Journal of Computers Vol. 33 No. 3, June 2022, pp. 99-111
doi: 10.53106/199115992022063303008

Semi-supervised Learning Based EEG Detection Approach for Rehabilitation Engineering

Zhi-Rong Zhong[1], Hong-Fu Zuo[1*], Shi-Ying Lei[2], Jia-Chen Guo[1], Heng Jiang[1]

[1] Civil Aviation Key Laboratory of Aircraft Health Monitoring and Intelligent Maintenance, College of Civil Aviation, Nanjing University of Aeronautics and Astronautics, Nanjing 211106, China
{zhongzhirong2017531, aerodiag, gjc, jiangheng}@nuaa.edu.cn
[2] Servo Technology Research Institute of China Aerospace Science and Industry Corporation, Nanjing Chenguang Group Company Ltd., Nanjing 210006, China
214485345@qq.com

Received 25 July 2021; Revised 13 November 2021; Accepted 13 December 2021

Abstract. A semi-supervised learning based EEG signal detection method was studied in this paper. The feature engineering system of this paper was established, which contains novel AutoEncoders mapping features. The optimal channel combination for all subjects was determined to improve recognition accuracy by ReliefF algorithm and recursive feature elimination. What's more, the semi-supervised learning method based on pseudo-labelling was introduced to the character recognition method, in which the training samples were dynamically reorganized and updated, so that the proposed method could complete the symbol recognition with limited number of training samples. Based on the features extacted and the optimal channel combination, the recognition accuracy of the character recognition method can reach up to 100%.

Keywords: EEG signals, P300 events, ReliefF, pseudo-labelling, recursive feature elimination

1 Introduction

EEG signals can be divided into evoked EEG signals and spontaneous EEG signals according to the way they are generated. Evoked brain electrical signals are brain electrical activities formed by certain external stimuli that cause potential changes in the brain. The P300 event-related potential is a kind of evoked brain electrical signal, a positive wave peak that appears about 300 milliseconds after the occurrence of a small-probability stimulus. Due to the differences between individuals, the occurrence time of P300 is also different. Fig. 1 shows the P300 waveform about 450 milliseconds after the stimulus occurs. As an endogenous component, P300 potential is not affected by the physical characteristics of the stimulus, and is related to perception or cognitive mental activities, and is closely related to processing processes such as attention, memory, and intelligence. The advantage of the P300-based brain-computer interface (BCI) is that users can obtain high recognition accuracy without complicated training, and have stable time-locking and high time accuracy.

It have been found that in the case of spinal cord injury, cerebral palsy, amyotrophy, amyotrophic lateral sclerosis and other patients with peripheral nerve disability, part of the information that the brain sends instructions can be characterized by some pathways [1-4]. The BCI technology for rehabilitation engineering aims to realize the communication between the patient's brain and rehabilitation auxiliary equipment without relying on the normal communication system of the output path composed of peripheral nerve or muscle tissue [5].

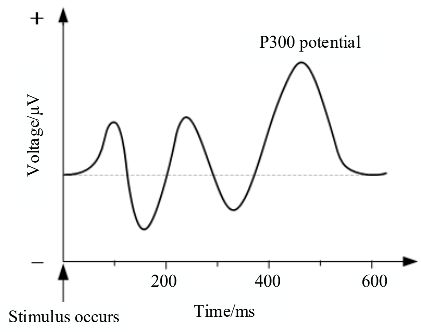

Fig. 1. The schematic of P300 waveform

* Corresponding Author

Traditional P300 classifcation method was based on classic machine learning algorithms, which highly relies on EEG signal preprocessing techinques, feature extraction methods and the performance of classic classifier model. For the preprocessing of EEG signal, it is common to use principal component analysis (PCA), wavelet transform, and coherent averaging methods to preprocess P300 signals [6-7]. As for feature extraction, Chen [8] proposed a method based on independent component analysis (ICA) to automatically extract the P300 component of the EEG signal. Huang [9] proposed a P300 feature extraction method based on constrained ICA for single-lead EEG signals. Wang [10] proposed a multi-channel lead P300 EEG signal feature extraction method based on energy entropy for rehabilitation and treatment of stroke patients. In the past decades, the classifier used in EEG signals classification has attracted widespread attention. For example, Linear discriminant analysis (LDA) classifiers [11], hidden Markov model (HMM) [12] and support vector machines (SVMs) [13-15] have been commonly used for P300 classification. The methods mentioned above are not suitable for classifying EEG signals with poor signal-to-noise-ratio, or the classification accuracy is low when the dimension is high and the signal-to-noise ratio is low.

In recent years, deep learning models such as Convolutional Neural Networks (CNNs) [16] and Recurrent Neural Networks (RNNs) [17] are proposed by many researchers for P300 classification due to its high precision. What's more, Lu [18] proposed a P300 classification method based on deep belief network (DBN), which can extract features from the raw data and classify them without data preprocessing. Abibullaev [19] proposed an accurate classifier for decoding P300 signal based on CNN-LSTM model. SELVİ [20] reported a P300 signal classification method using bi-directional long short term memory (Bi-LSTM) neural networks with spectral entropy as fusion feature. Based on the realizable large-scale real-time quadratic programming (QP) calculation, Zhang [21-22] proposed the fusion method of SVM and neural network for the classification of P300 EEG signals. The deep learning method does not need feature extraction, and has good classification ability for EEG signals with low signal-to-noise ratio. However, its complex network structure leads to massive training parameters and requires high-performance computing hardware, which is difficult to be applied in clinical practice.

Furthermore, the existing advanced methods mainly focus on training large-scale labeled sample data sets in exchange for high accuracy, and the trained classifier model is usually sensitive to the subjects. Paradoxically, the traditional EEG classification methods require less computing resources, but the classification accuracy is relatively low.

In the BCI system, not only the classification accuracy of the target must be considered, but also a certain information transmission rate must be ensured. In addition, irrelevant or redundant channel data increases the complexity of the system on the one hand, and affects the accuracy and performance of classification and recognition on the other hand. In particular, in the P300 BCI system, the training of the model usually takes a long time to obtain labeled samples.

