TRANSFORMERS FOR EEG EMOTION RECOGNITION

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ABSTRACT

Electroencephalogram (EEG) can objectively reflect emotional state and changes. However, the transmission mechanism of EEG in the brain and its internal relationship with emotion are still ambiguous to human beings. This paper presents a novel approach to EEG emotion recognition built exclusively on self-attention over the spectrum, space, and time dimensions to explore the contribution of different EEG electrodes and temporal slices to specific emotional states. Our method, named EEG emotion Transformer (EeT), adapts the conventional Transformer architecture to EEG signals by enabling spatiospectral feature learning directly from the sequences of EEG signals. Our experimental results demonstrate that "joint attention" where temporal and spatial attention are applied simultaneously within each block, leads to the best emotion recognition accuracy among the design choices. In addition, compared with other competitive methods, the proposed method achieves state-of-art results on SEED and SEED-IV datasets.

Index Terms— EEG, emotion recognition, transformer

1. INTRODUCTION

EEG emotion recognition is to detect the current emotional state of the user subject [1]. In recent years, with the development of deep learning and the availability of EEG data, many emotion recognition methods based on neural networks have dominated the state-of-art position [2, 3]. In general, the EEG signals collected by a spherical EEG cap have three-dimensional spatial characteristics which are spatial, spectral and temporal. Deep learning methods for EEG emotion recognition have been exploiting spatial, spectral and temporal dimensions.

Spectral Dimension Zheng et.al [4] introduce deep belief networks to investigate critical frequency bands and channels, which is a pioneering work in EEG-Based emotion recognition with neural networks. AlNafjan et al. [2] adopt Deep Neural Networks (DNN) using PSD feature to identify human emotions. Yang et al.

Temporal Dimension Fourati et al. [5] present an Echo State Network (ESN), which uses recursive layer projects the raw

EEG signals to the high-dimensional state space. Alhagry et al. [6] use a two-layer long-short term memory (LSTM) to get satisfactory emotion recognition results with the EEG signal as input. Bashivan et al. [7] propose a deep recursive convolutional neural network (R-CNN) for EEG-based cognitive and mental load classification tasks.

Spatial Dimension Li et al. [3] present a hierarchical CNN to capture spatial information among different channels. Zhang et al. [8] propose a deep CNN model to learn the spatio-temporal robust feature representation of the raw EEG data stream for motion intention classification. Lawhern et al. [9] propose an application of multi-layer pure CNN without full connection layer for P300-based oddball recognition task, finger motor task and motor imagination task.

Although many of the above methods are based on CNN and RNN, they are not flawless. CNN can capture local receptive field information, but ignore global information. RNN network cannot capture spatial information, and parallel computing efficiency is slow. To overcome these shortcomings, attention mechanism is introduced in CNN or RNN.

Self-Attention Kim et al. [10] propose a long short-term memory network and apply an attention mechanism to assign weights to the emotional states appearing at specific moments to conduct two-level and three-level classification on the valence and arousal emotion models. Tao et al. [11] propose an attention-based convolutional recurrent neural network (ACRNN) to extract more discriminative features from EEG signal and improve the accuracy of emotion recognition on the DEAP and DREAMER databases. Liu et al. [12] propose a novel multi-channel model based on sparse graphic attention long short-term memory (SGA-LSTM) for EEG emotion recognition.

Though the above EEG emotion recognition methods have achieved promising results, they more or less ignored the transmission characteristics and spatial characteristics of EEG signals. The convolution operation is the mixed multiplication and addition of local area signals, which destroys the spatial characteristics of EEG signals to a certain extent. Although the RNN calculation takes into account the temporal characteristics, it ignores the spatial characteristics of the EEG signal. Moreover, the impedance of different regions of the human skull is different so that the EEG signal transmission time of each channel is very different to the receiving

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device. In other words, different channel signals collected at a time point have different contributions to the expression of emotional states. The above method does not take this time delay into consideration when learning spatial attention.

Regarding the above problems, we propose a novel EEG emotion transformer (EeT) framework built exclusively on self-attention blocks. The variants of self-attention block include spatial attention (S), time attention (T), time attention after spatial attention (S-T), and spatial attention joint time attention (S+T). The spatial attention is to learn the spatial structure information. The time attention is to learn the different contributions of different time slices. The time attention after spatial attention is to do one-by-one. The spatial attention joint time attention is to do two attention simultaneously. The S+T attention achieves the state-of-art performance which demonstrate that it is important to consider both temporal and spatial contributions at the same time.

2. EEG EMOTION TRANSFORMERS

2.1. Framework of EeT

EEG-based emotion recognition is to classify the emotion states according to the EEG signal. As illustrated in Fig. 1 the overview of the proposed EEG emotion transformers consists of three sub-modules which are feature preparing and re-organization, the innovative self-attention block and classification loss. The four gray blue blocks in Fig. 1 are our contributions in this paper.

