



CYBSPEED CONGRESS 2023



FACULTY
OF COMPUTER
SCIENCE
UNIVERSITY
OF THE BASQUE
COUNTRY

EEG SIGNAL PROCESSING

from Time Series Classification to Emotion Recognition

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 - 08 IMPORTANT CONTRIBUTIONS



MOTIVATION

EMOTION

Emotions are psychological states comprised of thoughts, feelings, physiological changes, expressive behaviors, and inclinations to act.

DOMAIN

Emotion is a subjective attitude generated by a person's experience of external things, as well as an instinctive coordinated response made by the body, which may include the joint effects of language , behavior, and spirit.

AFFECTIVE COMPUTING

Affective Computing is the study and development of systems and devices that can recognize, interpret, process, and simulate human affects



Applications of EEG Signal Processing



01

CLINICAL DIAGNOSIS

EEG is widely used to diagnose various neurological disorders such as epilepsy, sleep disorders, and brain injuries.

02

COGNITIVE NEUROSCIENCE

It helps researchers understand cognitive processes, perception, attention, and memory.

03

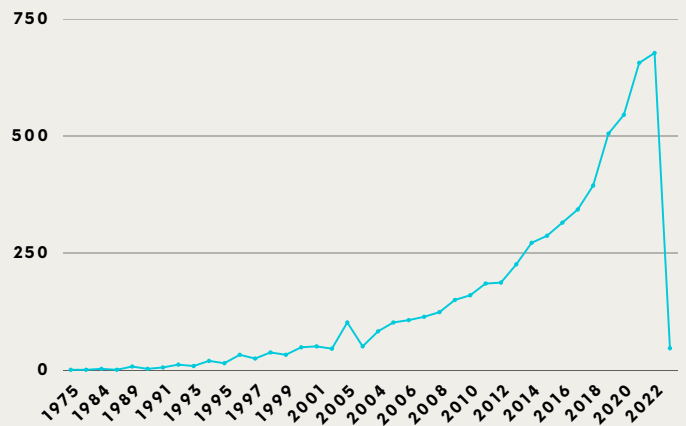
BRAIN-COMPUTER INTERFACES

EEG signals can be used to control external devices, enabling communication and mobility for individuals with physical disabilities.



Publications

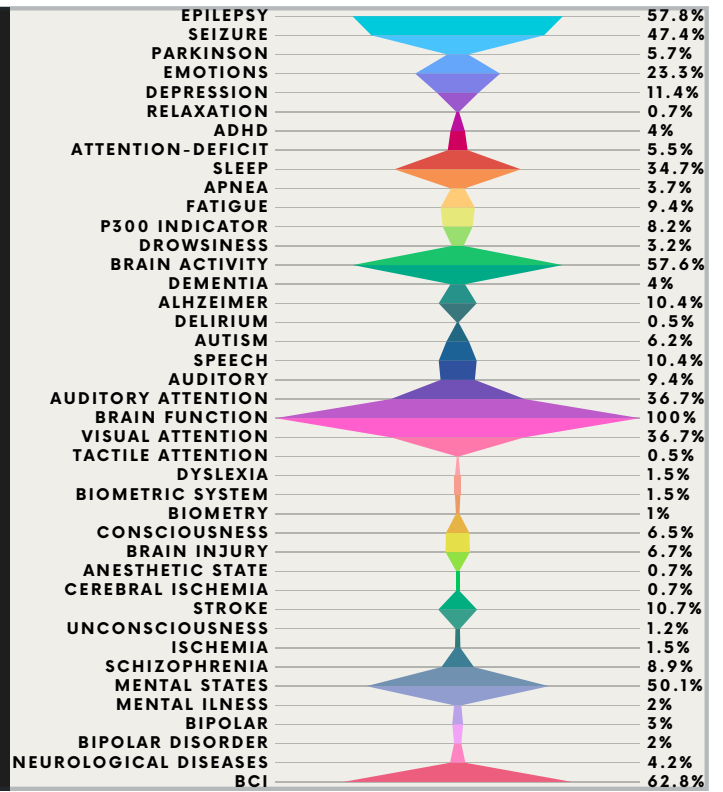
There has been an evolution in the number of publications in the signal processing area with classical Machine Learning technics, since 1975, the last 2 decades having the most number of contributions in EEG signal processing with Neural Networks





Clinical Diagnosis

According to the contributions seen in the previous chart, there is a distribution of them according to the clinical target, in which depending the area some features or characteristics of the signal may be taken into account in a different way