Therefore, the key problem to be solved in this paper is to improve the traditional EEG classification method to increase its classification accuracy, make it suitable for the case of low signal-to-noise ratio and small training sample data set, and make the trained classifier model subject-independent.

In response to the above problems, this paper designs a character recognition method based on a semi-supervised learning method. A novel AutoEncoders features extraction method is used, it will help to extract the most significant deep features of P300 signal. And a channel selection algorithm based on the ReliefF method is applied in algorithm testing, which can achieve accurate and efficient recognition of the target with a small sample. There is no precedent for applying the pseudo-labeling method to the P300 EEG signal. The method proposed in this paper can accelerate the application of P300-based BCI system to rehabilitation engineering to help some disabled patients to establish a new way of interaction with the real world.

The rest sections are organized as follows. Methodology of target character recognition method is described in Sec. 2. The experimental data set used in this paper and its preprocessing method are introduced in Sect. 3. Details of P300 feature extraction and channel selection methods are introduced in Sect. 4. The main results and discussion of results are elaborated in Sect. 5. Final conclusion are concluded in Sect. 6. And the main contributions of this paper are listed as follows.

(1) A novel semi-supervised learning based P300 classification method is proposed. It is the first time that the pseudo-labeling method is applied to solve EEG classification problem.

(2) The pseudo-labeling method allows training samples to dynamically reorganize and update. It is suitable to be applied in small sample data sets or the data sets with less labeled data and massive unlabeled data.

(3) Combing with the ReliefF based channel selection algorithm, the proposed method is able to realize subject-independent classification.

(4) The experimental results in Sect. 5 shows show that the classification accuracy for P300 EEG signals

reaches 100%, which improve the classification accuracy of typical SVM classifier by up to three times. The semi-supervised learning framework can be easily introduced to existing classifier model.

2 Target Character Recognition Methods

P300-based BCI system has been widely studied, and a variety of target character recognition methods based on machine learning classifier models have been established. This paper introduces a classic target character recognition method based on the SVM classifier model, and compares the accuracy of its recognition on the data set in this paper with the accuracy of the method proposed in this paper.

2.1 Target Character Recognition Method Based on SVM Classifier Model

The basic principle of character recognition through P300 signal is as follows. Firstly, the original EEG signal is preprocessed and features are extracted. Then, whether the corresponding signal fragment contains P300 fragment is predicted by classifying the feature values. Finally, the character recognition result is determined according to the coding rules of P300 speller experiment and the prediction results. Machine learning methods such as SVM, artificial neural network and random forest etc. can be well applied to P300-based BCI system.

In this paper, the specific steps of character recognition based on SVM classification model are as follows: (1) Preprocessing EEG data and extracting features; (2) According to the P300 speller experiment design, the features are labeled, and the features containing P300 are given the label “+1”, and vice versa, “-1”; (3) Divide the features data set into a train set and a test set according to a certain proportion; (4) Train the SVM model with the features of the training data set and their corresponding labels as input; (5) Input the features of the test data set into the trained SVM model, and output the predicted label of test set; (6) Combine the signal segment corresponding to the +1 label output by the SVM model with the coding rule of the P300 speller experiment to obtain the target character coding value; (7) Based on the prediction results of each target character in different experimental rounds, the frequency of the coding value is counted, and the final coding value is uniquely determined according to the conditional probability, that is, the target character is determined.

2.2 Target Character Recognition Method Based on Semi-supervised Learning

In practical engineering applications, clearly labeled data sets are difficult to obtain, while unlabeled data are usually easy to obtain. In fact, unlabeled data contains a lot of valid data information. Pseudo-labeling is a semi-supervised machine learning method that does not require manual labeling of data labels, and directly assigns data approximate labels based on predicted labels. The pseudo-labeling method requires that the data set be divided into a training set, a validation set, and a test set according to a certain proportion. For small sample data, adding pseudo-label data to the verification set can play a better predictive effect in semi-supervised learning. The model construction process of the pseudo-labeling method is shown in Fig. 2.

