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EEG signal processing based on genetic algorithm for extracting mixed features

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Abstract: In order to improve the classification of motor imagery EEG accuracy, this paper proposes a method based on Genetic Algorithm (GA) EEG signal classification method to extract mixed characteristics. This method uses wavelet analysis and Hilbert-Huang Transform (HHT) to analyze EEG signals and optimizes the characteristics through Common Spatial Patterns (CSP). Finally, the 14 sub features are optimized by genetic algorithm, and the weights and data credibility of different sub features are obtained. The experiment was tested with 2003BCI competition data and the EEG signal collected by the laboratory. The accuracy rate of competition data was increased from about 75% before weighting to more than 80% after weighting, and the laboratory data increased from about 65% before weighting to about 75% after weighting. Experimental results show that this method can effectively improve the classification accuracy of EEG signals, and the most useful EEG signals can be extracted from large amounts of data for feature extraction and classification. Finally, the online test is carried out to further verify the feasibility of the method.

Keyword: Genetic Algorithm; Hilbert-Huang Transform; Common Spatial Patterns; motor imagery

1 Introduction

Brain computer interface (BCI) is a direct communication and control channel between human brain and computer. This method can effectively improve the ability of patients with severe limb disability to communicate with the outside world or control the external environment, so as to improve the quality of life of patients [1]. The feature extraction of EEG is an important part of BCI system. The extraction and analysis of EEG features is the primary task of researchers.

With the development of nonlinear dynamics, it is proved that the brain is a nonlinear dynamic system, and EEG can be regarded as the output of the system. In order to get better classification results, some researchers try to use various complexity measures, such as dimension and entropy to extract the characteristics of EEG signals. However, their computation often faces the problem of insufficient data points. In addition, most of the defined dimensions and entropy show the limitations of the experimental data in the application because all recorded signals are contaminated to some extent by the noise, thus preventing accurate estimation [2].

At present, many methods have been studied to deal with EEG signals in motor imagery, and good results have been achieved. Xu Baoguo and others used the AR method combined with BP method to deal with the data of BCI2003 and achieved an 85% accuracy rate of [3]. Li Mingai et al. Using wavelet transform method and BP method, the EEG recognition method by combining off-line wavelet transform and BP neural network to classify the BCI competition data, also achieved good results of [4]. In addition, the SampEn of Mi-EEG signals is calculated by linear discriminant analysis (LDA) classifier by Zhou et al [5]. The classification accuracy is between 50% and 87.8%. Wang et al. Using SampEn as the characteristics of MI- EEG, using the genetic algorithm (GA) optimized support vector machine (SVM), the classification rate is between 75.48% and 78.68% [6]. Tian et al features of MI EEG signal based on FE, the average classification accuracy is 87.22%, using the LDA classifier [7]; Xu all use the FE to extract the level of attention EEG signal features, the average recognition rate reached 81% SVM classifier [8].

In these methods, the two most popular and popular methods in recent years are wavelet transform and Hilbert Huang transform. Through the expansion and translation of the wavelet base, the wavelet transform realizes the localization of the time frequency analysis of the signal. It can keep the time domain and frequency characteristics of the signal at the same time. It shows the analysis of the signal on the two-dimensional phase plane. Because of its multi-resolution characteristic, the effective components in the nonstationary signal are completely different from the noise at the appropriate scale [9]. By using the different transmission characteristics of signal and noise in the multiscale space, the effective detection of signals under the interference background can be obtained. This method of processing signals can maintain a good resolution of the mutation information while obtaining the signal to noise ratio gain and has its own superiority in the processing of non-stationary signals [10]. Hilbert-Huang transform is a newly developed time-frequency analysis method to deal with nonlinear non-stationary signals. Hilbert-Huang transform from wavelet transform multi-resolution advantages, but also overcome in wavelet transform need to choose the wavelet basis is difficult, so the method can also be used for filtering and denoising of non-stationary signal [11]. Because of the scale characteristics of the signal itself of the signal decomposition, this method has good adaptability to local, introducing the instantaneous frequency plus will be from the two aspects of signal time-frequency analysis at the same time, increase the flexibility and effectiveness of signal processing. Based on these two methods are combined, and the common spatial pattern (CSP) is optimized, and the characteristics of genetic algorithm are used to select, and finally use the SVM classifier to obtain good results and conducted the online verification.