SIGNAL PREPROCESSING

EEG = True EEG signals + artifacts

Interferences and noise generated by the EEG device or transmission line

Classification performance affected

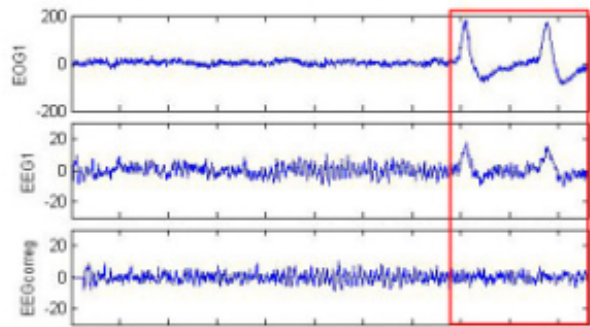
Original EEG signal >>> denoised and deinterferenced



Regression Method

Regression filter to remove artifacts

Reference channel (EOG) >>> Proportion of
reference signals in a single channel

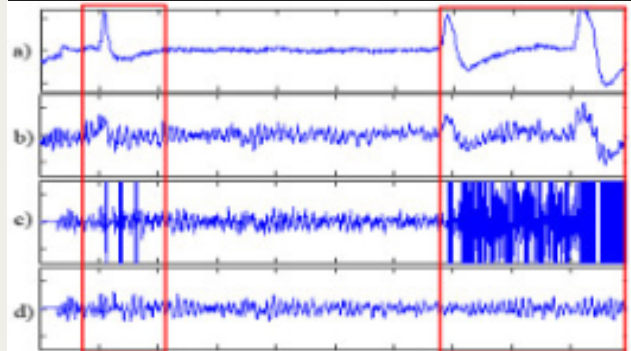




Adaptive Filtering Method

Recursive least-mean-square adaptive filtering to remove (EOG)

Effectively remove multiple EOG artifacts with stability and fast convergence





SIGNAL PREPROCESSING

STEPS

Channel Location

Filtering

Baseline Correction

Independent Principal
Component Analysis



NOISE SUPRESION

Butterworth band-pass
filter

Remove Electromagnetic
interference



ELECTROMAGNETIC INTERFERENCE

Eyeball movements (from
Blinking)

Muscle artifacts (muscle
extension and contraction)

ECG artifacts (heartbeat
expansion and contraction)

Power frequency
interference



EEG SIGNAL CLASSIFICATION

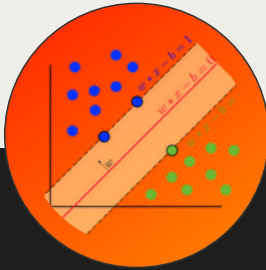
Draw a boundary (Separated hyperplane in a multidimensional feature space) between two or more categories

Label the category based on the features it chooses

The better the classifier >>> the better the hyperplane, and the larger the distance from all the categories



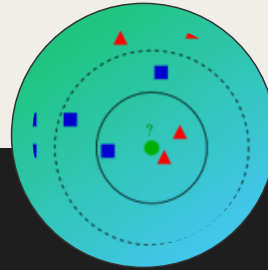
Classical Classifiers



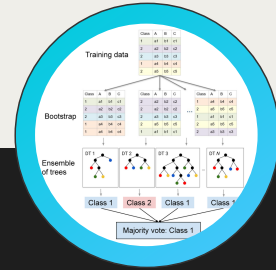
Support vector machine
SVM



K-means clustering
K-MEANS



K-nearest neighbor
K-NN



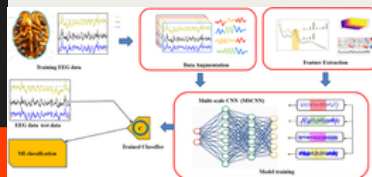
Random Forest
RF



EEG SIGNAL CLASSIFICATION (Inputs of the Deep Neural Networks)

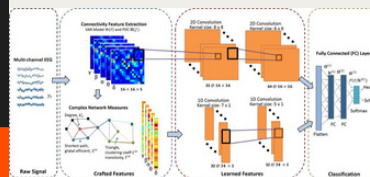
ORIGINAL SIGNAL CHANNEL

EEG-based MI BCI system based on DA and feature integration with CNN



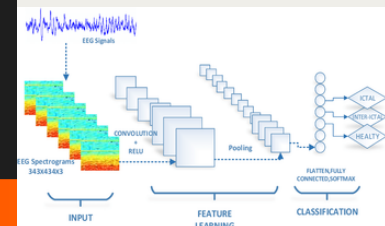
CONNECTIVITY MATRIX

MDC-CNN framework for classification of EEG-derived connectivity patterns



SPECTROGRAM (IMAGE)