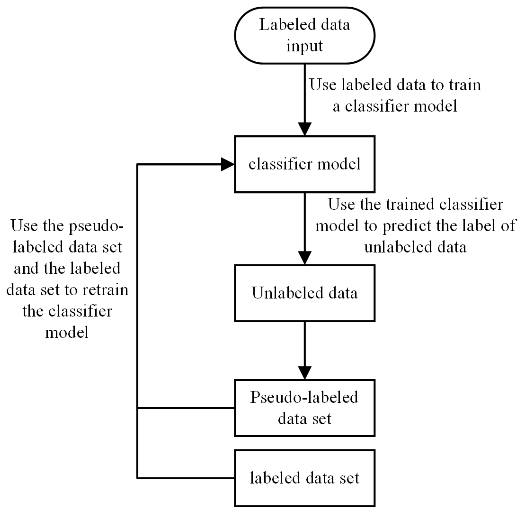

Fig. 2. Model construction flow chart of pseudo-labelling method

The target character recognition method based on semi-supervised learning proposed in this paper, the specific steps are as follows: (1) Preprocessing EEG data and extracting features; (2) According to the P300 speller experiment design, the features are labeled, and the features containing P300 are given the label "+1", and vice versa, "-1"; (3) Divide the features data set into a training set, a validation set, and a test set according to a certain proportion; (4) Use the features $\mathbf{X}_{\mathrm{Train}}$ of the train set and the corresponding known label $\mathbf{Y}_{\mathrm{Train}}$ as input to train the classifier model; (5) Input a set of features $\mathbf{X}_{\mathrm{Valid}}$ of the validation set to the trained classifier model for prediction, and output its predicted label $\mathbf{Y}_{\mathrm{Valid}}$; (6) Compare the predicted label $\mathbf{Y}_{\mathrm{Valid}}$ of the validation set output by the classification model with its known labels. If the recognition requirements are met, the current trained model is retained, if not, then step (7) is executed; (7) The samples whose predicted label is consistent with the actual situation are not processed. The samples whose predicted label does not match the actual situation can be divided into two categories: a. predict the "+1" label as "-1"; b. predict the "-1" label as "+1". These two types of small samples contain hidden feature information that does not belong to the feature space of the train set. Adding pseudo labels to these two types of abnormal samples which means that their label are reversed and their input feature data is still retained. Add the corrected label and feature data to the validation set, and input it together with the training set to retrain the classifier model; (8) Update and save the currently trained classifier model, input a new set of validation set into the model for prediction, output the predicted label $\mathbf{Y}_{\mathrm{Valid}}$, and skip to step (6) until all validation data sets are traversed; (9) Input the features $\mathbf{X}_{\mathrm{Test}}$ of the test data set into the saved classifier model, and output the predicted label $\mathbf{Y}_{\mathrm{Test}}$ of test set; (10) Utilizes the approach similar as steps 6 and 7 of the method introduced in Sect. 2.1 can recognize the target characters in the test set.

3 Experiment and Preprocessing of EEG Signals

This paper uses the data set of the 17th China Postgraduate Mathematical Modeling Competition of "Huawei Cup" to verify the proposed method. In this section, de-trending technology based on polynomial regression, wavelet threshold noise reduction method combined with median filtering, low-pass filtering and other methods are applied to the preprocessing of EEG signals.

3.1 Experiment

The data set provides P300 BCI experimental data of 5 healthy adult subjects (S1-S5) with an average age of 20 years. In the experiment, each subject can observe a character matrix with 6 rows and 6 columns, as shown in Fig. 3. The experiment steps are as follows: At first, the subjects are prompted to look at the "target character", such as the gray character "A" above the character matrix in Fig. 3; then, the character matrix enters the blinking mode, and each time a row or column of the character matrix is blinked in random order. The duration is 80 milliseconds and the interval is 80 milliseconds. When all rows and columns flashed once, the experiment ends. The experiment is repeated for five rounds. When and only when the row or column of the target character that the subject is looking at flashes, the P300 potential will appear in the EEG signal.

>A

A	B	C	D	E	F
G	H	I	J	K	L
M	N	O	P	Q	R
S	T	U	V	W	X
Y	Z	1	2	3	4
5	6	7	8	9	0

Fig. 3. The symbol matrix

There are 22 sets of experimental data, of which the first 12 sets are train sets, and the last 10 sets are test sets. The experiment uses 20 channels to collect EEG signals at a sampling frequency of 250 Hz, and the recording channels are numbered sequentially. The signal acquisition device is equipped with a reference electrode and a ground electrode, that is, the signal of the recording channel is the difference between the working electrode and the reference electrode. The recording channels and their identifiers are shown in Table 1, and the acquisition channels distribution is shown in Fig. 4. The acquisition channels is marked by the red area.

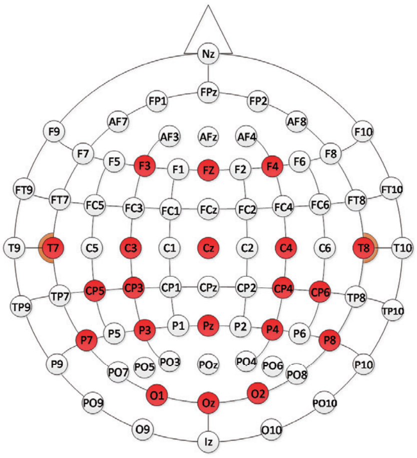

Fig. 4. Acquisition channels layout of EEG signal

Table 1. Identifiers of the acquisition channels

Identifier	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Channel	Fz	F3	F4	Cz	C3	C4	T7	T8	CP3	CP4	CP5	CP6	Pz	P3	P4	P7	P8	Oz	O1	O2

In the data set, the start label of each round of experiment is the identifier corresponding to the target character, followed by the flashing row or column identifier, and the end label of one round of experiment is "100". In the event labels of the data set, the first line gives the identifier of the target character and the corresponding acquisition channel identifier number, followed by the flashing row or column identifier and the corresponding channel number. Each round of the experiment ends with the "100" identifier and is repeated 5 times in total. After analyzing the EEG signal, the rows and columns where the P300 potential appears are obtained, and then the recognition result of the target character is judged and compared with the real target character given by the event label to verify the correctness of the recognition result. The identifiers corresponding to the target characters in the character matrix are shown in Table 2, and the row and column identifiers are shown in Fig. 5.

Table 2. Identifiers of symbols in the matrix

Identifier	101	102	103	104	105	106	107	108	109	110	111	112	113	114	115	116	117	118
Channel	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R
Identifier	119	120	121	122	123	124	125	126	127	128	129	130	131	132	133	134	135	136
Channel	S	T	U	V	W	X	Y	Z	1	2	3	4	5	6	7	8	9	10

Fig. 5. Identifiers of rows and columns of the matrix

3.2 Preprocessing of EEG Signals

The EEG signal is weak, the background noise is large. It contains a lot of internal interference of biological signals, such as eye electricity, ECG, and myoelectric artifacts. And it is susceptible to a variety of external interference, such as poor electrode contact, power frequency interference, environmental noise, etc. Therefore, before signal analysis and discrimination, it is necessary to preprocess the EEG signals collected in the experiment to eliminate noise and improve the signal-to-noise ratio of event-related potential signals.

Before analyzing the characteristics of the EEG signal, it is necessary to use the least squares method to estimate the best fitting polynomial to remove the trend term and remove the mean value for the original EEG signal. It has been verified that if the original signal without detrending is used directly for feature extraction, accurate time-frequency domain feature information cannot be obtained and the P300 signal will be overwhelmed by large fluctuation trends, which seriously affects the accuracy of analysis and discrimination. Taking the twenty channels in the first experiment of S1 subject as an example, the trend interference items in the original signal are obviously removed, and the signal comparison before and after detrending is shown in Fig. 6.