2 Materials and Methods

In any BCI system, preprocessing, feature extraction and classification are three main stages, we can be in a different way and technology to realize the three stages. Each technology and method have its own defects and advantages, and because the EEG signal is essentially nonstationary, the design of the BCI system becomes a challenging task. In the following discussion, we will submit our solution. Because the final experiment in this article is an online test, we first use data from BCI competition to test the off-line result, then we use data which are measured by electrode cap which is produced by Neuracle company.

2.1 dataset and preprocessing

In our work, we first rely on the Graz dataset III published for the 2003 BCI Competition [12] to take the off-line experiment. Meanwhile, in order to objectively evaluate the effectiveness of the algorithm, we use the left and right-hand motion imagination data to process the signal.

First, the body rest for two seconds. At t= 2S, the beep announced the start of a trial, and visual stimulation showed a cross of 1s. At t= 3S, the left arrow or the right arrow appear to indicate the direction in which the main body will move. Participants performed a motor imagery task from t = 3 s to t = 9 s, and movement's stop means the end of a single trial. Figure 1 describes the empirical paradigm of the experiment [13].

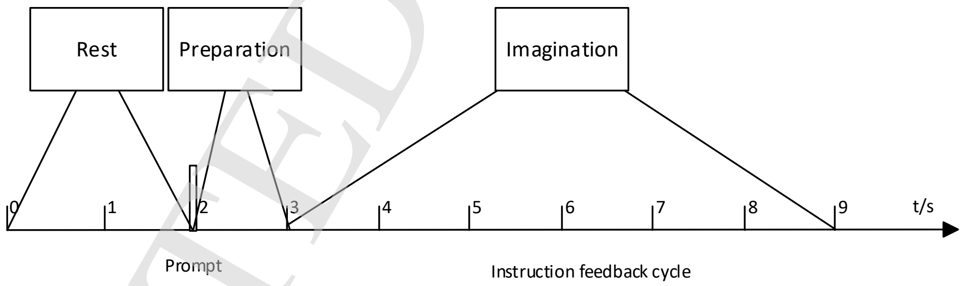

Figure 1. Graz dataset experience paradigm

As the results of online testing are often affected by the subjects, and the results of online testing are significantly lower than the results of off-line testing, we need to analyze online tests before we do online testing. The off-line data source for online testing is the motor imagery EEG data collected in our laboratory. Seven volunteers aged 19-23 years old each collected two sets of data, one set of data as training data, and one set of data as test data. Similar to Graz's experience paradigm, offline testing of online data is obtained with visual feedback hints. The length of each experiment is 9s. After 2s no prompting time, the direction of the screen is prompted, the prompting time 2s. After that, the left and right motor imaginations were taken, and the imaginary time is 5S. The experience paradigm diagram is shown in Figure 2 [14].

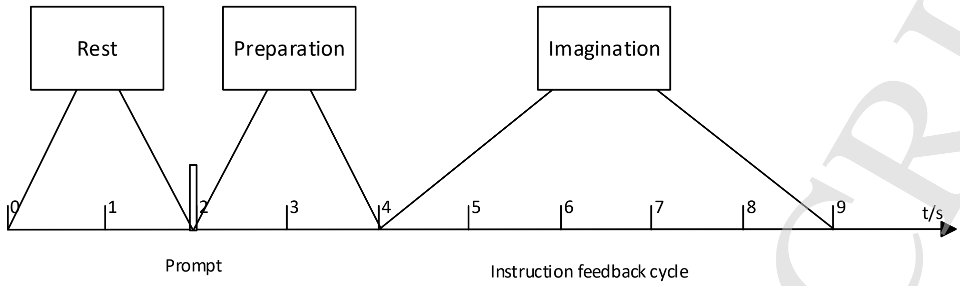

Figure 2. Lab dataset experience paradigm

And when we analyze, we do the following preprocessing steps for two types of data:

1. From the previous experience paradigm diagram of Figure 1 and Figure 2, the number of motion imaginary EEG signals between left hand and right hand has quite difference for the first 3.5 seconds to 7.5 seconds [15]. Therefore, we choose this time segment as a time window, and then calculate the average value of the 4S data in the 1s time period. Because the sampling frequency of the competition data is 100Hz, the average time window we obtained finally contains 100 sampling points. Similarly, we do similar processing for the collected online experimental data. Take the data from 4.5 to 8.5 seconds as the time window. Since the sampling frequency is 250Hz, our final average time window contains 250 sampling points.
2. As the EEG is a non-stationary signal, the data often deviates during the acquisition process. We take the detrending process to eliminate the impact of this deviation on the later calculation, so that the analysis can be concentrated on the fluctuation of the data trend itself [16]. The method adopted in this paper is to subtract an optimal (least square) fitting line from data, so that the mean value after detrended is zero.
3. Independent component analysis (ICA) is a very effective data analysis tool in recent years. It is mainly used to extract original independent signals from mixed data. In many ICA algorithms, FastlCA is widely used in signal processing because of its fast convergence speed and good separation effect. The algorithm can estimate the original signals with independent statistics and unknown factors from the observed signals. Since EEG can be considered to be statistically independent of each other, we use the FastICA algorithm to estimate the source signal after detrending. [17]
4. As the ERD/ERS phenomenon of motion imagination occurs mainly in α (8-13Hz) and β (18-24Hz) frequency band, we carry out the digital band pass filter of 8 to 24 Hz for the experimental data. The Butterworth filter is used in this paper. The passband cut-off frequency is 8-24 Hz, the stop band frequency is 6 Hz and 26 Hz, the pass band attenuation is 0.5 dB, the stopband attenuation is 50 dB [18].

2.2 feature extraction

As the feature extraction method for competition data and laboratory data is similar, the difference is that there are 59 channels in the competition data and the laboratory data are only 32 channels. Therefore, we take the competition data as an example to discuss the feature extraction algorithm. As the EEG is a non-stationary signal, in order to better analyze its characteristics, we need to analyze the two aspects of the amplitude domain and frequency domain. The features extracted in this paper are mainly based on the feature processing obtained by Hilbert yellow transform and wavelet transform.As the sampling rate of the competition data is 100Hz, then the EEG signals we need to handle each time we need to be processed are transformed into a matrix of 100*59, 59 for the number of channels and 100 for the number of sampling points. We need to carry out three layers of wavelet analysis and extract its wavelet coefficients as a set of features. At the same time, EEG is subjected to empirical mode decomposition (EMD), and the amplitude and frequency characteristics of the two groups are obtained. Then we analyze the above three sets of features in a co spatial mode and optimize it from 100*59 matrix to 100*16 matrix. Finally, the energy, the standard deviation, the kurtosis coefficient, the skewness coefficient, the Shannon entropy are calculated for each of the above features, and 14 of them are selected as the last extracted features, as shown in Table 1.

Table 1. Feature vector structure for a single time window.