CNN architecture for EEG Spectrograms classification



<https://www.biorxiv.org/content/10.1101/2022.01.05.475058v2.full>

https://www.researchgate.net/figure/Overview-of-the-proposed-MDC-CNN-framework-for-classification-of-EEG-derived-connectivity_fig1_335800970

https://www.researchgate.net/figure/CNN-architecture-for-EEG-spectrograms-classification_fig5_349336662



CLASSICAL NEURAL NETWORKS

Multi-Layer Perceptron
Fully Convolutional NN (CNN)
Echo-State Networks (based on Recurrent NNs)
Encoder
Multi-Scale Deep CNN
Time CNN



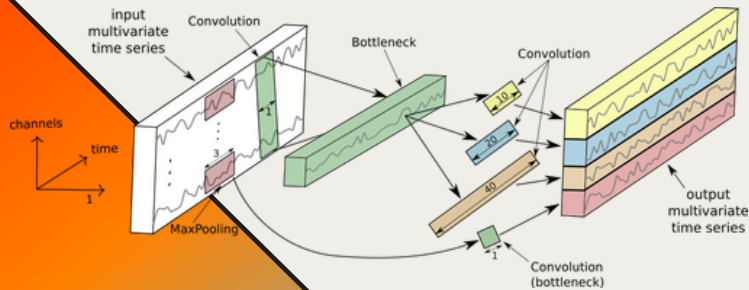
InceptionTime (2020)

Ensemble of five deep learning models, where each one is created by cascading inception modules first proposed by Szegedy et al.

These inception modules apply multiple filters of various lengths simultaneously to a time series while extracting relevant features and information from shorter, as well as longer, subsequences of the time series

It could consist of multiple inception modules stacked in a feedforward manner and additionally connected with residual connections

Finally, global average pooling combined with a simple fully connected NN produces the predictions





EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks

Journal: IEEE Transactions on affective computing

year of publication: September 2020

Authors: Tengfei Song, Wenming Zheng

Index terms: EEG emotion recognition, adjacency matrix, graph convolutional neural networks (GCNN), dynamical convolutional neural networks (DGCNN)

EEG Emotion Recognition Using Dynamical Graph Convolutional Neural Networks

Tengfei Song¹, Wenming Zheng², Member, IEEE, Peng Song³, Member, IEEE, and Zhen Cui⁴

Abstract—In this paper, a multichannel EEG emotion recognition method based on a novel dynamical graph convolutional neural network (DGCNN) is proposed. The basic idea of the proposed EEG emotion recognition method is to use a graph to model the multichannel EEG features and then perform EEG emotion classification based on this model. Different from the traditional graph convolutional neural network (GCNN) methods, the proposed DGCNN method can dynamically learn the intrinsic relationship between different electroencephalogram (EEG) channels, represented by an adjacency matrix, via training a neural network to learn more discriminative EEG feature extraction. Then, the learned adjacency matrix is used to learn more discriminative features for improving the EEG emotion recognition. We conduct extensive experiments on the SUTD emotion EEG dataset (SEED) and DREAMER dataset. The experimental results demonstrate that the proposed method achieves better recognition performance than the state-of-the-art methods, in which the average recognition accuracy of 98.4 percent is achieved for subject-independent experiment while 79.95 percent for subject-independent cross-validation one on the SEED database, and the average accuracies of 88.23, 94.54 and 95.02 percent are respectively obtained for valence, arousal and dominance classifications on the DREAMER database.

Index Terms—EEG emotion recognition, adjacency matrix, graph convolutional neural networks (GCNN), dynamical convolutional neural networks (DGCNN)

1 INTRODUCTION

EMOTION recognition plays an important role in the human-machine interaction [1], which enables machine to perceive the emotional states of human beings so as to make machine more "sympathetic" in the human-machine interaction. Basically, emotion recognition methods can be divided into two categories. The first one is based on non-physiological signals, such as facial expression images [2], [3], [4], [5], [6], body gesture [7], and voice signal [8]. The second one is based on physiological signal, such as electroencephalogram (EEG) [9], electrodermal activity (EDA) [10], and electrocardiogram (ECG) [11]. Among the various types of physiological signals, EEG signal is one of the most commonly used ones, which is directly captured from the brain cortex and hence it would be advantageous to reflect the mental states of human beings. With the rapid development of dry EEG electrode techniques and the EEG

signal processing methods, EEG emotion recognition has received more and more attentions in recent years [12], [13], [14], [15].