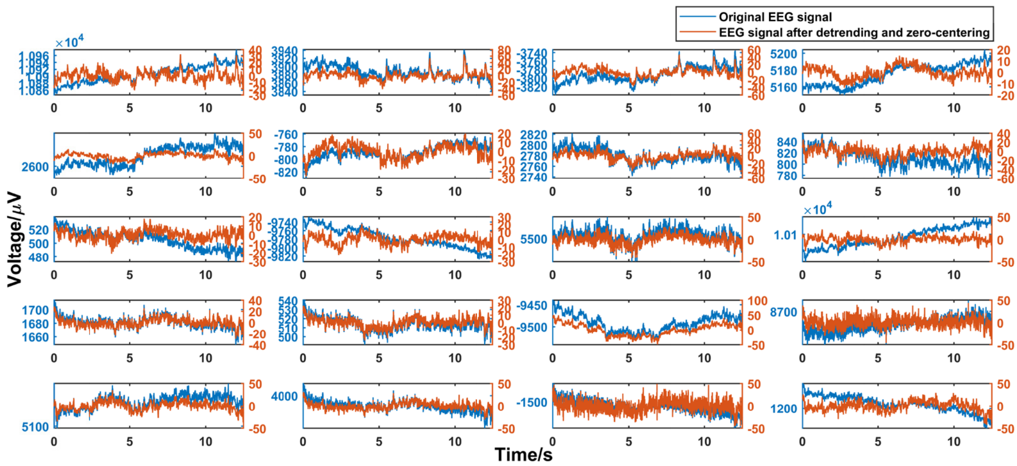

Fig. 6. Comparison of EEG signals before and after detrending

Before preprocessing the EEG signal, it is necessary to understand the basic characteristics of the EEG signal through various signal processing methods. Taking the Fz channel signal of the S1 subject in the first experiment as an example, the characteristic analysis conclusions obtained from other channel signals are consistent with it. The Morlet wavelet three-dimensional time-frequency diagram is used to obtain the relationship of frequency components with time, as shown in Fig. 7. From the figure, the frequency components of the EEG signal in an experiment are mainly concentrated in the low frequency band, and the frequency components do not change significantly over time.

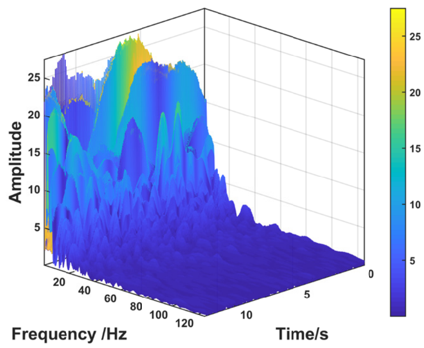

Fig. 7. Wavelet 3D time-frequency map of the EEG signal in a typical experiment

This paper uses the multi-scale wavelet transform based wavelet threshold denoising method combined with the median filtering method to preprocess the EEG signal. The wavelet transform decomposes the original signal S into approximate information cA_i and detail information cD_i. The approximate coefficient represents the low-frequency component information of the signal, and the detail coefficient represents the high-frequency component information. Multi-scale wavelet decomposition will continue to decompose the approximate information of the upper layer into the approximate information and detailed information of the next layer, as shown in Fig. 8. Noise mostly exists in high-frequency components, that is, the detailed information of wavelet decomposition. By setting a reasonable threshold to limit the detail intensity, the detail coefficients of each layer can only retain the part whose absolute value exceeds the threshold, so as to achieve noise reduction and retain valid data information, and then reconstruct the denoised EEG signal.

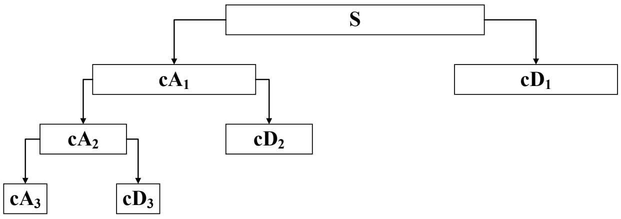

Fig. 8. Schematic diagram of wavelet decomposition

In this paper, 3-layer wavelet decomposition is used. Among them, the approximate coefficients of the third layer are not subjected to threshold limitation processing, and the detail coefficients of each layer are subjected to threshold limitation processing. The threshold value is determined according to the maximum value of the absolute value of the detail coefficient of each layer. After wavelet threshold denoising based on multi-scale wavelet transform, the EEG signal is processed by median filtering. Taking the Fz channel signal of the first experiment of S1 subject as an example, the signal comparison before and after preprocessing is shown in Fig. 9.

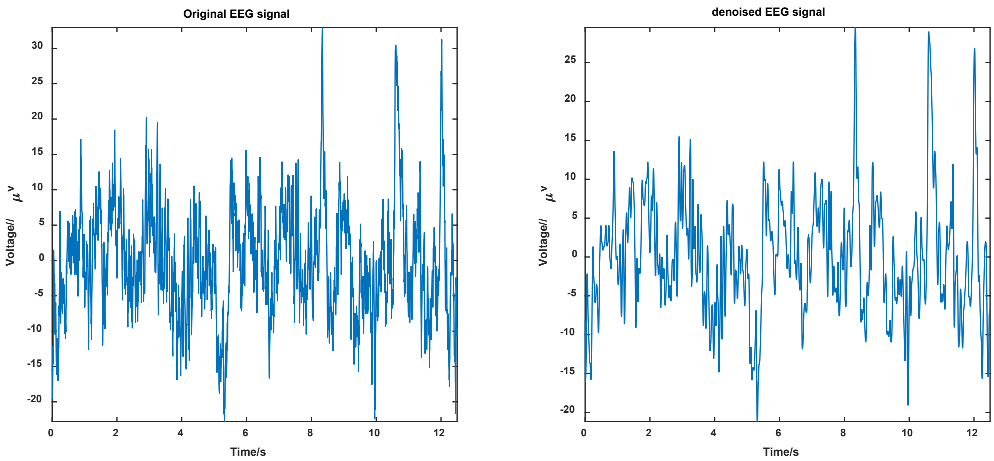

Fig. 9. Preprocessing effect of the EEG signals in a typical experiment

It can be seen from Fig. 9 that the disturbance and interference information in the original signal is eliminated, the main information of the signal is completely retained, and the signal waveform is smoother. And the median filter filters the spikes and avoids the spikes' influence on subsequent analysis. To measure the effect of preprocessing, calculate its signal-to-noise ratio, which is defined as the ratio of signal effective power to noise power, as shown in equation (1).

