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Sensitive Trans Formation and Multi-Level Spatiotemporal Awareness Based Eeg Emotion Recognition Model

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Abstract: Electroencephalography (EEG) emotion recognition has important research value in the fields of medical and criminal investigation, so in recent years, deep learning methods have been widely used in the field of EEG emotion recognition. Generally, the spatial and temporal features of EEG signals can reflect the spatial information of EEG in different brain regions and the long-term features of time-related continuous EEG signals. However, the problem of obtaining accurate spatial and temporal features of sequence signals has been neglected in previous studies. In addition, the spatial information transformation of electrode points on brain regions is not accurate enough. To address these issues, we propose a sensitive transformation and multi-level spatiotemporal awareness based EEG emotion recognition model. Through this method, accurate spatial information and more comprehensive EEG spatiotemporal features can be obtained. The evaluation results of SEED dataset show that the proposed approach improves on the state-of-the-art in EEG emotion recognition. The accuracy rates of subject-dependent and subject-independent emotion recognition are 98.49% and 97.95%, which exceeds the best previous accuracy by 1.18%.

1. Introduction

Emotion recognition from EEG signal is an active research topic in the field of computer vision in recent years. Compared with traditional non-physiological signals such as speech [1], expression [2], action [3], text [4], EEG signals have characteristics that cannot be disguised [5]. Therefore, the use of EEG signals for emotion recognition is of great significance in key fields such as medical treatment and criminal investigation.

It is important to accurately transform electrode points on different brain regions. The device that captures EEG signal is called an electrode cap. Electrode caps are connected by multiple electrode points and wires arranged in a ‘10/20 system’ [6]. According to the '10/20 system', researchers often use the sparse mapping method [7] and the compact mapping method [8] to obtain the spatial information of EEG signal. The sparse mapping method uses a 19*19 sparse matrix, which has a large amount of data and takes a long time to calculate the model. To solve this problem, compact mapping methods are proposed. The compact mapping matrix is 8*9, which greatly reduces the amount of data. However, the transformation positions of the electrode points did not meet the relationship between the electrode points and the brain area and the connection relationship between the electrode points as stipulated by the 10/20 system.

The processed data can be used for emotion recognition through machine learning or deep learning methods. EEG signal are sequential signal related to time. In machine learning methods, researchers usually first manually extract the wavelet energy feature of EEG [9], or differential entropy feature (DE) [10]. Then, support vector machine (SVM) [11] and radial basis function neural network (RBF-NN) [12] are used for emotion recognition. The manual extraction method is labor-intensive, and the method needs to segment the EEG signal into data segments, resulting in a reduction in the amount of data. And the feature extracted by the machine learning method are shallow, and the recognition accuracy is low. In order to solve these problems, with the development of deep learning, many researchers apply deep learning methods to emotion recognition based on EEG signal. Some studies [13-14] still manually extract local feature of EEG signal and then use deep models to learn deep feature. The shortcomings of manual feature extraction are still unavoidable. Therefore, the direct use of deep models for feature extraction and emotion recognition has become the key to research. Taking the EEG signal as input, a Convolutional Neural Network (CNN) [15] or Deep Belief Network (DBN) [16] model is employed for emotion recognition. Although this method can effectively learn data feature, it is poor in temporal feature learning. Therefore, Elham et al. [17] adopted a three-dimensional convolutional neural network (3D-CNN) for emotion recognition from EEG. However, this method can only learn the context information of adjacent moments, and the 3D model is computationally intensive. In order to effectively learn the long-term temporal feature of EEG signal, Acharya [18] et al. adopted a long short-term memory network (LSTM) model, but LSTM cannot learn the spatial feature of EEG signal well.

Through the above analysis, the field of EEG emotion recognition faces two problems. First, design an EEG signal transformation model to retain accurate spatial information. According to the electrode position and connection relationship specified by the '10/20' system, the design is more in line with the relationship model between electrode points and different brain regions. Second, design a more comprehensive model for feature learning. Deep models for EEG emotion recognition require the ability to learn both spatial and long-term temporal feature.

