Impulsion Assessment and Classification Based on EEG Features

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***Abstract*—The study describes a system which integrates EEG power spectrum, power spectrum density (PSD), sample entropy and other features in the β frequency band to evaluate, predict and verdict in an emotion classifier. The system proposed an accurate classification method based on EEG spectrum imported into SVM classifier for β wave. In the experiment, the EEG data of subjects in resting state, mild impulsive environment and high impulsive environment were extracted. From the variance analysis results, there was no significant difference in the β power spectral density between the resting state and the mild pulse environment ($p = 0.089$), but the β power spectral density changed significantly in the mild impulsive environment and the high impulsive environment ($p < 0.001$). The significant difference in the power spectrum of the β band under the two different states was successfully given, which has guiding significance. After power spectrum transformation, Support Vector Machine (SVM) classifier is used for classification. Our classifier showed an average accuracy of 88.46%.**

Keywords—classifier, EEG power spectrum, β band, impulsive state, feature selection

I. INTRODUCTION

Long-term self-control is considered to be difficult to achieve, and it is traditionally believed that the key to self-control is the human brain [1]. We all have impulsive emotions, which causes long-term self-control actions difficult to achieve. Impulse is considered to be a psychological phenomenon of intense emotion and weak rational control. When we make choices under impulse, although there is no evidence that this kind of impulse decision-making behavior will inevitably lead to negative consequences, our rich experience in life tells us that most of the decisions made under impulse will bring us unnecessary trouble (economic overhead or bear other bad consequences). According to medical research, severe uncontrolled impulsive behavior is also a subclass of Parkinson 's disease [2], which called ' Impulsive Control Disorder ' that was first defined by Esquirol in 1838 as 'kleptomania'. Continuous, severe uncontrolled impulses can be a major health threat that can generate the diseases.

Since brain is the center where our emotions are originated, so the brain activity recorded by EEG is considered to be an effective way to quantify individual impulses. For experimental purposes, we use the error-prone calculation method to induce the subjects' impulses. When the subjects see a formula like ' 39 + 23 = 52 ', it is very difficult for them to select seemingly simple answers calmly due to time constraints. The subjects will not be controlled by the answers they are thinking in their brains and make ' correct ' or ' wrong ' choices, but by changing the length of the answer time. We can get EEG records of subjects with different impulse levels.

Using fast Fourier transform (FFT) we can get the spectrum and power spectrum of EEG signals. Through the analysis of variance of power spectral density in different frequency bands, we can get that the characteristics of individuals in different degrees of impulsive behavior are obviously different. Similarly, we can also find significant differences by analyzing the sample entropy of each degree. In the reported literature, R.K. Sinha have successfully confirmed that the artificial neural network can effectively identify the EEG power spectrum of sleep-wake state in rats with depression [3]. In the Rakesh's experiment [4], with the help of non-invasive measurement indicators, the EEG power spectrum was input into the artificial neural network to accurately evaluate the thermal stress of the brain. Few of the existing experiments use power spectrum to evaluate impulse. Therefore, this experiment plans to study whether the neural network can detect the changes of EEG power spectrum under different states of individual impulse. By training the neural network for the power spectrum, we can get higher accuracy classification results.

The rest of the paper is organized as follows: Section II is a detailed description of our experiment. Section III discusses the analysis method of feature extraction of EEG signals and the relationship between frequency spectrum and subjects' impulsive emotions. Analysis method and result description of power spectrum trained by SVM classifier are presented in Section IV and Section V concludes the paper.

II. MATERIALS AND METHODS

A. Participants and Data Acquisition

Ten healthy men and ten women participated in the experiment. All participants have similar educational and intelligence level age distribution between 15-25 years old, no history of heart disease, they were told to prohibit drinking, smoking, drinking coffee before the experiment may affect the behavior of brain activity. And before the experiment started, they were told to focus and minimize head and other muscle activity.