Index	Feature
1	Mean of Amplitudes of Wavelet Coefficients
2	Mean of Amplitudes of EMD Amplitude Coefficients
3	Skewness of Wavelet Coefficients
4	Skewness of EMD Amplitude Coefficients
5	Skewness of EMD Frequency Coefficients
6	Kurtosis of Wavelet Coefficients
7	Kurtosis of EMD Amplitude Coefficients
8	Kurtosis of EMD Frequency Coefficients
9	Standard Deviation of Wavelet Coefficients
10	Standard Deviation of EMD Amplitude Coefficients
11	Standard Deviation of EMD Frequency Coefficients
12	Energy of EMD Frequency Coefficients
13	Shannon Entropy of Wavelet Coefficients
14	Shannon Entropy of EMD Amplitude Coefficients

2.2 classification

Support vector machine (SVM) is a kind of machine learning method based on statistical learning theory. It maps input vector to a high dimensional feature space by proper nonlinear mapping, so that the data (belonging to two classes) can be divided by a hyperplane. The so-called optimal classification plane is that the classification surface can not only correctly separate the two types of data, but also make the classification interval the largest [19].

In this paper, support vector machines are used to classify the extracted features. f_L and f_R ($f_L, f_R \in \boldsymbol{R}^{100*16}$) are used to visualize the left and imaginary right eigenvectors, corresponding to 1 and -1.

In this paper, 90% off cross validation method is used for data training. The 100 sets of data that imagine the movement of left hand and right hand are randomly divided into 10 groups of mutually exclusive data, each containing 10 sets of data, left hand and right hand [20]. 9 groups of data were used as the training set at a time. The remaining group was a validation set, and the 10 training and test were carried out. Finally, the classification results of 100 groups of each group that imagined the left hand and the right hand were returned.

The classification results of the test groups are compared with the actual results, and the correct rate of different time periods before weighting is obtained. The weights solved by genetic algorithm are weighted by classification results in different time periods. In this paper, the absolute value of the classification results is chosen as the credibility of the classification results. The reliability of test results is higher than that of preset reliability threshold. The predicted classification result is more than 0, which is considered to be the right hand; otherwise, it is left-handed, and the accuracy of the credible test data is compared with the actual results.

3 Genetic Algorithm for feature selection

Genetic Algorithm (GA) is a computational model to simulate the evolutionary process of the natural selection and genetic mechanism of Darwin's biological evolution theory. It is a method to search the optimal solution by simulating the natural evolution process [21].

3.1 Determination of weight

In order to reflect the contribution of different time periods to feature extraction, this paper uses genetic algorithm to determine the weight of different time periods, and then uses different weights to get the final classification results and data credibility.

The flow chart of the genetic algorithm is shown in Figure 3.

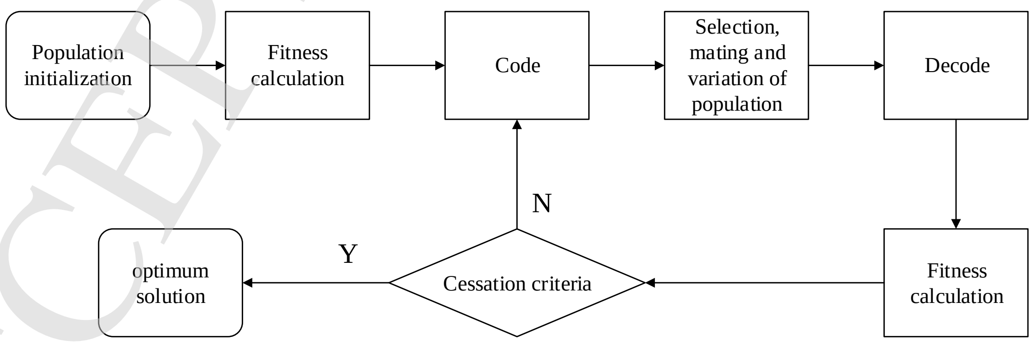

Fig.3 Genetic algorithm flow chart

3.2 population initialization

The population size is determined to be 100, and each individual has 8 variables, that is, the weight k_i of the classification result of 14 Sub eigenvector (i=1,2... 13,14), evolutionary algebra presupposes 100.