To address the above issues, this paper proposes a sensitive transformation and multi-level spatiotemporal awareness based EEG emotion recognition model (STSAM) model. The model consists of three parts. First, the sensitive transformation model. The normalized EEG signal data is used as the input, and the electrode point data at each moment is used for sensitive conversion, so as to retain the accurate brain area spatial information of the electrode points. Second, the multi-level spatiotemporal awareness model. Taking sensitively transformed data as input, it can effectively learn the long-term spatiotemporal feature of EEG signal. Third, the emotion recognition model. The emotion recognition function of EEG signal is realized by this model.

The main contributions of this paper include three aspects:

(1) A sensitive transformation model is proposed. This method completely transforms the electrode point positions specified in the "10/20 system", and retains more accurate spatial position information of EEG signals than other transformation methods.

(2) A multi-level spatiotemporal awareness model is proposed. The model effectively learns the spatiotemporal features of EEG signals. A self- awareness method is introduced to improve the

recognition accuracy.

(3) Evaluating our proposed approach on SEED dataset. The result suggest that our approach achieves significantly batter performance that state-of-the-art approaches.

2. Related Works

In order to effectively preserve the spatial information of EEG signal, Li et al. [19] proposed a sparse transformation method. The data size transformed by this method is a sparse matrix of 19*19. Training a sparse matrix requires a large amount of computation and low efficiency. To solve this problem, Shen et al. [8] adopted a compact transformation method. The size of the data is transformed by this method is 8*9. Compared with sparse transformation methods, the amount of data is reduced and the model computation is low. However, the compact transformation method does not fully comply with the positional relationship between electrode points and different brain regions and the connection relationship between electrode points specified in the '10/20' system. This method will lead to inaccurate spatial information of the transformed EEG signal, thereby affecting the learning of spatial feature by subsequent models.

Emotion recognition methods in EEG signal include machine learning and deep learning. Machine learning methods mainly treat EEG signal as time-correlated one-dimensional waveform signal. Manual feature extraction is first performed on the EEG signal. The extracted feature include time domain feature, frequency domain feature, time-frequency domain feature and nonlinear feature. The time-domain feature include the mean, skewness, variance, and standard deviation of EEG signal. Frequency-domain feature are methods of transforming time-domain signal into frequency space. The time-frequency domain feature is a combination of the time domain feature and the frequency domain feature of the EEG signal data, and the feature are more comprehensive. For example, Xu et al. [20] extracted the five-band feature of EEG signal, and then performed short-time Fourier transform (STFT) to calculate the power spectrum feature. However, the methods of extracting time-frequency feature all need to segment the EEG into data segments, which reduces the amount of data, and the learned feature are only current short-term feature. Since EEG signal are long signal that change continuously, it is important to extract long-term feature. This problem can be effectively solved by adopting the differential entropy feature (DE) [21] in nonlinear feature. Afterwards, classification methods such as Support Vector Machine (SVM) [11] and Radial Basis Function Neural Network (I-RBF-NN) [12] can be used for emotion recognition. The shortcomings of the machine learning method are that the feature extracted are shallow and the recognition accuracy is low.

To learn deep feature, the field has adopted deep learning methods for autonomous feature extraction and emotion recognition. With the advancement of deep learning methods, EEG-based emotion recognition has adopted deep learning methods for autonomous feature extraction and emotion recognition. Dan et al. [16] applied Deep Belief Network (DBN) to EEG-based emotion recognition. DBN models can learn deep data feature, but DBNs cannot learn high-level abstract feature. Therefore, Chao et al. [22] proposed a Deep Belief Network Conditional Random Field (DBN-CRF) model, which solves the problem that DBN cannot fully capture the contextual information of EEG signal. However, the DBN-CRF model cannot accurately learn the spatial characteristics of EEG in different brain regions. To solve this problem, Song et al. [23] introduced the graph structure into the EEG-based emotion recognition model, and proposed an EEG emotion recognition method based on Dynamic Graph Convolutional Neural Network (DGCNN). The method utilizes a graph structure to represent EEG signal. However, EEG signal are time-related signal, and temporal feature should also be fully considered in emotion recognition. Elham et al. [17] adopted a three-dimensional convolutional neural network (3D-CNN) for emotion recognition from

EEG. The model constructs the data of each moment into a 2D space matrix, and then superimposes the data of multiple moments to form a 3D matrix as the model input. Although this method can learn contextual information, it can only learn short-term feature, and the 3D model is computationally expensive. In order to learn the long-term feature of EEG signal, Acharya et al. [18] adopted the Long Short-Term Memory (LSTM) model. Although LSTM is suitable for learning long-term temporal feature, it cannot learn the spatial feature of EEG signal well. In order to effectively learn the spatiotemporal feature of EEG signal, some studies [24-25] employ a cascaded model of CNN and LSTM. These studies provide us with a good idea of model linking.