The device consists of 19 active electrodes, all of which were placed in the scalp of subjects in accordance with the international standard 10 / 20 EEG system. The sampling rate of EEG was set to 512 Hz, and the impedance was set to 5kΩ: the purpose was to reduce the noise caused by sudden changes in the environment during data recording.

B. Experiments of Inducing Pulse

Th This project is an emotion-induced experiment using E-prime. E-prime provides us with detailed time information and event details, which can help us understand the time problem of actual experiment operation [5]. Our experimental process is to 'error-prone' some double-digit additions and subtractions problems up to 100. 'Error-prone' process is assumed that we have known such equations as '34+28=62' and '49+15=64' are correct, and we input '34+28=52' or '49+15=55' (Fig. 1) into our question bank, and randomly select questions from our designed question bank for the participants to do.

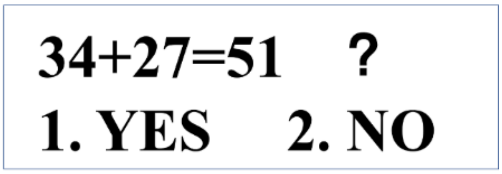

Fig. 1. We prepared 200 error-prone addition questions in advance and stored them in our database. Then we randomly shuffled them and presented them to participants through the program E-Prime, which required them to press a button within a specified time to select, and E-Prime recorded their time and accuracy

The participants will be required to use the keyboard to make correct or wrong choices within a specified time. The difficulty depends on our setting of the answer time. We set the medium difficulty as the answer time of 2s, and the advanced difficulty as 1s. The design of the overall experimental process is shown in the Fig. 2. Before setting up the experiment, about ten volunteers participated in the setting of our difficulty. The results showed that the average correct rate of the respondents was about 76.83 % after the completion of the moderately difficult questions, while only 49.67 % after the completion of the high-level difficult questions. The volunteers fed back that they could not help but make some choices in the process of doing these arithmetic questions, which was in line with our expectations for the subjects in the experiment.

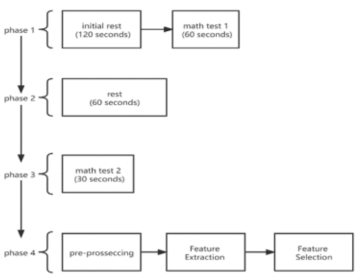

Fig. 2. Experiment sequence and the data acquisition progress

C. Selection of Electrode

We choose electrodes in strict accordance with international 10/20 EEG system. Therefore, we select Fp1, Fp2, O1, O2, T4 and T5 electrodes for data processing, where Cz was used as reference sensor.

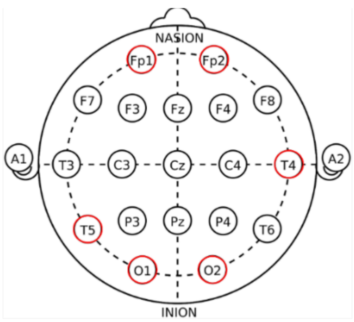

Fig. 3. EEG Electrode scheme

We know that β wave is a kind of fast low-amplitude brain wave that occurs in a large number of individuals when they are focused or emotionally stressed, and it exists in the temporal lobe and frontal lobe of the human brain. In the following paper, we will explain in detail why we choose where β wave dense potential.

III. Methods

A. Feature Prosessing

We first pre-processed the sampled 19-channel EEG signals by extracting them from 0.5 Hz to 50 Hz frequency by band-pass filter, and then removed the 50 Hz power frequency interference. The data size was reduced and the subsequent data processing was simplified by down-sample to 256Hz after baseline calibration. Independent component analysis (ICA) was an important signal analysis method that separates multivariate signals into additive sub-components. After the processed signals were passed through ICA, we removed artifacts such as electrocardiogram.