3.3 The determination of the fitness function

Weighted k_i after decoding is weighted for the classified T_i results of different time periods, and the smaller the difference between the weighted results and the actual result G, the greater the adaptation degree is, the smaller the fitness is [22]. By adding variable parameter N, the difference of fitness between excellent individuals and ordinary individuals increases, thus preventing the loss of excellent individuals. The fitness function (1) is as follows [23]:

$$\mathrm{F}(k)=\frac{1}{\left|\sum_{i=1}^{14}k_iT_i-G\right|^2-N} \qquad (1)$$

Note: the value of N is 14 in this article.

3.4 coding and decoding

The encoding is to convert the weight variables of different time periods into binary numbers. The length of the string depends on the number of variables, the range of values and the precision required. In this paper, there are 14 weights k_i, whose values range from (L, U), where L and U represent the minimum and maximum values of weights respectively. The precision is four bits after the decimal point. The calculation formula of digit m is [24]:

$$2^{m-1}<(U-L)\times 10^4\times 14<2^m-1 \qquad (2)$$

Note: L and U were 0 and 1 in this article.

Decoding is to restore the non-intuitive binary data string to decimal system, thus facilitating the calculation of individual fitness. The binary data string is divided into 8 parts in sequence, and the number of binary I strings is $b_{im}b_{im-1}\cdots b_{i2}b_{i1}$ corresponds to the weight k_i. In order to make the weight 0 and 1, the corresponding transformation formula (3) is [25]:

$$k_i=\frac{L+(\sum_{z=1}^{m}b_{iz}2^{i-1})\frac{U-L}{2^m-1}}{\sum_{i=1}^{8}(L+(\sum_{z=1}^{m}b_{iz}2^{i-1})\frac{U-L}{2^m-1})} \qquad (3)$$

3.4 selection, mating and mutation

According to the fitness of each individual in the population, a new population is selected according to the fitness of each individual in the population; the mating uses a single point cross method, a cross probability of 0.9, and a mutation probability of 0.1, that is, each binary number has a probability of 0.1 changing.

4 experimental results and discussion

4.1 classification accuracy of different time periods

Through 90% off cross validation, 10 training and testing are carried out for different time periods, and the classification accuracy of each time cross validation is obtained, and the average value of the correct rate of 10 cross validation as shown in Table 2 meanwhile.

Tab.2 The accuracy of classification before feature extraction

10 cross validation	Correct rate for different times of experience								
	1	2	3	4	5	6	7	8	average
Competition data	0.75	0.80	0.70	0.80	0.85	0.70	0.75	0.70	75.6
Lab data	0.55	0.60	0.70	0.70	0.65	0.70	0.55	0.70	64.3

4.2 genetic algorithm solution

The population is initialized by genetic algorithm, and the steps of population fitness, population selection, mating and mutation are repeated, and the 100 generations are iterated. The maximum average fitness is shown with the change curve of the number of iterations, as shown in Figure 4. The optimal solution is obtained: the corresponding weight of different sub feature vectors is K.

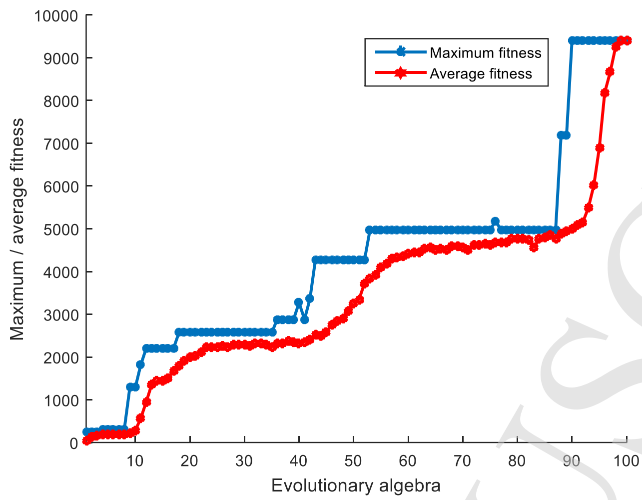

Fig.4 Population Adaptability with Evolutionary Algebra

4.3 limitation of credibility

The reliability test data is screened out, the number of trusted test data and the accuracy of the trusted test data are calculated. The correct rate and number of trusted test data vary with the reliability threshold, as shown in Figure 5 and figure 6.