In summary, how to effectively and accurately obtain the spatial information of EEG signal and learn the long-term spatiotemporal feature of EEG signal is the main research direction in this field.

3. Methods

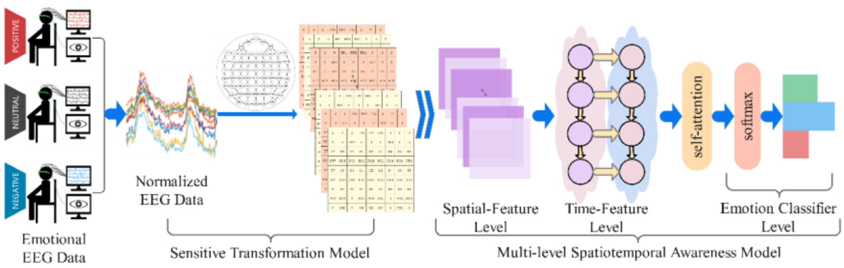


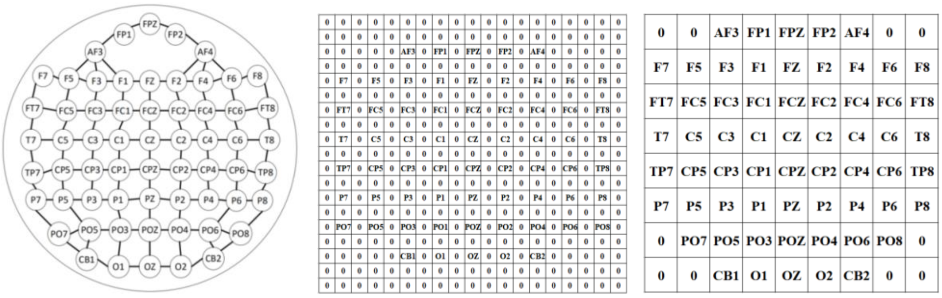
Figure 1: STSAM architecture

In this paper, we propose a sensitive transformation and multi-level spatiotemporal awareness based EEG emotion recognition model (STSAM), in order to accurately preserve EEG spatial information and learn spatiotemporal feature. The model diagram of STSAM is shown in Figure 1. The data is EEG signal data with 62 electrode points. The data for each electrode point is a time-correlated one-dimensional signal. First, normalize the data to be between [-1,1]. Then, the EEG data obtained from 62 electrode points per unit time was used as the input to the model. Through the sensitive transformation model, the input data has accurate spatial information of electrode points. Through a multi-level spatiotemporal awareness model, the long-term spatiotemporal characteristics of EEG signal are learned. Finally, the softmax classifier is used to classify emotions into three categories: positive, neutral and negative, and the accuracy of emotion recognition is obtained.

3.1 Sensitive Transformation Model

EEG signal are acquired by electrode points on the electrode cap. The '10/20' system electrode placement method [6] specifies the positional relationship between the electrode points on the standard electrode cap and different brain regions and the connection relationship between the electrode points. Figure 2(a) shows the regular distribution of electrode points in the '10/20' system. In the process of data transformation, it is necessary to be sensitive to the position of electrode points in order to retain accurate spatial information of EEG signal.