$$\mathrm{SNR}=10\cdot\lg\left(\sum_{i=1}^{N}x_i^{2}\Big/\sum_{i=1}^{N}\left(x_i-y_i\right)^{2}\right) \tag{1}$$

In equation (1), x is the original signal and y is the denoised signal. The SNR=11.4 is obtained by substituting the denoised signal into calculation, which shows that the pre-processing method proposed in this paper works well.

Each row or column of the character matrix is a single stimulus for the subject, so the EEG signals obtained from the experiment need to be segmented according to the stimulus. To ensure that the segmented signal covers the P300 signal information, the segmented signal is taken as a segment 660 ms after stimulus onset. And further preprocess each segmented signal segment, including baseline correction and low-pass filtering.

Baseline correction serves to eliminate deviations of the EEG signal relative to the baseline. Although the original signal has been detrended, baseline correction is still necessary because the EEG signal after stimulation occurs is closely related to the adjacent signal segment before stimulation occurs and the EEG signal when unstimulated is a spontaneously smooth signal. It is more meaningful to use the adjacent signal segment before stimulation as a reference signal against which the post-stimulation EEG signal can be corrected. In this paper, the signal in the 100ms period before stimulation is used as the reference signal. In the correction, the mean value of the reference signal is obtained first, and the baseline corrected signal is obtained by subtracting the mean value of the reference signal from the post-stimulation signal. The EEG signal is typically low-frequency, so a low-pass Butterworth filter with a cut-off frequency of 30Hz was applied to each segment of the signal. The results of the baseline correction and low-pass filtering are shown in Fig. 10.

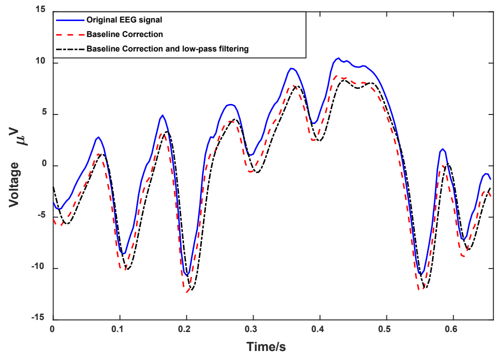

Fig. 10. Effect of baseline correction and low-pass filtering

4 Feature Extraction and Channel Optimization

4.1 Feature Extraction

The raw EEG signals are multi-channel continuous time domain data with high data dimensionality, and in a BCI system, both the target classification accuracy and the information transmission rate have to be considered. So the P300 signal segments need to be extracted from signals and construct feature engineering for subsequent model training.

This paper selects the hidden layer node values of AutoEncoders (AE) as features. AE is a special three-layer neural network, including an input layer, a hidden layer and an output layer, as shown in Fig. 11. The so-called automatic encoding means that the output is equal to the input, and the number of hidden layer nodes is lower than the dimension of the input layer to achieve data dimensionality reduction. AE with this structure can capture the most significant features in the input signal and complete feature extraction. In this paper, EEG signal fragments are used as AE input and output, and the number of hidden layer nodes is set to one third of the input and output, that is, the extracted feature dimension is only one third of the original signal fragment. The sigmiod function is selected as the transfer function in this paper.

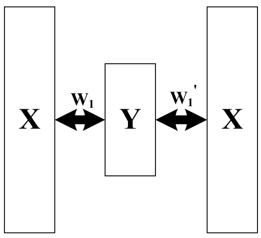

Fig. 11. The network structure of AE

4.2 Channel Optimization

In order to identify effective channel data and reduce channel dimensions, channel optimization is required. In this paper, the optimal features characterizing the original features are first obtained using the ReliefF algorithm; then the importance of each channel is determined based on a recursive feature elimination (RFE) algorithm, which in turn determines a combination of channels containing different numbers of channels, and evaluates the merits of the channel combination in terms of the target character recognition accuracy; finally the optimal channel combination for generalisation is determined based on the optimal channel combination for each subject. This section uses the SVM classifier-based character recognition method for channel optimization.

ReliefF is a multiclass feature selection algorithm proposed by Kononenko [23] in 1994 based on the work of KIra [24]. The essence of ReliefF algorithm is to evaluate the merit of features in terms of the ability of a single feature to distinguish between nearest neighbor samples. Let there be l ($l \geq 2$) classes of sample data, a set of class labels of samples $C=\{c_1, \ldots, c_l\}$, and a randomly selected sample from the train set data as R. In contrast to the traditional Relief, ReliefF selects k samples from each class of sample subset that are closest to R. The k samples of the same kind as R form the set H, and the samples that are different from R form the set $M(c)$. The weights of the feature vectors are calculated and updated according to equation (2), and this calculation process is repeated m times. m is the empirical value.

$$W(f)=W(f)-\sum_{j=1}^{k} d(f,R,H_j)\Big/(m\bullet k)+\sum_{c\neq class(R)}\left[\frac{p(c)\sum_{j=1}^{k} d(f,R,M_j(c))}{1-P(class(R))}\right]\Bigg/(m\bullet k)\cdot \tag{2}$$

where $W(f)$ denotes the weight of feature f, c denotes the class label different from R, p denotes the prior probability of each class. d (f, R, R_0) denotes the distance between samples R and R_0 on feature f, which is shown in equation (3), where $value(f, R)$ denotes the value of sample R on feature f.

$$d\left(f,R,R_0\right)=\left|v\left(f,R\right)-v\left(f,R_0\right)\right|/\left(f_{\max}-f_{\min}\right) \tag{3}$$

From the above calculation, it is obtained that the features with high weights have strong classification ability and those with small weights have weak classification ability. The feature matrix is input to the ReliefF feature selection algorithm process, and the corresponding feature weight vector is output, according to which the features with a high percentage of weights are selected to construct the fusion feature matrix with the corresponding weights. In this paper, SVM-based RFE is used for channel selection, which was first proposed by Guyon [25] in their study of gene selection. SVM-RFE is a method that uses feature ranking to select a subset of features. It starts from the full set of features and use the classification performance of the SVM as the basis for feature elimination; then eliminate one feature at a time that has the least satisfactory classification performance for the SVM, and iterate until the last feature remains; finally, we output the feature ranking results in terms of the relevance of the features.