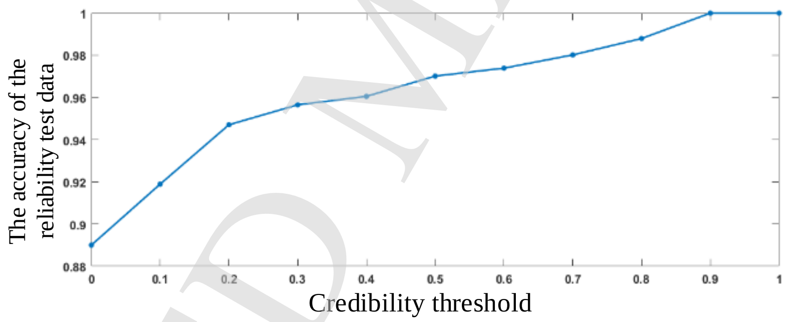

Fig.5 The correct rate of trusted test data varies with the threshold of confidence

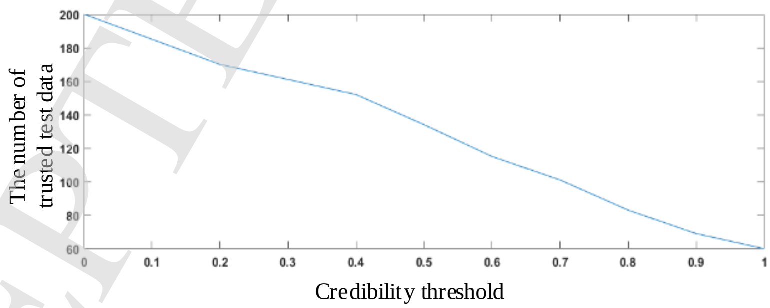

Fig.6 The number of trusted test data varies with the threshold of confidence

4.4 algorithm verification

The weights and credibility of the competition data and laboratory data are calculated, and then each test data is tested. The confidence threshold is set at 0.4, and for off-line testing, a new feature vector is formed from the sub feature vectors of the first three of the K value. That is, the length of the feature vector before the genetic algorithm is 14, and the length of the feature vector after the selection of genetic algorithm is 3. Then the classification accuracy and weighted classification accuracy without weighting are obtained. as shown in Figure 7 and Figure 8. Experimental results show that after setting the threshold of credibility, the algorithm improves the classification accuracy obviously.

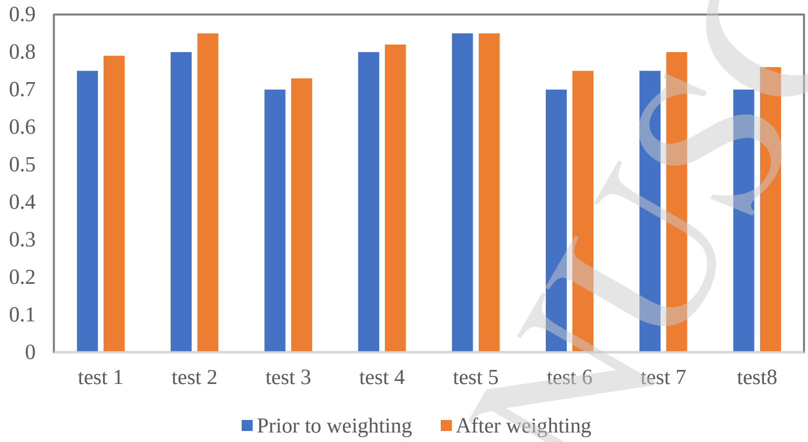

Fig.7 Comparison of correctness before and after weighting of BCI competition data

