Research on EEG Signal Emotion Recognition Based on BPSO

Nan Zhang [1, a], Xiaodan Zhang [1, b], Yawen Zhai [1, b], Yige Li [1, b], Zitong Bai [1, b], Xuanyu Liu [1, b], and Guangxu Zhang [1, c]

[1] School of Electronic and Information, Xi'an Polytechnic University, Xi'an, Shaanxi, China;

[a] 995326806@qq.com, [b] zhangxiaodan@xpu.edu.cn, [c] 644808470@qq.com, [b] x1719614085@qq.com, [b] x481127592@qq.com, [b] 1694928144@qq.com, [b] x120706754@qq.com

Abstract. The discrete binary particle swarm optimization algorithm proposed in this work can address the difficulty of imprecise emotion-related typical features and localization of emotion recognition. Eighteen classes of features in the time domain, frequency domain and time-frequency domain and differential entropy features are used as features for holistic emotion recognition accuracy using linear and nonlinear methods. Then, the next particle position, velocity and fitness are updated according to the recognition rate accuracy, so as to obtain the optimal feature combination by the emotion recognition accuracy, and lastly the subjects were identified using SVM to get the emotion recognition outcome. The initial experiments reveal that the percentage of correctness was 88.95% and 76.12% for BPSO and PSO, respectively. and the highest correct rate of happy among the four categories of emotions is 91.78%, which is improved by up to 12.83% using the BPSO algorithm.

Keywords:emotion recognition; feature extraction; BPSO; support vector match.

1. Introduction

Emotion recognition technology is an important part of artificial intelligence field, and it has great potential in emotional care, human-computer interaction, multimedia content pushing, etc., and EEG signal emotion recognition can be more objective and realistic response to its emotional state.Khalili et al. exploited the temporal features such as mean, skewness, peak, and variance in the EEG and assembled them into the combined temporal features[1]. Zouridakis et al. have mapped the electroencephalogram over five frequency bands by band-pass filtering and calculated their band energies as EEG frequency domain features[2]. He H et al. used the wavelet energy corresponding to δ 、 θ 、 α 、 β and γ waves as time-frequency features by discrete wavelet decomposition[3]. Zheng et al. extracted differential entropy features as EEG emotion features and used them to identify nonlinear features for emotion classification[4]. In this study, feature extraction is performed from four perspectives: time-domain, frequency-domain, time-frequency-domain and nonlinear, based on different emotion recognition accuracies, combining linear and nonlinear features.

In the above research progress, the same problem of inaccurate representative features related to emotion recognition and low emotion recognition rate due to localization in the selection of features and overall emotion recognition is confronted. In order to solve these problems, this paper put forwards the BPSO algorithm, which can be optimized to solve the problem of low accuracy of emotion recognition from a holistic perspective by selecting more representative features and localizing from emotion recognition, i.e., focusing only on the specific technique used for feature selection.

2. Materials and methods

2.1 DEAP dataset

DEAP is a publicly available multimodal dataset that includes data from 32 channels of EEG, EEG, EMG, and electrical skin responses[5]. Only EEG recordings were used in the classification task. There are 32 subjects participating in the experiment, all of them healthy, with the same number of men and women, and with a mean age of 24.9. Each subject was asked to watch 40 emotion-related videos, with each trial lasting 63 seconds, and at the end of the music videos, subjects were asked to rate the validity, arousal and dominance of these videos[6].

2.2 Pre-processing

We used a pre-processed version of the data prepared in the DEAP database with a sampling frequency of 128 Hz. These data were band-pass filtered at 4-45 Hz for 32 channels of 32 subjects according to the study requirements to ensure that the retained EEG signals were those containing emotional information, and only the first 3 seconds of the experiment were removed to maintain consistency. Next, the data were cut using the sliding window idea to increase the sample size.

2.3 Feature set

We use mean, standard deviation, variance, covariance, mean absolute deviation, median, median absolute deviation, skewness, kurtosis, maximum, minimum, peak difference, upper quartile, lower quartile, Hjorth feature, power spectral density corresponding to the δ、θ、α、β、γ band, band power and band power ratio, wavelet energy, and differential entropy for a total of 32 features.

2.4 BPSO algorithm

The BPSO algorithm selects the features related to the subject's emotion i.e., the representative features related to emotion are selected based on the emotion recognition accuracy. The particle swarm selection is performed until a more accurate EEG feature information is found and matched to a recognition accuracy corresponding to the current optimal feature, and the composition of features associated with the accuracy rate is considered to be optimum at the present time.