Basically, there are two major ways to describe human's emotions [16], i.e., the discrete basic emotion description approach and the dimension approach. For the discrete basic emotion description approach, the emotions are classified into a set of discrete states, e.g., the six basic emotions (i.e., joy, sadness, surprise, fear, anger, and disgust) [17]. Different from the discrete emotion description approach, the dimension approach describes emotions in continuous form, in which the emotions are characterized by three dimensions (valence, arousal and dominance) [18], [19] or simply two dimensions (valence and arousal), in which the valence dimension mainly characterizes how positive or negative the emotions are, whereas the arousal dimension aims to characterize the degree of how excited or apathetic the emotions are [16].

The research of applying EEG signal to the emotion recognition can be traced back to work of Maibach et al. in [20]. During the past decades, many machine learning and signal processing methods are proposed to deal with the EEG emotion recognition [21], [22]. A typical EEG emotion recognition method usually consists of two major parts, i.e., discriminative EEG feature extraction and emotion classification. Basically, the EEG features used for emotion recognition can be generally divided into two kinds, i.e., time-domain feature type and frequency-domain feature type. The time-domain features, e.g., Hjorth features [23], frontal dimension feature [24] and higher order crossing feature [25], mainly capture the temporal information of EEG signals. Different from the time-domain feature, the frequency-domain feature aims to

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Digital Object Identifier 10.1109/TAFFC.2018.2817022

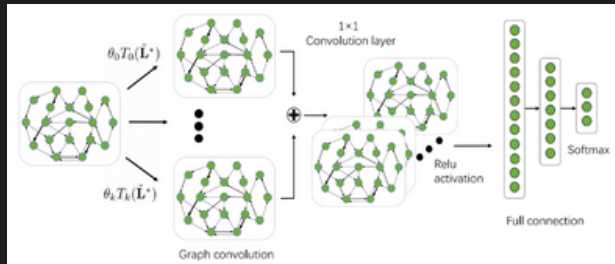
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DGCNN Framework

Model for EEG emotion recognition, which consists of the dynamical graph convolutional operation via the learned graph connections, convolution layer with 1×1 kernel, ReLU activation and the full connection. The inputs of the model are the EEG features extracted from multiple frequency bands, e.g., five frequency bands (dband, uband, aband, bband, and gband), in which each EEG channel is represented as a node of the graph. The outputs are the predicted labels through softmax.



01

DREAMER DATABASE

EEG data via 14 EEG electrodes of 23 subjects (14 males and 9 females). To build this database, 18 film clips are used for eliciting 9 different emotions, i.e., amusement, excitement, happiness, calmness, anger, disgust, fear, sadness, and surprise. Each film clip lasts for a period time between 65 to 393s, which is thought to be sufficient for eliciting single emotions.

02

SEED DATABASE

EEG data of 15 subjects (7 males and 8 females) are collected via 62 EEG electrodes from the subjects when they watch fifteen Chinese film clips with three types of emotions, i.e., negative, positive, and neutral.

03

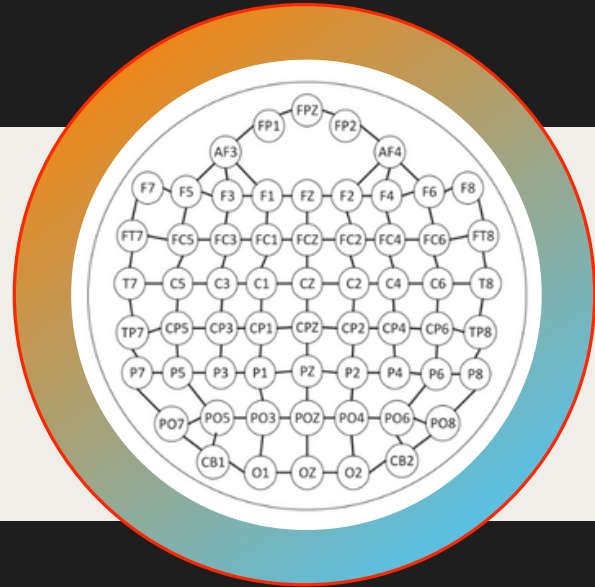
FEATURES EXTRACTED: SEED DATABASE

Feature type	Number of the Five Types of EEG Features Extracted from Each Frequency Band on SEED Database				
	δ	θ	α	β	γ
PSD	62	62	62	62	62
DE	62	62	62	62	62
DASM	27	27	27	27	27
RASM	27	27	27	27	27
DCAU	23	23	23	23	23



DYNAMICAL GRAPH CONNECTIONS

Illustration of the connections among the 62 EEG channels, which is used for constructing the adjacency matrix of GCNN.