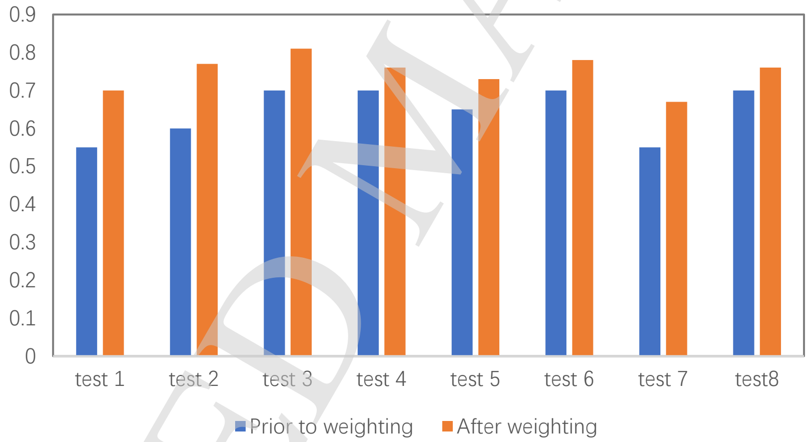

Fig.8 Comparison of correctness before and after weighting of Lab data

5 online test

The online analysis experiment of motor imagery data is also carried out in this paper. Figure 9 is an online experiment interface written in C#. The on-line experiment connection method is as follows: the subjects first put on the electrode cap and connect the electrode cap software on the computer, and then open the experimental interface after the connection is completed. Enter the IP address of the machine in the upper right corner of the interface, click the "Link" button, and then run the corresponding MATLAB online experiment program. Then click on the "Play" button to test. The test is divided into 10 experiments, each time the subjects can control the black block to the left and right sides by moving in the order about left, right, left, right and so on. The black block moves one grid per second, and it drops automatically every second. The whole box is a 7*10 lattice. If the block touches the corresponding left or right blue border according to the set order, the test is successful. If it touches the opposite blue frame or it falls to the blue bottom frame, the test is fail. Finally, the success rate of the experiment can be displayed on the top right of the interface.