The BPSO particles formed by the binaries code are each two made bit to generate the velocity and the velocity can be expressed as:

$$v_{ij}(t+1) = \omega v_{ij}(t) + c_1 r_1(t)\left[p_{ij}(t) - x_{ij}(t)\right] + c_2 r_2(t)\left[p_{gj}(t) - x_{ij}(t)\right] \tag{1}$$

Within the BPSO algorithm, 0 or 1 is used to indicate the placement and best location to locate each particle in each and all dimensions. The individual location of the particles x_{ij} whether the individual position is 1 or not goes depends on the per-dimensional velocity of the particle v_{ij} Eq. (2) is to yield the value of the velocity as well as the possibility of the binaries bit taking the value 1. The $Sigmoid$ function is in the value series [0,1] and may be denoted as:

$$Sigmoid(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The velocity can be mapped to the region of [0,1], which is used as the probability of the $Sigmoid$ function, and the possibility of the particle being 1 in the next step is the probability sought. Therefore, the individual optimal position p_{best} global optimal position g_{best} in BPSO can only take the value of each bit in the range of [0,1]. Its position $x_{i,j}$ The update equation is expressed as follows.

$$s\left(v_{i,j}\right) = 1/\left[1+\exp\left(-v_{i,j}\right)\right] \tag{3}$$

where the location $x_{i,j}$ is taken to be 1 with probability by $s\left(v_{i,j}\right)$, and changing the particle its location is changed by using $x_{i,j}$.

$$x_{i,j} = \begin{cases} 1, r < s\left(v_{i,j}\right) \\ 0, \text{other} \end{cases} \tag{4}$$

where the number of random digits that can be derived from the uniform distribution $rand\left(0,1\right)$ is r .

2.5 Support vector machines (SVMs) classifiers

Support vector machines use kernel tricks and separation hyperplanes to classify new observations using support vectors from the training data. Support vector machines can be used for regression and classification. In support vector machines, The category label for finding predictions involves the observable x.

$$\hat{f}(\mathrm{x}) = \mathrm{sgn}\left(\hat{w}_0 + \sum_{i=1}^{N} \alpha_i k\left(x_i, x\right)\right) \tag{5}$$

where , λ is the $\ell 1$ regularizer, and is the kernel function. For a Gaussian kernel support vector machine, the kernel function is defined as:

$$k\left(x_i, x\right) = \exp\left(-\frac{1}{2}\left(x_i - x\right)^T \sum^{-1}\left(x_i - x\right)\right) \tag{6}$$

2.6 Classification assessment indicators

In the experiment, five classification metrics were used to validate the method of comparison, including true positive rate (Recall), positive predictive value (Precision), F1 value, negative predictive value (NPV), and classification accuracy (ACC). They can be defined separately as follows.

$$\text{Recall=}\frac{\text{TP}}{\text{TP+FN}} \tag{7}$$

$$\text{Preicision=}\frac{\text{TP}}{\text{TP+FP}} \tag{8}$$

$$\text{F1=}\frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision+Recall}} \tag{9}$$

$$\text{NPV=}\frac{\text{TN}}{\text{TN+FN}} \tag{10}$$

$$\text{ACC=}\frac{\text{TP+TN}}{\text{TP+TN+FP+FN}} \tag{11}$$

3. Results and discussion

Emotion recognition experiments based on the BPSO algorithm and the PSO algorithm were conducted with eight groups of feature iterations, each group of feature iterations was selected 50 times, and eight optimal recognition accuracies were output in each of the eight groups of feature iterations selected, as shown in Fig. 1. The discrete binary particle swarm algorithm continues to improve in accuracy as it continues to find optimal features and output recognition accuracies.

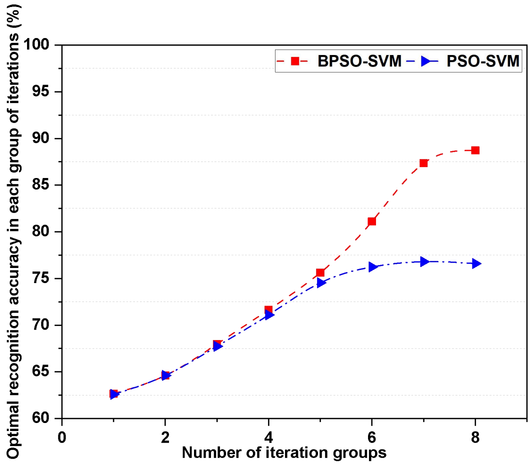


Fig 1 Recognition rate of SVM classification based on BPSO and PSO

As seen in Fig. 1, the recognition accuracy of the optimal features selected by BPSO-SVM in the first iteration is 62.66%, and that of PSO-SVM is 62.58%, with only 0.08% difference; there is a significant difference in the sixth iteration, with an increase of 4.86%, after which the performance of PSO-SVM in finding the optimal features gradually slows down, while the recognition accuracy of BPSO-SVM increased to 87.34%.