Li et al. [26] proposed a sparse transformation method as shown in Fig. 2(b). The size of the sparse transformation matrix is 19*19, which is computationally intensive. Therefore, Shen et al. [27] adopted a compact transformation method, as shown in Fig. 2(c). The compact transformation matrix size is 8*9, which greatly reduces the amount of data. The connection relationship between adjacent electrode points in the matrix is stronger. But the mapped matrix is not sensitive to the spatial information of electrode points. In view of the shortcomings of the above two transformation methods, this paper proposes a sensitive transformation model, as shown in Figure 3. The size of the sensitive transformation matrix is 9*9. Compared with the sparse transformation method, this transformation model matrix is small and the model computation is small. Compared with the compact transformation method, the connection relationship between FP1, FPZ, FP2, P3, P4, P5, P6, P7, P8 electrode points and F1, FZ, F2, PO5, PO6, PO7, PO8 electrode points is more in line with '10/ 20' system. And the positional relationship between FP1, FPZ, FP2, AF3, AF4 electrode points and brain regions is more in line with the '10/20' system. The sensitive transformation model preserves accurate spatial information of EEG signal, which helps subsequent models learn accurate spatial feature.



(a) (b) (c)

(a) ‘10/20’ system (b) Sparse transformation (c) Compact transformation

Figure 2: ‘10/20’ system electrode placement method and EEG signal transformation

0	0	0	FP1	FPZ	FP2	0	0	0
0	0	AF3	0	0	0	AF4	0	0
F7	F5	F3	F1	FZ	F2	F4	F6	F8
FT7	FC5	FC3	FC1	FCZ	FC2	FC4	FC6	FT8
T7	C5	C3	C1	CZ	C2	C4	C6	T8
TP7	CP5	CP3	CP1	CPZ	CP2	CP4	CP6	TP8
P7	P5	P3	P1	PZ	P2	P4	P6	P8
PO7	PO5	0	PO3	POZ	PO4	0	PO6	PO8
0	CB1	0	O1	OZ	O2	0	CB2	0

Figure 3: Sensitive transformation

3.2 Multi-Level Spatiotemporal Awareness Model

The multi-level spatiotemporal awareness model consists of multi-layer convolution channels, multi-layer Gate Recurrent Unit (GRU) channels and self-attention modules.

The multi-layer convolution channel consists of a lightweight 3-layer convolution for learning the spatial feature of EEG signal. The three layers of convolution all use 3*3 convolution kernels, and the number of channels is 32, 64 and 128 respectively. The model uses ReLu as the activation function to speed up the calculation and the convergence of the model. The input and output data size of each layer of convolution remains the same, which is 9*9. Since the training EEG samples are high-dimensional small sample data, Dropout is introduced to solve the overfitting problem. And its calculation method is shown in formula (1), where y is the input and y' is the output, a Bernoulli distribution with probability p is used to randomly generate the same 0 or 1 value as the number of nodes.

$$y' = Bernoulli(p) * y \tag{1}$$

The multi-layer GRU channel consists of 2-layer GRUs to learn long-term temporal feature of EEG signal. The definition of the GRU formula is shown in formula (2) to (5), where x_t is the current input, h_{t-1} is the hidden state passed from the previous node, h_t is the hidden state of the previous node, σ is the sigmoid function, W_z、W_r、W is the parameter of forward propagation learning, z_t is the update gate, r_t is the reset gate, and $\widetilde{h_t}$ is the hidden state after reset using the tanh activation function. Two layers loop gate channels are 64 and 32. Recurrent neural networks (RNNs) commonly used to learn long-term temporal feature include LSTMs and GRUs. Compared with LSTM, GRU has fewer parameters and faster computation speed [28]. Therefore, our multi-level spatiotemporal awareness model uses GRU to learn temporal feature for easier model training.

$$z_t = \sigma(W_z \cdot [h_{t-1}, x_t]) \tag{2}$$

$$r_t = \sigma(W_r \cdot [h_{t-1}, x_t]) \tag{3}$$

$$\tilde{h}_t = tanh(W \cdot [r_t * h_{t-1}, x_t]) \tag{4}$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t \tag{5}$$

According to the review of the self-attention mechanism in reference [29], this paper adopts the attention mechanism approach described below. The input data X has a total of n nodes. The probability distribution $P(X)$ of each input node on each category is calculated by softmax and its calculation method is shown in formula (5). Then the obtained probability distribution $P(X)$ is re-acted on the input data X according to the formula (6). Through this method, each node of the input data becomes the output data X' with a class probability distribution. The higher the probability of some nodes of the data on a certain category, the more relevant the category is, and it is necessary to be more aware of this part of the nodes.

$$P(X) = softmax(XX^T) \tag{6}$$

$$X' = P(X)X \tag{7}$$

In the multi-level spatiotemporal awareness model, multi-layer convolution channels are used to learn spatial feature of EEG signal, multi-layer GRU channels are used to learn long-term temporal feature of EEG signal, and self-attention is used to improve recognition accuracy. Learning spatiotemporal feature through this model is beneficial for subsequent sentiment classification.