B. Time-Frequency Domain Analysis

The preprocessed electrode signals of Fp1, Fp2, O1, O2, T4, T5 channels were filtered by the self-designed Butterworth filter to obtain the EEG images of each frequency band of 0.5hz-4hz, 4hz-8hz, 8hz-14hz and 14hz-30hz respectively. Then, the spectrum of each frequency band was obtained by fast Fourier transform with Hamming window, and the overlap is 50 %. The length of FFT was set to 1280, which means that we segment the time domain data every 5s for feature processing. We can get the data of 45s resting state, 90s mild impulse state and 60s high impulse state in each sample after segmentation.

The average power was computed by this formula:

$$P=\frac{1}{T}\int_{-\frac{T}{2}}^{\frac{T}{2}} f^2(t)dt \tag{1}$$

By FFT we can get the power spectrum function of a specified signal:

$$P=\int_{-\infty}^{+\infty}\lim_{T\to+\infty}\frac{|F_T(\omega)|^2}{2\pi T}d\omega \tag{2}$$

Then the PSD can be computed as:

$$S_x(w)=\lim_{T\to+\infty}\frac{1}{2T}E[|F_T(w)|^2] \tag{3}$$

It should be noted that the power spectral density here is the average power spectral density value obtained from the six electrodes of our participants.

C. Sample Entropy

For the time series EEG $x(i)$ of the subjects, we used a new matrix X to reconstruct the phase space of $x(i)$, and then obtained:

$$X=\begin{bmatrix} X(1) \\ X(2) \\ \cdot \\ \cdot \\ \cdot \\ X(w) \end{bmatrix}=\begin{bmatrix} x(1) & x(2)\ldots x[1+(m-1)] \\ x(2) & x(3)\ldots x[2+(m-1)] \\ & \ldots \\ x(w) & x(w+1)\ldots x[w+(m-1)] \end{bmatrix} \quad (1\le w\le N-m+1) \tag{4}$$

$d[X_m(i),X_m(j)]$ was denoted as the absolute value of the maximum difference between the corresponding elements in the two arrays, then:

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$$d[X_m(i),X_m(j)]=\max\max_{k=0,1,\ldots,m-1}(|x(i+k)-x(j+k)|) \quad (5)$$

B_i was calculated as the number of distances less than or equal to r between $X_m(i)$ and $X_m(j)$, and the similar tolerance threshold is denoted as r. We took r = 0.25D, and D is the standard deviation of $x(i)$

$$B_i^m(r)=\frac{1}{N-m}B_i \quad (6)$$

The average value of $B_i^m(r)$ is:

$$B^m(r)=\frac{1}{N-m-1}\sum_{i=1}^{N-m-1}B_i^m(r) \quad (7)$$

Let $m = m + 1$, repeat the above steps to get $B^{m+1}(r)$. The sample entropy of the time series is:

$$\text{SampEn}=\lim_{N\to\infty}\left\{-\ln\left[\frac{B^{m+1}(r)}{B^m(r)}\right]\right\} \quad (8)$$

Chen's research has shown that some oscillations of β band are related to the evaluation of some negative emotions [6], and the sample entropy of β band reflects its complexity in individuals. So it can be selected as an evaluation basis. In our experiment, we can get their average sample entropy by calculating the filtered β band signals in six electrodes in three states. We can get the average sample entropy of β band in six electrodes in the resting state is 0.5742, and the average sample entropy of mild impulse state is 0.5907, and the average sample entropy of high impulse state is 0.6126.

The box plots are presented in Fig. 4. The + indicates an outlier, and the red line within the box represents the median value. From the shape of the box, the difference in the characteristics of the data is not particularly large, and the level of the red line position directly shows the level of the sample entropy in different environments. In impulsive environments, the value of sample entropy is higher, and the overall box for highly impulsive environments is slightly higher than the medium. In these two impulsive environments, the median is relatively located in the center of the distribution, indicating that β band is a good candidate to be used in our project.