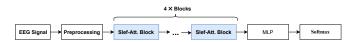


Fig. 1: Overview of EEG Emotion Recognition Transformer (EeT)

The EEG emotion classification problem is to learn a mapping function F that maps the EEG input to the corresponding emotion labels:

$$Y = F(X') \tag{1}$$

where $X^{'}$ denotes the representation of EEG signals. F denotes the mapping function i.e., neural network transformations. $Y \in \{y_1, y_2, ..., y_n\}$ denotes the emotion classification labels. In this paper, the classification cross entropy is adopted as loss function, which is defined as the formula:

$$L = -\sum_{c=1}^{C} y_c log(y'_c)$$
 (2)

where L denotes the loss function of the task of EEG emotion recognition, C denotes number of emotion classes, y_c is the ground truth emotion label and $y_c^{'}$ is the predictors of neural networks.

2.2. Preprocessing

Since the EEG signal collected by a spherical EEG cap, we use a feature representation organization method to organize the signals into 4D matrices to keep as much spatial structure information as possible. We define X = $(E_1, E_2, ..., E_T) \in \mathbb{R}^{C \times T}$ as an EEG sample collected in T time stamps, where C is the number of electrodes. E_t denotes the EEG signal of C electrodes collected at time stamp t. Here, we use the DE features denoted as F_t $(D_1, D_2, ..., D_S) \in \mathbb{R}^{C \times S}$ from E_t as described in [32]. We set $\delta[1 - 3Hz]$, $\theta[4 - 7Hz]$, $\alpha[8 - 13Hz]$, $\beta[14 - 30Hz]$, $\gamma[31 - 50Hz]$ as the spectral band set S. To explore the interactions among spatial and temporal dimensions, we re-organize F_t of the sample X into 4D EEG representation. Specifically, the sth band feature D_s from C channels is transformed into a 2D map $D_s' \in R^{V \times H}$. In other words, we reshape the 1D tensor $D_s \in R_C$ into 2D tensor $D_s' \in R^{V \times H}$ $(C \leqslant (V \times H))$. When we do the same operation in each band, F_t will be transformed into a 3D map $F_t^{'} = (D_1^{'}, D_2^{'}, ... D_S^{'}) \in \mathbb{R}^{S \times V \times H}$. Finally we stack all the transformed 3D feature map along the temporal dimension to get the 4D EEG representation $X' = (F'_1, F'_2, ..., F'_T) \in R^{T \times S \times V \times H}.$

2.3. Spatial Electrodes Position Encoding

We divided the EEG feature of each second $D_i(i=1,2,3..S)$ into G non-overlapping regions, just like the different brain regions in neuroscience. Here we regroup the C EEG electrodes in the $V \times H$ matrices into region sequences, the size of each divided region is $P \times P$, so we get $G = VH/P^2$ regions. Each region is flatten into a vector $I(x)_{(p,t)} \in \mathbb{R}^{5P^2}$ with p=1,2...,G representing spatial layout of EEG electrodes and t=1,2,...T denoting the index over seconds. Then we linearly map each region $I(x)_{(p,t)}$ into a latent vector $z_{(p,t)}^{(0)} \in \mathbb{R}^D$ by means of learnable matrix $M \in \mathbb{R}^{D \times 5P^2}$:

$$z_{(p,t)}^{(0)} = MI(x)_{(p,t)+e_{(p,t)}^{pos}}$$
(3)

where $e_{(p,t)}^{pos} \in \mathbb{R}^D$ stands for a positional embedding added to encode the spatiotemporal position of each region. The resulting sequence of embedding vectors $z_{(p,t)}^{(0)}$ stands for the input to the next layer of the self-attention block. Note that z^i is output of the ith layer in self-attention block. p=1,...G and t=1,...,T are the spatial locations and indexes over time slices respectively.

2.4. Query-Key-Value Mechanism

Our Transformer consists of L encoding blocks. At each block l, a query/key/value vector is computed for each region from the representation $z_{(p,t)}^{(l-1)}$ encoded by the preceding block:

$$q_{(p,t)}^{(l,a)} = W_Q^{(l,a)} z_{(p,t)}^{(l-1)} \in \mathbb{R}^{D_h}$$
(4)

$$k_{(p,t)}^{(l,a)} = W_K^{(l,a)} z_{(p,t)}^{(l-1)} \in \mathbb{R}^{D_h}$$
 (5)

$$v_{(p,t)}^{(l,a)} = W_V^{(l,a)} z_{(p,t)}^{(l-1)} \in \mathbb{R}^{D_h}$$
 (6)

 $z_{(p,t)}^{(l-1)}$ need to do layer normalization before above operations. a=1,2...,A is an index over multiple attention heads and A denotes the total number of attention heads. The latent dimensionality for each attention head is set to $D_h=D/A$.

