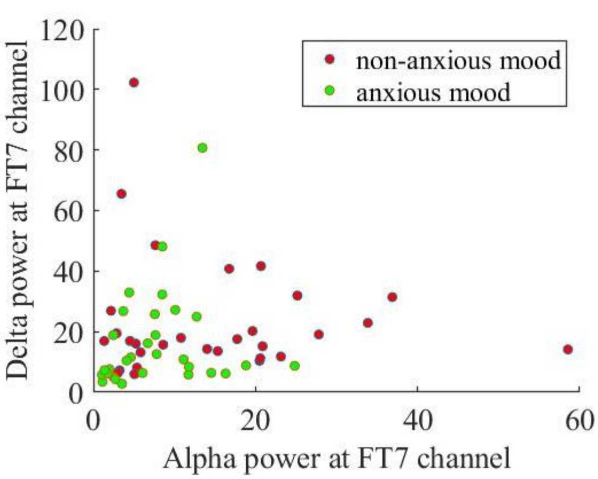

Fig. 3. Scatter plots of training and test samples.

We also tried to put the 3 EEG features with eyes open into the initial feature set and repeated the feature selection and classifier training process, and the results are shown in Fig. 4. However, the 21-dimensional initial feature set did not provide performance increase of the model, and the best validation and corresponding LOSO-test accuracies were respectively 58.7% and 76.67%, with 8-dimensional EEG feature subset.

IV. CONCLUSION

We applied EEG signals of subjects with eyes closed to construct recognition model of anxious mood. The best model contained the decision tree classifier trained by 59 EEG samples described as the data vector of delta-band power and alpha-band power of the FT7 channel. The model had a subject-independent generalization performance much higher than random guess.

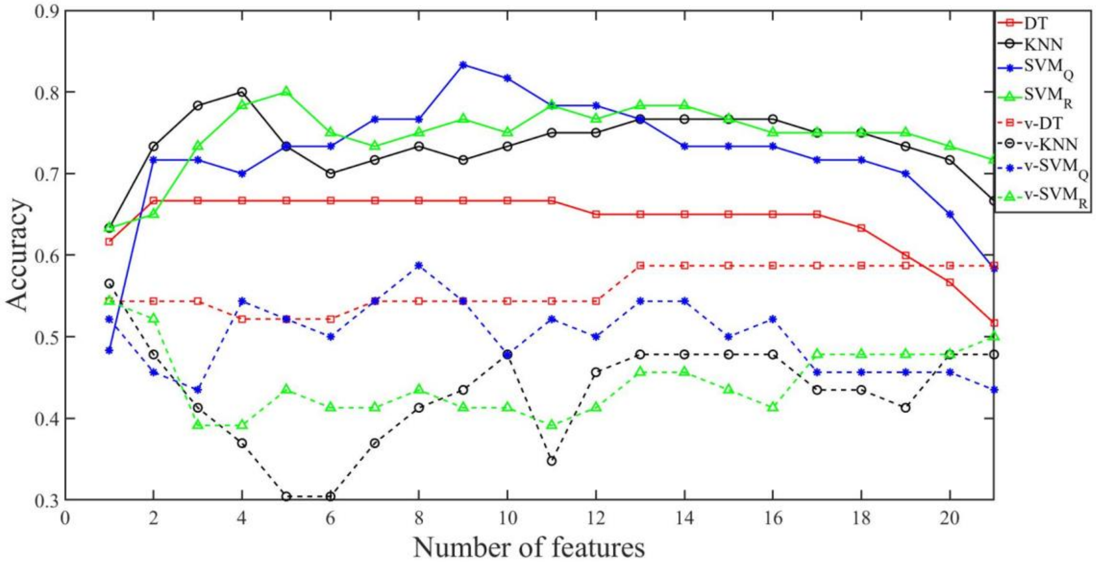

Fig. 4. Accuracies of the classifiers in the LOSO-test and validation processes with 21-dimensional initial feature set. The solid lines show the LOSO test accuracies, and the dashed lines show the validation accuracies.

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