Algorithm for DGCNN

optimize the optimal network parameters, we adopt the back propagation (BP) method to iteratively update the network parameters until the optimal or suboptimal solutions are achieved. For this purpose, we define a loss function based on cross entropy cost, which is expressed as the following form:

$$Loss = cross_entropy(\mathbf{1}, \mathbf{I}^p) + \alpha \|\Theta\|,$$



Algorithm 1. Procedures of Training Optimal DGCNN Model for EEG Emotion Recognition

Require: Multichannel EEG features associated with multiple frequency bands, the class labels corresponding to the EEG features, the number of Chebyshev polynomial order K , the learning rate ρ ;

Ensure: The desired adjacency matrix \mathbf{W}^* and model parameters of DGCNN;

- 1: Initialize the adjacency matrix \mathbf{W}^* and other model parameters;
- 2: **repeat**
- 3: Regularizing the elements of the matrix \mathbf{W}^* using Relu operation such that the elements are non-negative;
- 4: Calculating the Laplacian matrix \mathbf{L}^* ;
- 5: Calculating the normalized Laplacian matrix $\tilde{\mathbf{L}}^*$;
- 6: Calculating the Chebyshev polynomial items $T_k(\tilde{\mathbf{L}}^*)$ ($k = 0, 1, \dots, K-1$);
- 7: Calculating $\sum_{k=0}^{K-1} \theta_k T_k(\tilde{\mathbf{L}}^*) \mathbf{x}$;
- 8: Calculating the 1×1 convolution results and regularizing the results using the Relu operation;
- 9: Calculating the results of the full connection layer;
- 10: Calculating the loss function using (14);
- 11: Updating the adjacency matrix

$$\mathbf{W}^* = (1 - \rho) \mathbf{W}^* + \rho \frac{\partial Loss}{\partial \mathbf{W}^*}$$

and other model parameters;

- 12: **until** the iterations satisfy the predefined algorithm convergence condition.



TABLE 2
Comparisons of the Average Accuracies and Standard Deviations (%) of Subject Dependent EEG-Based
Emotion Recognition Experiments on SEED Database Among the Various Methods

Feature	Method	δ band	θ band	α band	β band	γ band	all ($\delta, \theta, \alpha, \beta, \gamma$)
DE	DBN [19]	64.32 / 12.45	60.77 / 10.42	64.01 / 15.97	78.92 / 12.48	79.19 / 14.58	86.08 / 8.34
	SVM [19]	60.50 / 14.14	60.95 / 10.20	66.64 / 14.41	80.76 / 11.56	79.56 / 11.38	83.99 / 9.72
	GCNN	72.75 / 10.85	74.40 / 8.23	73.46 / 12.17	83.24 / 9.93	83.36 / 9.43	87.40 / 9.20
	DGCNN	74.25 / 11.42	71.52 / 5.99	74.43 / 12.16	83.65 / 10.17	85.73 / 10.64	90.40 / 8.49
PSD	DBN [19]	60.05 / 16.66	55.03 / 13.88	52.79 / 15.38	60.68 / 21.31	63.42 / 19.66	61.90 / 16.65
	SVM [19]	58.03 / 15.39	57.26 / 15.09	59.04 / 15.75	73.34 / 15.20	71.24 / 16.38	59.60 / 15.93
	GCNN	69.89 / 13.83	70.92 / 9.18	73.18 / 12.74	76.21 / 10.76	76.15 / 10.09	81.31 / 11.26
	DGCNN	71.23 / 11.42	71.20 / 8.99	73.45 / 12.25	77.45 / 10.81	76.60 / 11.83	81.73 / 9.94
DASM	DBN [19]	48.79 / 9.62	51.59 / 13.98	54.03 / 17.05	69.51 / 15.22	70.06 / 18.14	72.73 / 15.93
	SVM [19]	48.87 / 10.49	53.02 / 12.76	59.81 / 14.67	75.03 / 15.72	73.59 / 16.57	72.81 / 16.57
	GCNN	57.07 / 6.75	54.80 / 9.09	62.97 / 13.43	74.97 / 13.40	73.28 / 13.67	76.00 / 13.32
	DGCNN	55.93 / 9.14	56.12 / 7.86	64.27 / 12.72	73.61 / 14.35	73.50 / 16.6	78.45 / 11.84
RASM	DBN [19]	48.05 / 10.37	50.62 / 14.02	56.15 / 15.28	70.31 / 15.62	68.22 / 18.09	71.30 / 16.16
	SVM [19]	47.75 / 10.59	51.40 / 12.53	60.71 / 14.57	74.59 / 16.18	74.61 / 15.57	74.74 / 14.79
	GCNN	59.70 / 5.65	55.91 / 8.82	59.97 / 14.27	79.45 / 13.32	79.73 / 13.22	84.06 / 12.86
	DGCNN	57.79 / 6.90	55.79 / 8.10	61.58 / 12.63	75.79 / 13.07	82.32 / 11.54	85.00 / 12.47
DCAU	DBN [19]	54.58 / 12.81	56.94 / 12.54	57.62 / 13.58	70.70 / 16.33	72.27 / 16.12	77.20 / 14.24
	SVM [19]	55.92 / 14.62	57.16 / 10.77	61.37 / 15.97	75.17 / 15.58	76.44 / 15.41	77.38 / 11.98
	GCNN	62.60 / 12.88	65.05 / 8.35	66.41 / 11.06	77.28 / 11.55	78.68 / 13.00	79.02 / 11.27
	DGCNN	63.18 / 13.48	62.55 / 7.96	67.71 / 10.74	78.68 / 10.81	80.05 / 13.03	81.91 / 10.06