2.5. Variants of Attention Mask Learning

The variants of self-attention block include spatial attention (S), time attention (T), time attention after spatial attention (S-T), and spatial attention joint time attention (S+T). The spatial attention is to learn the spatial structure information. The time attention is to learn the different contributions of different time slices. The time attention after spatial attention is the concatenation of two operations. The spatial attention joint time attention is to do two attention simultaneously.

2.5.1. Spatial Attention

In the case of spatial attention, the self-attention weights $\alpha_{(p,t)}^{(a,l)} \in \mathbb{R}^{N+1}$ for query brain region (p,t) are given by:

$$\alpha_{(p,t)}^{(l,a)space} = \sigma \left(\frac{q_{(p,t)}^{(l,a)}^{T}}{\sqrt{D_h}} \right) \cdot \left[k_{(0,0)}^{(l,a)} \left\{ k_{(p',t')}^{(l,a)} \right\}_{p'=1,...,N} \right],$$
(7)

where p' denotes the index of the brain regions. σ denotes the softmax activation function. The formula is to calculate the contribution of different brain regions to emotion recognition at one specific time.

2.5.2. Temporal Attention

For the temporal attention, the self-attention weights $\alpha_{(p,t)}^{(l,a)} \in \mathbb{R}^{T+1}$ for query brain region (p,t) are given by:

$$\alpha_{(p,t)}^{(l,a)} = \sigma \left(\frac{q_{(p,t)}^{(l,a)}^T}{\sqrt{D_h}} \right) \cdot \left[k_{(0,0)}^{(l,a)} \left\{ k_{(p',t')}^{(l,a)} \right\}_{t'} = 1, ..., T \right],$$
(8)

where t' denotes the index of the time slots. It is to estimate the weights of different time slots of the same EEG electrode to a specific emotion recognition.

2.5.3. Spatial-Temporal (S-T) Attention

Spatial-Temporal (S-T) attention is to do spatial and temporal attention one-by-one. Firstly, the spatial self-attention weights are calculated as Eq. 7. Then recalibrate the output of previous layer. After that, the the temporal attention weights are learned Eq. 8 from the output of spatial attention layer.

2.5.4. Spatial+Temporal (S+T) Attention

The spatial+temporal (S+T) attention is to do spatial and temporal attention simultaneously. The self-attention weights $\alpha_{(p,t)}^{(a,l)} \in \mathbb{R}^{NT+1}$ for query brain region (p,t) are given by:

$$\alpha_{(p,t)}^{(l,a)} = \sigma \left(\frac{q_{(p,t)}^{(l,a)}}{\sqrt{D_h}} \right) \cdot \begin{bmatrix} k_{(0,0)}^{(l,a)} \left\{ k_{(p',t')}^{(l,a)} \right\} p' = 1, \dots, N \\ t' = 1, \dots, T \end{bmatrix},$$
(9)

Different from S-T Attention, which regards space and time separately, the S+T attention considers contribution of the spatial and temporal dimensions simultaneously.

2.6. Multi-head Attention Recalibration

The encoding $z_{(p,t)}^{(l)}$ at block l is obtained by the first computing the weighted sum of value vectors using self-attention coefficients from each attention head:

$$s_{(p,t)}^{(l,a)} = \alpha_{(p,t),(0,0)}^{(l,a)} v_{(0,0)}^{(l,a)} + \sum_{p'=1}^{N} \sum_{t'=1}^{F} \alpha_{(p,t),(p',t')}^{(l,a)} v_{(p',t')}^{(l,a)},$$
(10)

Then, the concatenation of these vectors from all heads is projected and passed through an multi-layer perceptron (MLP), using residual connections after each operation:

$$z'_{(p,t)}^{l} = W_{O}^{(l-1)} \begin{bmatrix} s_{(p,t)}^{(l,1)} \\ \vdots \\ \vdots \\ s_{(p,t)}^{(l,A)} \end{bmatrix} + z_{(p,t)}^{(l-1)}, \tag{11}$$

where W_O is the **Value** of $z_{(p,t)}^{(l-1)}$ by concatenating $v_{(p,t)}^{(l,a)}$.

$$z_{(p,t)}^{l} = MLP(z_{(p,t)}^{\prime l}) + z_{(p,t)}^{\prime l}$$
(12)

The $z'^{l}_{(p,t)}$ goes through the MLP layer to get the output of lth layer.

3. EXPERIMENTS

3.1. Datasets

We validate our model on SEED [13, 14] and SEED-IV [15] databases.