3.3 Emotion Recognition

We divided the emotions expressed by EEG signal into three categories, namely positive, neutral and negative. STSAM finally uses the full connection and softmax function to calculate the probability of the input sample data on different categories. We introduce the softmax_cross_entropy loss function to pass the deviation of the predicted value from the label value during backpropagation. The purpose is to avoid the phenomenon of numerical overflow due to the relatively large probability value of the output node, and to ensure the stability of numerical calculation. The category with the largest output probability value is the predicted category of the input sample data. The probability of correct recognition of all EEG signal samples is the accuracy of emotion recognition.

4. Experiment

In this experiment, we explored the impact of the proposed STSAM in the field of EEG emotion recognition. First, we introduce the dataset and experimental setup we used. Then, compare the data transformation models proposed by other researchers to explore the effect of our proposed sensitive transformation model. Then, subject-independent and subject-dependent EEG emotion recognition experiments were carried out using STSAM. Explore the effect of STSAM by comparing it with models proposed by other researchers. Finally, the ablation experiment is carried out, which proves that every part of the model plays a role in the emotion recognition task.

4.1 Dataset

To verify the effectiveness of the proposed model, we perform validation on the SEED dataset [30] published by Shanghai Jiao Tong University in 2015. EEG emotions in this dataset are divided into three categories: positive, neutral, and negative. The dataset consists of 15 subjects, and each subject has 15 experiments, including 5 positive, 5 neutral, and 5 negative emotional stimuli experiments. That is, a total of 225 experiments are included in the SEED dataset. Each experiment contained 4 min of continuous EEG signal data recording at 62 electrode points. The sampling frequency of the EEG signal is 200Hz.

4.2 Experiment Setup

The sampling frequency of the EEG signals in the SEED dataset is 200Hz, that is, 200 frames of EEG signal data with 62 electrode points can be acquired per second. In order to avoid the problem of subject emotional instability at the beginning and end of the experiment, we intercepted the data from the first minute to the third minute of each experiment. That is, a total of 5.4*106 frames of data samples can be obtained from 225 experiments. Normalize the data samples between [-1, 1] as model input.

First, the data in the input STSAM is transformed to preserve the spatial information. Each frame of data is the EEG data acquired by 62 electrode points, so the data of each frame can use sensitive transformation to include its electrode point position information. Then, subject-independent and subject-dependent EEG emotion recognition experiments were performed using the multi-level spatiotemporal awareness model respectively. In the subject-independent experiments, we use one of the 15 subjects as the test set and the other as the training set for 15 experiments. The results of 15 experiments were averaged as the subject-independent EEG emotion recognition accuracy. In the subject-dependent experiments, we conduct ten-fold cross-validation experiments with each of the 15 subjects' own data. A total of 15 experiments were performed. The results of 15 experiments were averaged as the subject-dependent EEG emotion recognition accuracy.

The experimental parameters of STSAM are set as follows, using the Tensorflow framework, Batch-size is 64, Dropout is 0.5, the loss function is softmax_cross_entropy, and the L2 regularization coefficient is set to 10^{-4}. The feature extractor is optimized using the Adam optimization algorithm with a learning rate of 1×10^{-3}, and 5% of the data is selected as the validation set. The experiment uses a combination of theoretical analysis and emotion recognition accuracy as evaluation criteria. The hardware platform is Intel i7-6700, the memory is 16G, and the GPU is NVIDIA 1070.

4.3 The Effectiveness of Sensitive Transformation

The input EEG data are mapped by the sparse mapping method, the compact mapping method and the sensitive transformation mentioned in 3.1 respectively. The multi-level spatiotemporal awareness model in STSAM was used for subject-independent EEG emotion recognition. Table 1 shows the performance comparison of the three data transformation methods on the SEED dataset. Among them, the sensitive transformation method contains more accurate spatial information of electrode points and brain regions than other methods, so the recognition accuracy is higher. In addition, the time-consuming of our method is close to that of the compact mapping method, which is one third of that of the sparse mapping method. By comparing the performance of the three data mapping methods, the sensitive transformation method has high accuracy and relatively low time consumption. Therefore, the following experiments adopt the sensitive transformation method proposed in this paper.