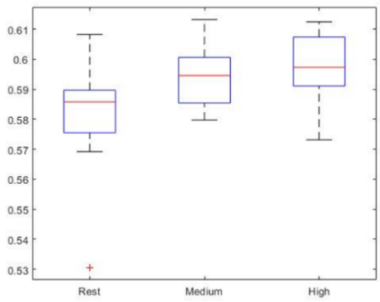

Fig. 4. Box plots of sample entropy of β

D. *Posts Hoc Tests in ANOVA*

Before the t-test, the power spectral density values of β band of the three groups of subjects were analyzed by one-way ANOVA. Table I shows our result.

TABLE I. HOMOGENEITY TEST OF VARIANCES

	Levene test	**Degree of freedom 1**	**Degree of freedom 2**	**p value**
Based on Average	0.366	2	21	0.698
Based on Median	0.263	2	21	0.771
Adjusted degrees of freedom based on median	0.263	2	18.872	0.771
Average based on cut	0.366	2	21	0.698

Through the least significant difference (LSD) method, we can obtain that whether based on the average or median, the significant difference is greater than 0.05, indicating that the results of variance analysis are homogeneous, and our variance analysis is statistically significant. In the one-way analysis of variance table, through the F test, we can see that the significant difference is 0.000< 0.05, indicating that there are at least two significant differences in the three states. In our experiment, that is, different impulse states have an impact on the power spectral density of β band. Table II shows the ANOVA results.

TABLE II. ANOVA RESULTS

	Quadretic sum	**Mean Square**	**F**	**p value**
Groups	4570.719	2285.360	137.820	0.000
Interclass	348.227	16.582		

After the homogeneity of variance is tested, the data are subjected to multiple comparisons. The asterisk indicates that the mean difference of this group is significant. In the 95 % confidence interval, we can see that four groups of data are marked with the asterisk, and only two groups are unmarked. These two groups are the comparison between the resting state and the mild impulse state, and the comparison between their respective states shows a significant mean difference. In addition, we can also see the difference in the power spectral density of the three states through the mean Fig. 5.

TABLE III. POSTS HOC TESTS

KEY (I)	**Component(J)**	**Mean Difference(I-J)**	**Standard Error**	**p value**	**95% upper and lower confidence limits**	
R	M	-3.2929	2.0361	0.121	-7.5272	0.9413
	H	-30.7819*	2.0361	<0.01	-35.0163	-26.5477
M	R	3.2929	2.0361	0.121	-0.9413	7.5272
	H	-27.4890*	2.0361	<0.01	-31.7233	-23.2548
H	R	30.7819*	2.0361	<0.01	26.5477	35.0162
	M	27.4890*	2.0361	<0.01	23.2548	31.7233

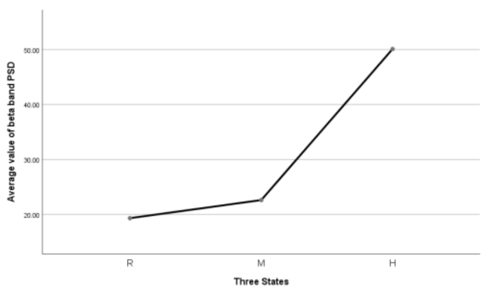

Fig . 5. Mean Figure

E. Feature Selection using T-test

Here we conducted paired sample t-test between the resting state and the power spectral density of β wave in mild and high impulsive environments respectively. Before the t-test, we ensured that our data follows a Gaussian distribution. The results were shown in the Table IV. Here resting state is denoted as R, mild impulsive environment is denoted as M while the last state denoted as H.