SEED contains three different states of emotion, namely positive, negative, and neutral. Fifteen participants' EEG data were collected while they were watching the stimulus videos. The participants are asked to give feedback immediately after each experiment. The EEG signals of 62 channels are recorded at a sampling frequency of 1000 Hz and downsampled with 200 Hz by an EEG cap. The DE features are

pre-computed over different frequency bands for each sample in each channel.

SEED-IV contains four different categories of emotions, including happy, sad, fear, and neutral emotions. The experiment consists of 15 participants. Three experiments are designed for each participant on different days, and each session contains 24 video clips and six clips for each type of emotion in each session. The DE feature is also pre-computed over five frequency bands in each channel.

3.2. Experimental Setup

We train our model on NVIDIA RTX 2080 GPU. Cross entropy loss is used as the loss function. The optimizer is Adam. The initial learning rate is set to 1e-3 with multi-step decay to 1e-7. The number of the attention blocks is set to 4 and the length of each sample is set to 10s. We conducted experiments on each subject. For each experiment, we randomly shuffle the samples and use 5-fold cross validation. The ratio of the training set to test set is 9:6.

3.3. Compared Models

We compare the proposed EeT with other competitive models.

- SVM [16]: A Least squares support vector machine classifier.
- DBN [4]: Deep Belief Networks investigate the critical frequency bands and channels.
- DGCNN [17]: Dynamical Graph Convolutional Neural Networks model the multichannel EEG features.
- BiDANN [18]: Bi-hemispheres domain adversarial neural network maps the EEG feature of both hemispheres into discriminative feature spaces separately.
- BiHDM [19]: Bi-hemispheric discrepancy model learns the asymmetric differences between two hemispheres for EEG emotion recognition.
- 3D-CNN with PST-Attention [20]: a self-attention module combined with 3D-CNN to learn critical information among different dimensions of EEG feature.

3.4. Experimental Results and Analysis

Table 1 presents the average accuracy (Mean) and standard deviation (Std) of the compared models for EEG based emotion recognition on SEED and SEED-IV datasets. Compared with our previous work 3D-CNN with PST-Attention, the means of proposed joint spatial+temporal (S+T) attention EeT framework have 0.52%/0.54% improvements on SEED and SEED-IV respectively. The Stds of Eet with S+T attention achieve 0.59%/0.59% reductions on SEED and SEED-IV

Table 1: Experimental Results on SEED and SEED-IV Dataset

Models	SEED		SEED-IV	
	Mean (%)	Std (%)	Mean (%)	Std (%)
SVM [16]	83.99	9.72	56.61	20.05
DBN [4]	86.08	8.34	66.77	7.38
DGCNN [17]	90.40	8.49	69.88	16.29
BiDANN [18]	92.38	7.04	70.29	12.63
BiHDM [19]	93.12	6.06	74.35	14.09
3D-CNN with PST-Attention[20]	95.76	4.98	82.73	8.96
EeT (S+T Attention)	96.28	4.39	83.27	8.37

Table 2: Experimental Results of Variant Transformers

Models	SEED		SEED-IV	
	Mean (%)	Std (%)	Mean (%)	Std (%)
Spatial (S) Attention	93.14	9.31	73.31	13.67
Temporal (T) Attention	92.74	10.21	72.37	12.83
Spatial-Temporal (S-T) Attention	95.65	6.73	80.31	8.51
Spatial+Temporal (S+T) Attention	96.28	4.39	83.27	8.37

respectively compared with those of 3D-CNN with PST-Attention. Moreover, EeT with S+T attention gets superior performance compared with other competitive models.

3.5. Ablation Experiments

The Table 2 presents the results of different variants of proposed transformer framework, from which we can see that Joint Spatial-Temporal Attention gets the best results, achieving 0.63%/2.96% improvements compared with the second best variant, divided Spatial-Temporal Attention on SEED and SEED-IV respectively, indicating comprehensively considering the temporal and spatial characteristics of EEG may boost the emotion recognition results most notably. As for single dimensional attention, the results are a bit of lower than those of combined variants'. Spatial Attention is 0.4% /0.94% higher than that of Temporal Attention, implying the spatial dimension may have more emotion-related message than the temporal dimension.

4. CONCLUSION

In this paper, we propose a new EEG emotion recognition framework based on self-attention, which is built exclusively on self-attention. Our approach considers the different contributions of different brain regions and time slots in the EEG samples as well as the intrinsic spatiotemporal characteristics of EEG signals. The results of our methods show that the attention mechanism can boost the performance of emotion recognition evidently. Furthermore, the joint spatiotemporal attention can get the best results among the four designed structures, the results are also better than most of the state of art methods, indicating that considering the spatiotemporal feature jointly is more in line with the principles of brain science.

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