Based on the fusion feature matrix constructed by ReliefF feature selection and the recognition accuracy, the SVM-RFE method is used to obtain a correlation ranking list of 20 channels. The corresponding scores are assigned from the ranking. Then the total score of each channel is obtained, whereby the optimal combination of channels is determined. To be concluded, channel optimization is implemented by as follows: (1) Apply ReliefF feature selection algorithm to obtain the weight ranking of multiple features for different subjects; (2) According to the weights obtained in (1), the fusion features of all the features corresponding to the 20 channels are obtained; (3) Apply RFE using the fused features to obtain the channel importance ranking; (4) Determine the channel combinations of subjects according to the channel scoring and import the channel optimization results to SVM, then reduce the number of channels according to the classification accuracy to finalize the best selected channel combination; (5) Comprehensive evaluation of the 5 subjects channel scores to initially determine the generic optimal channel combination and import the initial channel optimization results into the SVM classifier, then reduce the number of channels according to the classification accuracy to finalize the generic optimal channel combination.

According to the optimized channel combination results obtained, the data of the corresponding channels in the S1~S5 subjects data sets were taken to form new training samples for model training and prediction to verify the effectiveness of the channel optimization. The prediction accuracy results of S1~S5 subjects with different number of channel combinations are shown in Fig. 12, and the optimal channel combination for each subject can be determined from the prediction accuracy and cumulative number of channels. The frequency of each channel in the optimal channel combination can be obtained by counting the component channels of the optimal channel combination for each subject, as shown in Fig. 13.

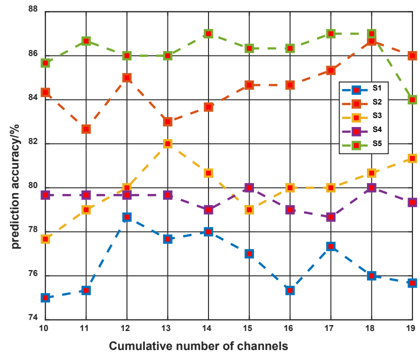

Fig. 12. Prediction accuracy with different combinations of channels

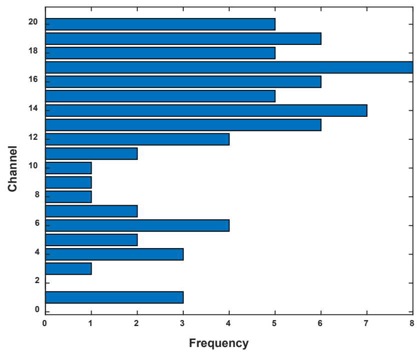

Fig. 13. Occurrence of channels

Based on the frequency of occurrence in each optimal channel combination, the channels are ranked from the highest to the lowest. The top 10 to 19 channels are selected to form the channel combination, and the SVM based target character recognition method is used to predict the results. Take S5 test set as an example, the number of data rounds is 5 rounds, and the prediction results are shown in Fig. 14.

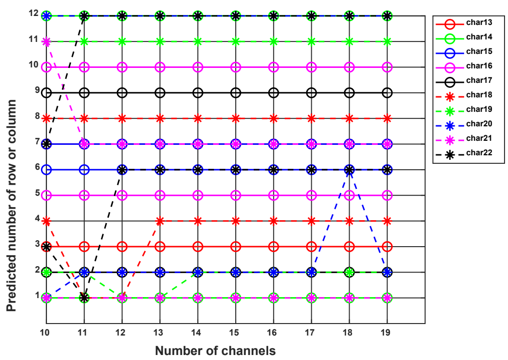

Fig. 14. Prediction results of different combinations with different number of channels

It can be seen from Fig. 14 that when the number of channels is 14, the prediction results of each data set have stabilized. When the number of channels is 18, only the row number of one set of data changes. It can be considered that the combination of the first 14 channels can meet the recognition requirements of the target characters. Therefore, the generic optimal channel combination obtained in this paper has a channel number of 14, specifically {Fz Cz C4 T7 CP5 CP6 Pz P3 P4 P7 P8 Oz O1 O2}, as shown in the blue marked channel in Fig. 15.

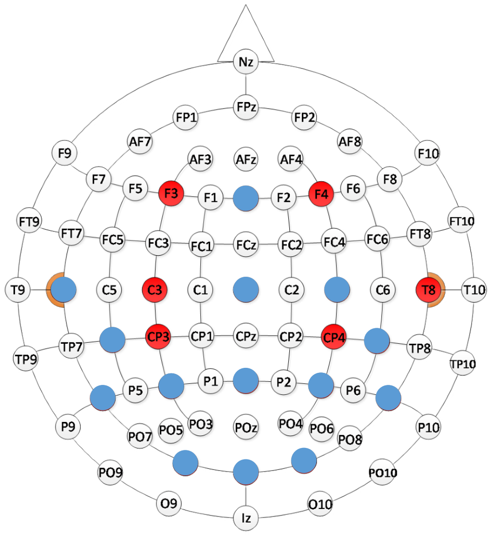

Fig. 15. Layout of the selected channels

From the analysis of Fig. 15, it can be concluded that the P300-related event potentials were mainly distributed in the posterior and middle regions of the brain. And the relevant EEG signals were generated in both the left and right brain, while the P300-related signals were not easily detected in the anterior half of the brain.