A Bi-Hemisphere Domain Adversarial Neural Network Model for EEG Emotion Recognition

Journal: IEEE Transactions of affective computing

year of publication: April-June 2021

Authors: Yang Li, Wenming Zheng, Zhen Cui, Tong Zhang, and Xiaoyan Zhou

Index terms: EEG emotion recognition, long short term memory (LSTM), cerebral hemisphere asymmetry, adversarial network

A Bi-Hemisphere Domain Adversarial Neural Network Model for EEG Emotion Recognition

Yang Li¹, Wenming Zheng², Senior Member, IEEE, Yuan Zong³,
Zhen Cui⁴, Tong Zhang⁵, and Xiaoyan Zhou⁶

Abstract—In this paper, we propose a novel neural network model, called bi-hemisphere domain adversarial neural network (BIDANN), for electroencephalogram (EEG) emotion recognition. The BIDANN model is inspired by the neuroscience finding that the left and right hemispheres of human brain are asymmetric to the emotional response. It contains a global and two local domain discriminators that work adversarially with a classifier to learn discriminative emotional features for each hemisphere. At the same time, it tries to reduce the possible domain differences in each hemisphere between the source and target domains so as to improve the generality of the recognition model. In addition, we also propose an improved version of BIDANN, denoted by BIDANN⁺, for subject-independent EEG emotion recognition problem by lowering the influences of the personal information of subjects to the EEG emotion recognition. Extensive experiments on the IEEG database are conducted to evaluate the performance of both BIDANN and BIDANN⁺. The experimental results have shown that the proposed BIDANN and BIDANN⁺ models achieve state-of-the-art performance in the EEG emotion recognition.

Index Terms—EEG emotion recognition, long short term memory (LSTM), cerebral hemisphere asymmetry, adversarial network

1 INTRODUCTION

Emotion, as a conscious mental phenomenon, is closely related to human's cognition and behavior [1]. Although emotion can be easily captured by human beings, it is still hard to be understood by machines. As one of the most active research topics of affective computing [2], emotion recognition had received substantial attention from computer vision and pattern recognition research communities. Basically, the responses of emotion can be roughly divided into the external and the internal responses. The typical external responses include facial expression, gesture or speech of human beings, and the typical internal responses include skin conductance response, heart rate, blood pressure, respiration rate, electroencephalograph (EEG), magnetoencephalogram (MEG) [3]. From the neuroscience view of point [4],

there are some major brain cortex regions, e.g., the orbital frontal cortex, ventral medial prefrontal cortex, and amygdala, are closely related to emotions [5, 6]. [7], which provides us a potential way to decide emotion by recording human's brain signals over these brain regions. For example, by placing the EEG electrodes on the scalp, we can record the neural activities of the brain, which can be used to recognize human's emotions.

Traditional EEG emotion recognition system usually consists of two major parts, i.e., feature extraction part and classifier design part. EEG features can be extracted either from time domain, frequency domain, or from time-frequency domain [8]. Jorke et al. [9] provided a comprehensive survey on the EEG feature extraction approaches. For dealing with the classification problem, many EEG emotion recognition models and methods were proposed over the past several years [9]. [10] Zheng et al. [11] proposed a novel group sparse canonical correlation analysis (GSCCA) method for simultaneous EEG channel selection and emotion recognition. Li et al. [12] proposed a graph regularized sparse linear regression (GSLR) method to deal with EEG emotion recognition problem. Recently, using deep learning methods for EEG emotion recognition had been widely adopted and had demonstrated better performance than traditional methods. In [13], Zheng et al. proposed to use Deep Belief Network (DBN) for EEG emotion classification. In [14], Song et al. used a graph to model the multichannel EEG features and then perform EEG emotion classification based on it.