Table 1: Performance Comparison of Three Mapping Methods on SEED dataset.

2D map	Map shape	ACC	Time cost per epoch
Compact Mapping	8*9	96.97%	88s
Sparse Mapping	19*19	97.55%	255s
Sensitive Transformation (ours)	9*9	97.95%	91s

4.4 STSAM for Subject-Independent EEG Emotion Recognition

Table 2 shows the performance comparison between the proposed STSAM in this paper and current methods for subject-independent emotion recognition on the SEED dataset. Compared with the method of manual feature extraction first, STSAM uses a deep model to learn features, and the learned features are deeper. Compared with other deep models, our sensitive transformation method preserves more accurate spatial information, and our multi-level spatiotemporal awareness model learns more comprehensive long-term spatiotemporal features. Therefore, we have achieved the current highest recognition accuracy rate, reaching 97.95%.

Table 2: The results of the subject-independent emotion recognition experiments.

Method	Ave-Acc
MSFBEL[31]	74.23%
GAN [32]	84.00%
3D-CNN[17]	88.49%
DGCNN[23]	90.40%
DECNN[33]	90.41%
4DCNN-LSTM[27]	92.88%
MSPCA-TQWT[34]	93.10%
K-NN[35]	95.85%
CNN-SAE-DNN[36]	96.77%
ATT-CRNN(ours)	97.95%

4.5 STSAM for Subject-Dependent EEG Emotion Recognition

Table 3 shows the performance comparison between the proposed STSAM in this paper and current methods for subject-dependent emotion recognition on the SEED dataset. Compared with other deep models, STSAM has the advantage of preserving accurate spatial information and learning long-term spatiotemporal features. Therefore, it has achieved the best recognition accuracy rate in recent years, reaching 98.49%.

Table 3: The results of subject-dependent emotion recognition experiments.

Method	Ave-Acc
SSFBEL[31]	85.75%
MSFBEL[31]	87.87%
DGCNN[23]	90.40%
DE-GELM[37]	90.83%
DE-CNN[38]	91.68%
ATT-CRNN(ours)	98.49%

4.6 Ablation Experiment

In order to verify that each part of the STSAM proposed in this paper affects the experimental results, four models are designed for ablation experiments. The model structure and experimental results are shown in Table 4. By comparing M2 and M1, it is necessary to use sensitive transformation to preserve spatial information. Through the comparison of M3, M4 and M1, it is valuable to learn the temporal and spatial characteristics of EEG signals in the field of emotion recognition.

Table 4: Ablation experimental models

Model	Model Structure			ACC
	sensitive transformation	multi-layer convolution	multi-layer GRU	
M1	√	√	√	97.95%
M2	×	√	√	95.31%
M3	√	×	√	94.07%
M4	√	√	×	94.83%

In summary, the STSAM proposed in this paper effectively preserves the spatial information of electrode points and learns comprehensive long-term spatial and temporal features. In the field of EEG emotion recognition, state-of-the-art results have been achieved.

5. Conclusions

EEG signal have the advantage that they cannot be camouflaged, so EEG emotion recognition has important research value in the fields of medical treatment and criminal investigation. In order to solve the problem of accurate spatial information between electrode points and brain regions and EEG signal combined with spatiotemporal features, which were ignored in previous studies. This paper proposes a sensitive transformation and multi-level spatiotemporal awareness based EEG emotion recognition model (STSAM). A sensitive transformation model is adopted to preserve accurate spatial information. A multi-level spatiotemporal awareness model is used to learn comprehensive spatiotemporal features of EEG signal. The SEED dataset is used for subject-dependent and subject-independent EEG emotion recognition, and the accuracy rates are 98.49% and 97.95%. The experimental results are 1.18% higher than the previous best accuracy, reaching the state-of-the-art in this field.

In future work, we will use other EEG signal datasets to learn and optimize the model. In addition, self-collected data will be considered for experiments, in order to enhance the generalization ability of the emotion recognition model proposed in this paper.

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