5 Results and Discussion

Based on the extracted AE features and the optimal combination of generic channels determined by channel optimization, the character recognition method is validated using data from all five experimental rounds. In this paper, SVM classifier is used for two kind of character recognition methods. The SVM kernel function is chosen as a linear kernel function, and the penalty factor C=1 is set.

Firstly, the dataset of S1~S5 subjects are divided into train set and test set. Let the data sets corresponding to the first 12 target characters be the train set and the data sets corresponding to the remaining 10 target characters be the test set. It is imported into the process of target character recognition method based on SVM classifier, and the test results are shown in Table 3. In fact, char13~char22 are actually {'M' 'F' '5' '2' 'I' 'T' 'K' 'X' 'A' '0'}.

Table 3. Test results by using target character recognition method based on SVM classifier

	char13	char14	char15	char16	char17	char18	char19	char20	char21	char22	Error rate/%
S1	'G'	'K'	'5'	'V'	'U'	'T'	'A'	'L'	'A'	'B'	70
S2	'M'	'F'	'5'	'V'	'I'	'T'	'K'	'X'	'G'		30
S3	'M'	'L'	'M'	'J'	'I'	'T'	'K'	'T'	'E'		60
S4	'G'	'E'	'5'	'2'	'I'	'T'	'E'	'N'	'B'	'6'	60
S5	'M'	'F'	'A'	'2'	'I'	'T'	'K'	'L'	'A'	'0'	20

The data sets of S1-S5 subjects are divided into train set, validation set, and test set. Similarly, let the data sets corresponding to the first 12 target characters be the train set, the data sets corresponding to the last 5 target characters be the test set, and the data sets corresponding to the remaining target characters be the validation set. The test results are shown in Table 4 after importing them into the semi-supervised learning-based target character recognition algorithm process proposed in Sect. 2.2.

Table 4. Test results by using target character recognition method based on semi-supervised learning

	char13	char14	char15	char16	char17	char18	char19	char20	char21	char22	Error rate/%
S1	'M'	'F'	'5'	'2'	'I'	'T'	'K'	'X'	'A'	'A'	10
S2	'M'	'F'	'5'	'2'	'I'	'T'	'K'	'X'	'5'	'0'	10
S3	'M'	'F'	'5'	'2'	'I'	'T'	'K'	'X'	'A'		10
S4	'M'	'F'	'5'	'2'	'I'	'T'	'E'	'X'	'B'	'0'	20
S5	'M'	'F'	'5'	'2'	'I'	'T'	'K'	'X'	'A'	'0'	0

By comparing the test results of applying the two target character recognition methods shown in Table 3 and

Table 4, it can be seen that both methods are based on the same SVM classifier model, and the error rate of target character recognition is significantly reduced by applying the pseudo-labeling method. For S1-S5 experimental subjects, the accuracy of semi-supervised based method is significantly improved compared with traditional SVM method, and the growth rates of accuracy are 300%, 150%, 225%, 200% and 125% respectively. At the same time, the proposed method can greatly improve the classification accuracy of EEG signals for all experimental subjects, which proves that the trained classifier model is subject-independent. Due to the appropriate validation set is set in this paper, the over fitting phenomenon is effectively prevented. The method proposed in this paper can greatly improve the problem of low recognition rate of the target character recognition method based on the classifier model.

As we can observe in Table 3, the test error rate of the corresponding data sets of subjects S1, S3 and S4 was high. Combined with the actual EEG signals waveform, the signal-to-noise ratio of S1, S3 and S4 EEG signals collected from subjects is low. The traditional SVM model is difficult to effectively classify such P300 EEG signals, which leads to high error rate. In Table 4, the test accuracy of the corresponding data sets of subjects S1, S3 and S4 has been improved to an acceptable level, which fully shows that the proposed method can be used for the classification of P300 EEG signals with low signal-to-noise ratio and can obtain considerable accuracy rate.

The general premise of machine learning methods is “assuming that all samples in the sample space obey independent identical distribution”. In fact, the training samples often do not have overall representativeness. There is a “learning blind spot” phenomenon which means that there are some individual cases that are not easily learned, so that the train and test sets do not meet the independent identical distribution condition. In other words, the model obtained from the train set alone is not representative and cannot meet the classification accuracy requirement. By using the semi-supervised learning method of pseudo-labeling, samples from the validation set that are not in the feature space of the training samples can be continuously added to the model for training to achieve dynamic adjustment of the training sample distribution. With the increase of training times, the model will be more representative and the prediction accuracy will be higher. The final recognition results in this paper reflect the superiority of the pseudo-labeling based semi-supervised learning method and its short training time. This means that the proposed method can be integrated into the edge computing device to complete the classification and prediction of P300 EEG signals in real time, and the P300 speller can really become practical.

6 Conclusion

This paper proposes a semi-supervised learning method for EEG signal analysis, and validates the effectiveness of the proposed method based on the data set of the 17th China Graduate Student Mathematical Modeling Competition of “Huawei Cup”. In the validation stage, the data are preprocessed with multi-scale wavelet threshold noise reduction to obtain P300 signal fragments with high signal-to-noise ratio. A feature representation method based on AE mapping features is adopted. ReliefF algorithm and RFE method are used to determine the universal optimal channel combinations and significantly improve the target character recognition accuracy, and this makes the classifier model based on the optimized channel subject-independent. In particular, the semi-supervised learning-based target character recognition method proposed in this paper can accomplish classification recognition well under the condition of limited number of training samples, and its accuracy and efficiency are higher, and the recognition accuracy is no less than 80% in the data set of this paper. The classification accuracy of proposed method is up to three times higher than that of typical SVM classifier. The semi-supervised learning framework proposed in this paper can enhance the traditional EEG classification methods, robustly process EEG signals with low signal-to-noise ratio on the premise of requiring a small number of labeled training samples, and the trained classification model is object independent. Compared with the deep learning method, the proposed method has the characteristics of light weight and high efficiency.