TABLE IV. STATISTICS ANALYSIS OF THE COMPARISON BETWEEN EACH TWO DIFFERENT STATES

Paired Index	Average Value	MSE	t value	p value
R-M	-3.292	1.678	-1.974	0.089
R-H	-30.784	2.117	-13.595	<0.001
M-H	-27.491	2.635	-9.467	<0.001

For the t-test, the degree of freedom is 7. Obviously, the power spectral density of β wave in the mild impulsive environment and the resting state was not statistically significant ($p = 0.089$) at the confidence level of 0.05, indicating that within 2s of the answer time, the subjects had sufficient time to complete the thinking of the problem and to answer relatively calmly. However, when we compare the power spectral density value of β wave of the in the high impulsive environment and in the resting state, we find that the data obtained in this comparison are statistically significant ($p < 0.001$). Similarly, we also draw the same conclusion after comparing the data obtained in the emotional impulsive environment and the highly impulsive environment, which indicates that the subjects may face the situation of fuzzy conclusion or incomplete conclusion in the brain due to the limitation of objective time (1s) that they are forced to make subjective choices without sure whether their choices are correct or not. The impulse response behavior induced in this case is of great reference value for our experiment. The results of t-test also show that the data obtained in this case are statistically significant.

IV. CLASSIFICATION

The previous process above showed that β waves represented obvious characteristics in individuals during mild impulsive environments and high impulsive environments. Thus, EEG generated in other environments can be fed into classifiers to be distinguished. We conducted a series of experiments using Supporting Vector Machine (SVM), Radial Basis Function (RBF) and Extreme Learning Machine (ELM) classifiers to test and verify the proposed model. These classifiers are used to test the classification accuracy of six electrodes of β band average power spectrum.

A. SVM

In SVM, data items are placed in an n-dimensional space to find the optimal hyper-plane. SVM is an efficient classifier. Many people have been widely used in the classification of stress and other emotions based on EEG [7,8] for its efficiency. An SVM selects a hyper-plane, which separates the data features in the best way according to the labels provided. In the process of cross-validation, the original data were divided into k=101 groups, including 1 group of validation set and k-1 group of training set, and k models were obtained after training respectively. The average classification accuracy rate of the final validation set of k models was taken as the final accuracy rate of the classifier. SVM uses iterative training algorithms to minimize error functions, and we use kernel function with complexity constant 1. When selecting the optimal hyperplane, we define the penalty coefficient as c, whose value can determine the severity of the hyperplane, and the value of the gamma parameter g affects the number of support vectors. By constantly adjusting the parameters, we determine that the system has high accuracy and high robustness when $c = 0.758$ and $g = 0.02$.

B. RBF

The optimal approximation and global optimality of RBF make it widely used in nonlinear time series prediction. RBF network uses Gaussian kernel function to transform low-dimensional input data into high-dimensional space, and the output is obtained by weighted summation of hidden layer units. RBF network has very fast convergence speed and good classification ability, so it has been used in the classification of EEG [9]. We set the spread value of the RBF to 5 according to our massive tests to avoid the output value of the activation function becoming large under the condition of ensuring accuracy.

C. ELM

ELM is a Single-hidden Layer Feedforward Networks (SLFNs) which randomly all the hidden nodes parameters of generalized SLFNs and analytically determines the output weights of SLFNs. All hidden nodes are independent of the objective function and the training data set. Compared with other neural networks, the iterative parameter adjustment process is omitted, and the network tends to obtain good generalization performance at a very fast speed [10]. In the classification experiment of impulsive emotion, we choose sigmoid function as the transfer function of ELM classifier.

D. Evaluation of Classifier Performance

The performance indexes of the classifier are Precision, Recall and F1 Score. It is often used as a classifier performance evaluation index in some multi-classification problem artificial intelligence competitions. It is the harmonic mean of accuracy rate and recall rate, defined as:

$$F1=2\times\frac{\text{precision}\times\text{recall}}{\text{precision}+\text{recall}} \tag{9}$$

F1 Score (F1 Score) is usually an indicator used in statistics to measure the accuracy of a binary classification model. It takes both the precision and recall of the classification model into account. F1 score can be regarded as a weighted average of model precision and recall, where precision and recall are defined as:

$$\text{Precision}=\frac{TP}{TP+FP} \tag{10}$$

$$\text{Recall}=\frac{TP}{TP+FN} \tag{11}$$

TP represents the correctly marked data points at the corresponding level. FN is donated as the number of missed data points with no correct match. The number of misreported data points with classifier is FP, while TN is the number of mismatched data points correctly rejected by classifier.
The calculation result of F1 Score will be displayed in Table V.