In this study, the SVM classifier was used to train 75% of the subjects in the DEAP database for four categories of emotion recognition: happy, angry, sad, and neutral, and 25% of the subjects for four categories of emotion recognition accuracy. As shown in Table 1.

Table 1 Emotion recognition accuracy based on BPSO and PSO

Subjects	PSO-SVM				BPSO-SVM			
	happiness (%)	anger (%)	sadness (%)	neutral (%)	happiness (%)	anger (%)	sadness (%)	neutral (%)
1	80.86	74.84	72.81	71.95	94.14	91.09	91.48	91.80
2	82.66	82.27	77.58	70.78	93.36	91.8	92.03	91.17
3	80.86	75.78	67.42	*61.09	92.81	90.63	92.19	88.44
4	78.13	67.27	66.56	62.66	93.59	93.52	92.73	91.17
5	*76.33	*63.36	*63.98	64.92	93.75	93.28	91.33	90.39
6	83.20	81.95	81.02	78.98	94.53	90.78	89.61	*81.72
7	81.72	77.73	68.2	71.25	95.23	93.13	*88.83	82.19
8	81.33	76.8	74.3	74.69	*91.48	*84.61	89.92	86.41
Average recognition rate	80.64	76.66	72.56	70.75	93.61	91.11	91.33	87.91

*Indicates low accuracy in classifying emotions

As BPSO looked for features matched with high recognition accuracy, the average recognition rate of happy was 93.61%, the average recognition rate of angry was 91.11%, the average recognition rate of sad was 91.33% and the average recognition rate of neutral emotion was 87.91%; all were higher than the average classification accuracy results of PSO-SVM, i.e., based on BPSO-SVM happy, angry, sad and neutral emotion recognition rates were higher than PSO-SVM by 12.97%, 14.45%, 18.77%, and 17.76%, respectively.

The average recognition rate of happy, angry, sad and neutral emotions, as shown in Table 2, reaches 88.95% for BPSO-SVM, and 91.78% for happy emotions, which is an 11.23% improvement in the recognition rate of BPSO-SVM compared with PSO-SVM. The lowest improvement is the NPV value of anger, which is 7.86%, and the highest is the recall rate of sadness, which is 31.14%.

Table 2 Evaluation indexes based on BPSO-DT and BPSO-SVM

Evaluation indicators	Emotion classification based on BPSO-SVM					SVM-based sentiment classification				
	happiness	anger	sadness	neutral	Average recognition rate	happiness	anger	sadness	neutral	Average recognition rate
	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)	(%)
Acc	91.78	89.95	88.27	85.81	88.95	80.55	76.73	74.95	72.24	76.12
Recall	90.05	83.29	79.11	64.18	79.16	73.76	58.55	47.97	38.67	54.21
Precision	85.42	71.02	70.53	66.56	73.39	75.32	57.6	49.11	40.6	55.22
F1	86.61	73.68	70.71	57.38	72.09	70.68	47.63	39.98	30.98	49.18
NPV	94.11	94.66	93.61	90.44	93.20	85.13	86.8	85.28	83.4	84.74

The accuracy, recall, value and NPV of the emotion classification results under BPSO-SVM are evaluated as 88.95%, 79.16%, 73.39%, 72.09% and 93.20%, which are 12.83%, 24.95%, 18.17%, 22.91% and 8.46% higher than the classification accuracy of PSO-SVM, as seen in Fig. 2. The BPSO-SVM emotion recognition model, on the other hand, is more adaptive to the interaction of different features of nonlinear EEG signals and is highly fault-tolerant.