Considering that the semi-supervised learning based P300 EEG signal classification method proposed in this paper can improve the accuracy of traditional P300 EEG signal classification methods, the follow-up research will be carried out from two aspects: 1. Extend the proposed semi-supervised learning framework to other traditional P300 EEG signal classification methods based on machine learning classifier models such as random forest; 2. Extend the semi-supervised learning method to EEG signal identification models of other experimental paradigms, such as motor imagination signals. The ultimate goal is to apply different paradigms of BCI to clinical therapists.

7 Acknowledgement

This work was supported by the National Natural Science Foundation of China (Grant No. U1933202 and No. U1733201) and Foundation of Graduate Innovation Center in Nanjing University of Aeronautics and Astronautics (Grant No. kfjj20200723).

References

[1] J.R. Wolpaw, N. Birbaumer, D.J. Mcfarland, G. Pfurtscheller, T.M. Vaughan, Brain-computer interfaces for communication and control, Supplements to Clinical Neurophysiology 113(6)(2002) 767-791.
[2] J.N. Mak, J.R. Wolpaw, Clinical Applications of Brain-Computer Interfaces: Current State and Future Prospects, IEEE Reviews in Biomedical Engineering 2(1)(2009) 187-199.
[3] D. Zhang, H. Song, R. Xu, W. Zhou, Z. Ling, B. Hong, Toward a minimally invasive brain–computer interface using a single subdural channel: A visual speller study, Neuroimage 71(5)(2013) 30-41.
[4] E.W. Yin, Z. Zhou, J. Jiang, Y. Yu, D. Hu, A Dynamically Optimized SSVEP Brain–Computer Interface (BCI) Speller, IEEE transactions on bio-medical engineering 62(6)(2015) 1447.
[5] H. Sun, J. Jin, Y. Zhang, B. Wang, X.Y. Wang, Parameter Optimization in Face-Based P300 Speller System, Chinese Journal of Biomedical Engineering 37(01)(2018) 25-32.
[6] W. Yi, S. Qiu, H. Qi, L. Zhang, B. Wan, D. Ming, EEG feature comparison and classification of simple and compound limb motor imagery, Journal of neuroengineering and rehabilitation 10(1)(2013) 1-2.
[7] Z. Wang, Research on SVM-Based Recognition Technique for P300 Signal in BCI System, [dissertation] Tianjin: Tianjin University, 2007.
[8] H. Chen, B. Li, Z. Chen, Automatically Extract P300 Within Several Trials from EEG Based on ICA, Acta Electronica Sinica 40(6)(2012) 1257-1262.
[9] L. Huang, H. Wang, Research on the classification of P300 in single channel EEG, Chinese Journal of Scientific Instrument 35(4)(2014) 814-819.
[10]Y. Wang, EEG processing based on multi-channel signals and its application in analysis of stroke patient' EEG, [dissertation] Hangzhou: Zhejiang University, 2015.
[11]J. Qu, F. Wang, Z. Xia, T. Yu, J. Xiao, Z. Yu, Z. Gu, Y. Li, A novel three-dimensional P300 speller based on stereo visual stimuli, IEEE Transactions on Human-Machine Systems 48(4)(2018) 392-399.
[12]S. Solhjoo, A.M. Nasrabadi, M.R.H. Golpayegani, Classification of chaotic signals using HMM classifiers: EEG-based mental task classification, in: Proc. 2005 13th European Signal Processing Conference, 2005.
[13]Y. Li, H. Liu, S. Wang, Exploiting eeg channel correlations in p300 speller paradigm for brain-computer interface, IEICE Transactions on Information and Systems 99(6)(2016) 1653-1662.
[14]S. Kundu, A. Samit, P300 detection with brain–computer interface application using PCA and ensemble of weighted SVMs, IETE Journal of Research 64(3)(2018) 406-414.
[15]S. Kundu, A. Samit, P300 based character recognition using sparse autoencoder with ensemble of SVMs, Biocybernetics and Biomedical Engineering 39(4)(2019) 956-966.
[16]A. Farahat, C. Reichert, C.M. Sweeney-Reed, H. Hinrichs, Convolutional neural networks for decoding of covert attention focus and saliency maps for EEG feature visualization, Journal of neural engineering 16(6)(2019) 066010.
[17]R. Joshi, P. Goel, M. Sur, H.A. Murthy, Single trial P300 classification using convolutional LSTM and deep learning ensembles method, in: Proc. International Conference on Intelligent Human Computer Interaction, 2018.
[18]Z. Lu, N. Gao, Y. Liu, Q. Li, The detection of p300 potential based on deep belief network, in: Proc. 2018 11th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, 2018.
[19]B. Abibullaev, Z. Amin, A Systematic Deep Learning Model Selection for P300-Based Brain-Computer Interfaces, IEEE Transactions on Systems, Man, and Cybernetics: Systems (2021).
[20]A.O. Selvi, A. Ferikoğlu, D. Güzel, Classification of P300 based brain computer interface systems using long short-term memory (LSTM) neural networks with feature fusion, Turkish Journal of Electrical Engineering & Computer Sciences 29(SI-1)(2021) 2694-2715.
[21]Z. Zhang, G. Chen, S. Chen, A Support Vector Neural Network for P300 EEG Signal Classification, IEEE Transactions on Artificial Intelligence 3(2)(2022) 309-321.
[22]Z. Zhang, G. Chen, S. Yang, Ensemble Support Vector Recurrent Neural Network for Brain Signal Detection, IEEE Transactions on Neural Networks and Learning Systems (2021).
[23]I.M. Robnik, I. Kononenko, Theoretical and Empirical Analysis of ReliefF and RReliefF, Machine Learning 53(1-2)(2003) 23-69.
[24]K. Kira, L. Rendell, The feature selection problem: traditional methods and a new algorithm, in: Proc. the tenth national conference on Artificial intelligence, 1992.
[25]I. Guyon, J. Weston, S. Barnhill, V. Vapnik, Gene Selection for Cancer Classification using Support Vector Machines, Machine Learning 46(1-3)(2002) 389-422.