Although many algorithms or models have been proposed for the EEG emotion recognition problem, most of them focused on the scenarios where both training and testing data come from the same domain, in which we usually assume that the feature distributions of training and testing data are

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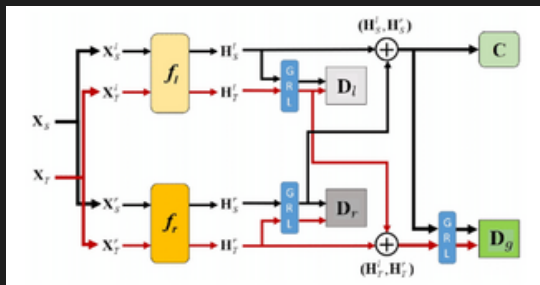
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BiDANN Framework

The target of BiDANN is to alleviate the possible feature distribution difference between source and target domains, either in each hemisphere or the whole brain cortex area. To achieve this goal, we borrow the basic idea of the DANN method by leveraging the adversarial operation between the source and the target domains into the discriminative EEG feature learning module and also make use of the neuroscience findings that the left and right hemispheres of the human brain are asymmetric to the emotional response to further enhance the discriminative ability of the EEG features



01

DREAMER DATABASE

EEG data via 14 EEG electrodes of 23 subjects (14 males and 9 females). To build this database, 18 film clips are used for eliciting 9 different emotions, i.e., amusement, excitement, happiness, calmness, anger, disgust, fear, sadness, and surprise. Each film clip lasts for a period time between 65 to 393s, which is thought to be sufficient for eliciting single emotions.

02

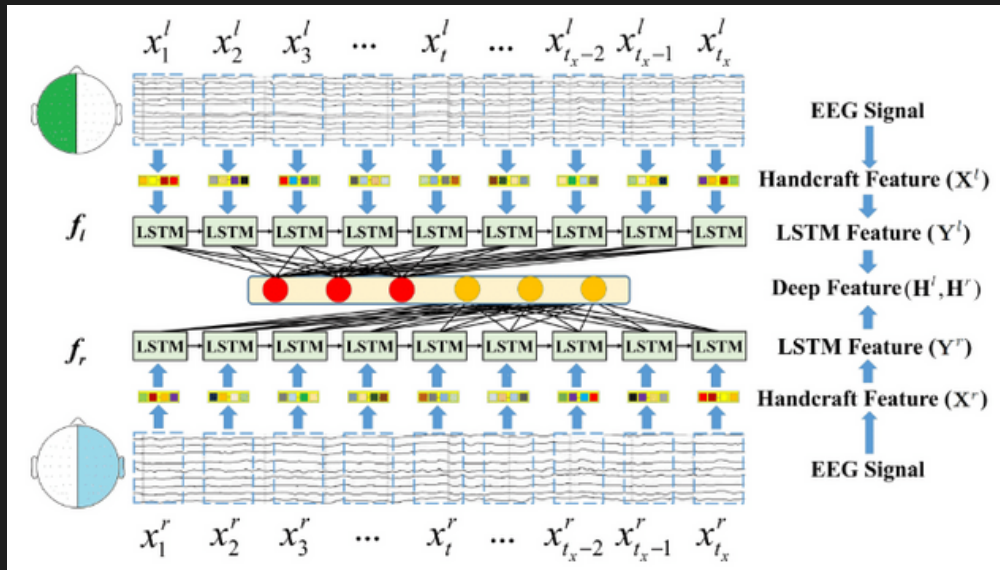
SEED DATABASE

EEG data of 15 subjects (7 males and 8 females) are collected via 62 EEG electrodes from the subjects when they watch fifteen Chinese film clips with three types of emotions, i.e., negative, positive, and neutral.

03

FEATURES EXTRACTED: SEED DATABASE

Extract more discriminative features from handcraft EEG features to improve the EEG classification performance. The whole feature extraction, which consists of the handcraft EEG feature extraction part and the discriminative deep feature learning part.