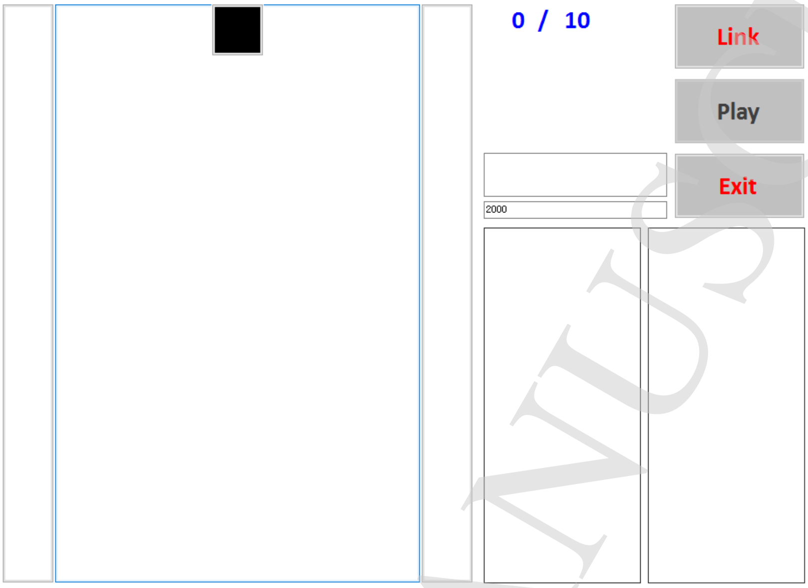

Figure 9. Online test interface

In the online analysis, the online data is preprocessed according to the previous 2.1 sections, then the features described in the 2.2 section are extracted, and the genetic algorithm features of the 2.3 section are selected to select the suitable features. It is important to note that in the offline test we only choose the first three of the K values calculated by the genetic algorithm to recombine, while on the online test we choose the first six features of the K value to combine. This is due to the influence of the electrode cap and the subjects; each channel data will be different in each data collection. Therefore, in the first test of the online test, the 6 features are selected to select the features of the genetic algorithm again, select the first three features of the K value to make up the final selection, and formally start the online test. The results of experience shown as Figure 8.

5 conclusion

From table 1, it can be seen that the average accuracy of cross validation at different times is not very different. It is between 0.7-0.8, indicating that the characteristics of each time period are effective, and it is necessary to classify the results of each time period by weighted synthesis. The common weight determination methods include expert scoring, analytic hierarchy process and fuzzy evaluation. These weight determination methods are usually given by experience, and cannot objectively reflect the actual situation, and the evaluation result may be "distorted" [21]. In this paper, genetic algorithm is used to calculate the contribution of different time periods to feature extraction, and the weight calculated is more objective and effective.

From Figure 4, we can see that the genetic algorithm iterates 100 generations, and the population reaches a more stable state, which indicates that the corresponding weight K at different time periods is an excellent solution for the corresponding objective function. And by weighting K weighted classification results in different time periods, the accuracy rate is significantly higher than that of weighted optimization. Not only limited to this, but also the weighted classification results of different algorithms can be weighted to improve accuracy and increase stability.

From Figure 5 and figure 6, it is known that the accuracy of trustworthy test data increases with the increase of confidence threshold, and the accuracy rate is very satisfactory. However, with the decrease of the number of credible test data, the requirement of data quality is increased. According to the accuracy rate requirement and the actual data quality, the suitable threshold of credibility can be determined.

Figure 7 shows that after weighting and setting the credibility threshold for different time periods, the accuracy of feature extraction and classification results of motion imaginary EEG increases greatly, from about 75% before weighting to about 80% after weighting, which validates the effectiveness of this method. For laboratory self-test data, our results increased from 65% before weighting to about 75% after weighting. The effect is also obvious.

In the process of online testing, we set the number of experiments 20 times. That is, the blocks in the lower computer interface fell 20 times. When the credibility threshold is set to 0.6, about four experiments can be transferred to the lower machine with one effective classification result. After many experiments, the best result is 15 times. That is, we can achieve the correct rate of 75% in the online experiment. When we set the confidence threshold to 0.6, about four experiments can get an effective classification result and transmit the result to the next machine. After many experiments, the best result of online testing is 15 times, that is, we can reach the accuracy rate of 75% in the online experiment.

In order to take into account, the classification results of the EEG characteristics in different time periods and improve the classification accuracy, this paper uses the HHT and the wavelet transform to obtain the characteristics of different time periods. The support vector machine is used as the classifier, and the 90% off cross validation method is used to practice and test the different time periods. In order to reduce the Euclidean distance between the weighted result and the actual result, we determine the weight K by GA. Subsequently, all the sub feature vectors are weighted. At the same time, this paper discusses the effect of the credibility threshold. By setting the credibility threshold, the most effective time data can be selected and the invalid data are abandoned. The result is a large increase in the correct rate. For the competition data, when the credibility threshold is set to 0.4 and the weight value of different time periods is introduced, the classification accuracy rate rises from about 75% to about 80%. For the laboratory data, the reliability threshold is set to 0.6 and the weight value of different time periods is introduced, the classification accuracy is about 65% from the original. Up to about 75%. The method proposed in this paper can not only take into account the classification results obtained by the combination of eigenvectors, but also take into account the classification results of different algorithms or the characteristics of different frequency and frequency. It is also the potential of this method to determine better weights and weighted object selection.

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