V. DISSCUSION

We first extract the data of four frequency bands from the six leads of Fp1, Fp2, O1, O2, T4 and T5 through the self-designed Butterworth filter, and then obtain satisfactory results through the calculation of power spectral density and sample entropy. In the two state tests, we found that β wave has a high correlation with power spectral density and sample entropy.

We proposed an experimental method to find a suitable stage to record EEG data, dividing the impulsive emotion induced by individuals into two levels. The results of t test showed that β wave (14-30hz) showed significant differences in three conditions (resting state, moderate impulsive state, severe impulsive state). The data of 30 subjects indicated that SVM was the most effective classifier. When impulsive emotions were induced by error-prone questions, the accuracy rate could achieve 87.09 %, which is the result of averaging the accuracy of k-group cross validation.

Although EEG still has some difficulties in the study of the identification of impulsive emotion, the use of EEG is still valuable for it has clinical significance in many cases. For example, electrocardiograms cannot be used as a direct measurement system when we detect signals from the brain. Our experiments also showed the effectiveness of EEG. Although EEG has not been widely used in clinical practice for impulse-induced diseases, such as impulse control disorders, we tried to establish this method. Studies have shown that changes in β activity [11] and prefrontal γ changes [12] are conducive to the assessment of some negative emotions. Therefore, we have evidence that some oscillations in the prefrontal cortex can be recorded and evaluated by EEG.

When we compare the performance of the three classifiers, we found that all the three classifiers obtained desirable accuracy. The performance evaluation parameters of these classifiers are shown in the Table. 5. SVM-based classifier gives the highest accuracy when the power spectrum of β wave is used as the feature. We also observed that the Mean Absolute Error (MAE) of SVM was 0.12, which was the smallest among the three classifiers. While the classification accuracy of RBF and ELM was relatively similar, but the Root Mean Square Error (RMSE) of RBF was smaller and better fitting effect was obtained. Meanwhile, the Mean Absolute Percentage Error (MAPE) of ELM was slightly smaller than RBF. In the actual operation process, the running speed of ELM is about half of RBF. Although SVM has the longest running time, its three indicators as well as its accuracy are all perform better than the other two classifiers. Based on F1 Score and the above indicators, we concluded that SVM may be a better choice for an assisting system for impulsive recognition.

TABLE V. THE PERFORMANCE EVALUATION PARAMETERS OF THREE CLASSIFIERS

Classifier	Average Accuracy	MAE	MAPE	RMSE	F1
RBF	83.34%	0.23	0.83	0.36	0.778
SVM	88.46%	0.12	0.36	0.09	0.912
ELM	80.77%	0.24	0.72	0.49	0.765

VI. CONCLUSION

In this study, we extracted EEG signals of subjects in three different states. Three groups of EEG features of subjects were extracted and analyzed: power spectrum, power spectrum density, and sample entropy. The significant differences of β-wave power spectral density values at three levels are reported by two-sample t-test. By marking the power spectrum of β wave in three states, EEG signals are used to classify and identify human impulse. It's evident from our experimental results that SVM has the highest accuracy (88.46%), while RBF and ELM are 83.34% and 80.77% respectively. Considering multiple factors, SVM is a classifier with good performance as an auxiliary emotion classification. To the best of us acknowledges that there are few studies on impulsive emotion and impulsive control disorders through EEG. More features and participants will be considered for analysis in the future. With more data availability, neural network-based strategies may have potential improvements. We also hope to apply our research methods to the monitoring and evaluation of some patients.

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