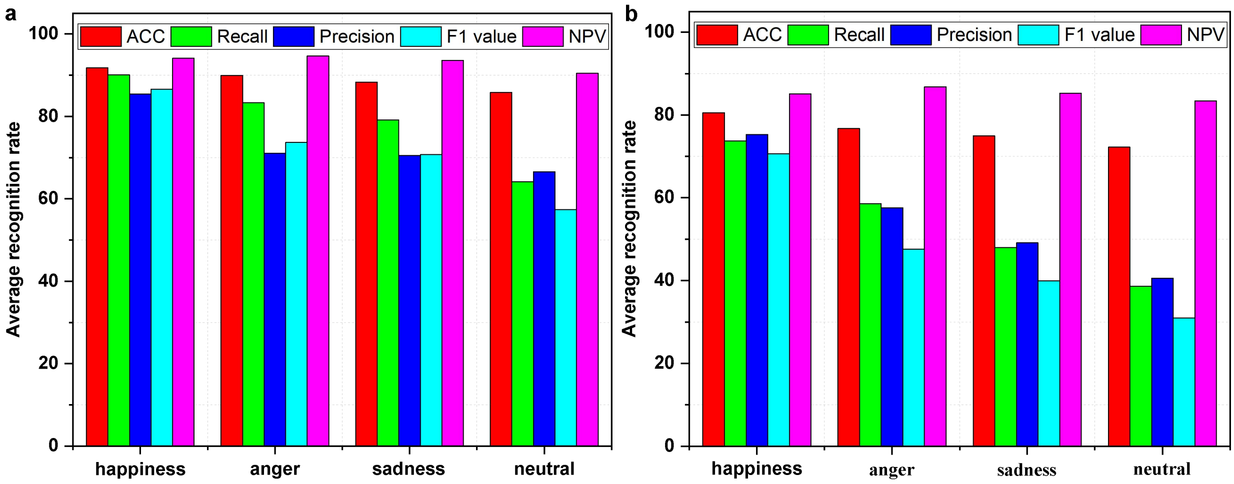
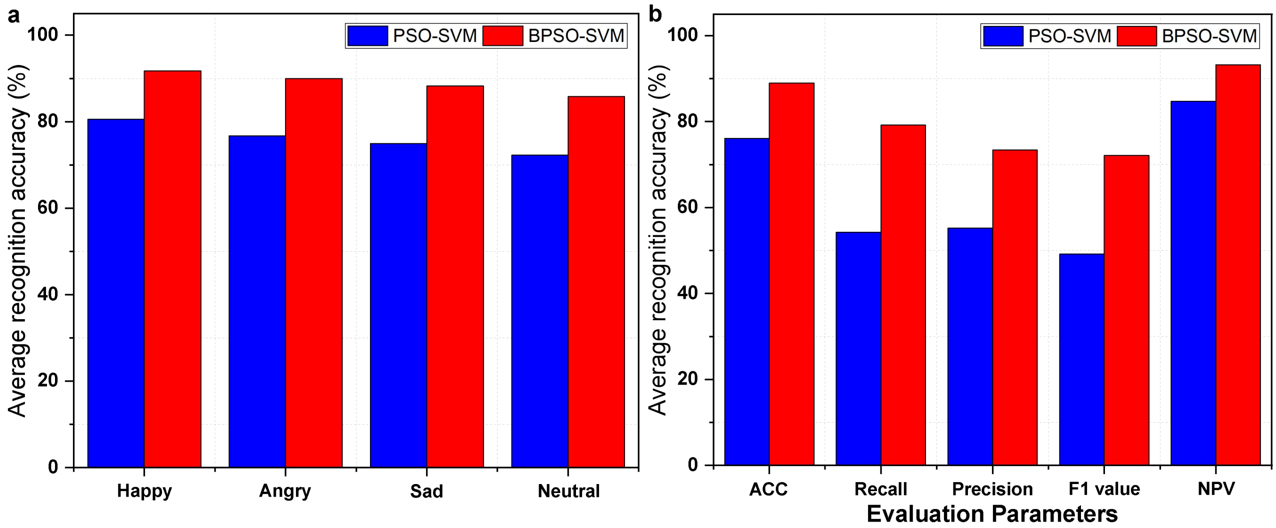


Fig 2 Emotion classification results based on BPSO and PSO with SVM: (a) Emotion classification based on BPSO-SVM (b) Emotion classification based on PSO-SVM

The four categories of emotion recognition rate happy has the highest recognition rate in the experiment, anger and sadness have the second highest recognition rate, while neutral emotion has the lowest recognition rate. As shown in Fig. 3, the highest recognition rate of happy emotion reached 91.78% in the classification results based on BPSO-SVM.



4. -Summary

BPSO effectively solves the problem of poor feature finding accuracy by using the classification accuracy as the judging criterion for finding the optimal features, and after repeated searching, the feature combination corresponding to the highest recognition rate is considered as the optimal feature, and the best feature selection is found to improve the recognition rate. The effect of feature selection is accurately evaluated by classification accuracy, and the results of each search for the optimal feature are directly connected with the classifier to output the recognition accuracy, and the EEG emotion features with stronger correlation with each classified emotion are obtained, which better avoid the non-important EEG emotion classification features taken due to imprecise localization, thus achieving the purpose of improving the recognition rate of emotion classification. It also shows that finding features with higher adaptability to the classifier has a positive effect on the improvement of different emotion recognition accuracy, and that feature selection and classification do not exist independently, but interact with each other and influence each other.

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