Algorithm for BiDANN

We can iteratively train the classifier and three discriminators and update the parameters with the similar approach of standard deep learning methods by chain rule. Specifically, to solve the optimal solution of BiDANN, we adopt the stochastic gradient descent (SGD) algorithm [35] to find optimal model parameters (ulf,urf,uc)

$$(\hat{\theta}_f^l, \hat{\theta}_f^r, \hat{\theta}_c) = \arg \min_{\theta_f^l, \theta_f^r, \theta_c} L(\mathbf{X}_{S,T}; (\theta_f^l, \theta_f^r, \theta_c), \hat{\theta}_d^l, \hat{\theta}_d^r, \hat{\theta}_d^g).$$



Algorithm 1. Procedures of Training BiDANN Model

Input: Source data set $\{\mathbf{X}_S\}$ and Target data set $\{\mathbf{X}_T\}$;
Ground-truth label set $\mathbf{L}_S = \{y\}$ of source data set;
Source domain label set $\mathcal{D}_S = [\mathcal{D}_S^l, \mathcal{D}_S^r] = \{0\}$ and target domain label set $\mathcal{D}_T = [\mathcal{D}_T^l, \mathcal{D}_T^r] = \{1\}$;
1: Initialize model parameters and learning rate α ;
2: **repeat**
3: Update the parameters of the classifier:
 $\theta_c \leftarrow \theta_c - \alpha \frac{\partial L_c}{\partial \theta_c}$, $\theta_f^l \leftarrow \theta_f^l - \alpha \frac{\partial L_f^l}{\partial \theta_f^l}$, and
 $\theta_f^r \leftarrow \theta_f^r - \alpha \frac{\partial L_f^r}{\partial \theta_f^r}$;
4: Update the parameters of the global discriminator:
 $\theta_d^g \leftarrow \theta_d^g - \alpha \frac{\partial L_d^g}{\partial \theta_d^g}$, $\theta_f^l \leftarrow \theta_f^l + \alpha \frac{\partial L_d^g}{\partial \theta_f^l}$, and
 $\theta_f^r \leftarrow \theta_f^r + \alpha \frac{\partial L_d^g}{\partial \theta_f^r}$;
5: Update the parameters of the local discriminator corresponding to the left hemisphere:
 $\theta_d^l \leftarrow \theta_d^l - \alpha \frac{\partial L_d^l}{\partial \theta_d^l}$, $\theta_f^l \leftarrow \theta_f^l + \alpha \frac{\partial L_d^l}{\partial \theta_f^l}$;
6: Update the parameters of the local discriminator corresponding to the right hemisphere:
 $\theta_d^r \leftarrow \theta_d^r - \alpha \frac{\partial L_d^r}{\partial \theta_d^r}$, $\theta_f^r \leftarrow \theta_f^r + \alpha \frac{\partial L_d^r}{\partial \theta_f^r}$;
7: If the model has been trained for 100 epochs, then
 $\alpha \leftarrow 0.9 \times \alpha$ and goto step 3;
8: **until** The iterations satisfies the predefined condition, i.e., the loss function satisfies:

$$L(\theta_f^l, \theta_f^r, \theta_c, \theta_d^l, \theta_d^r, \theta_d^g) < 10^{-3}.$$

Output:

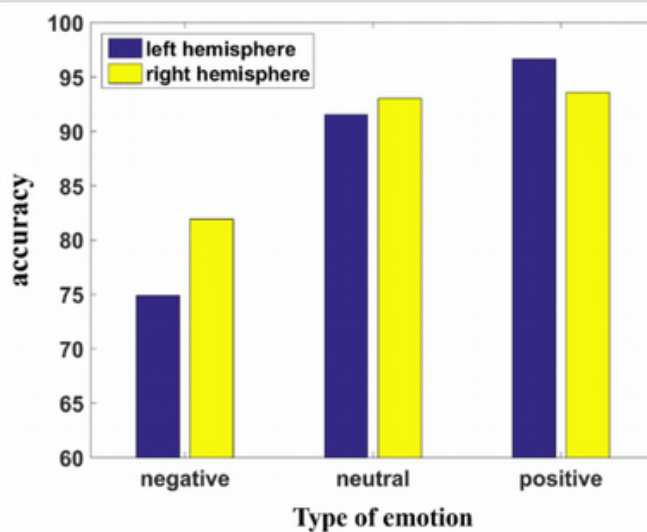
9: Parameters: $\hat{\theta}_f^l, \hat{\theta}_f^r, \hat{\theta}_c, \hat{\theta}_d^l, \hat{\theta}_d^r, \hat{\theta}_d^g$.



TABLE 3
The Mean Accuracies (and Standard Deviations) Using Different
Frequency Bands for Subject-Dependent EEG Emotion
Recognition Experiment on SEED Database

Methods	Frequency bands				
	δ	θ	α	β	γ
SVM [37]	60.50 (14.14)	60.95 (10.20)	66.64 (14.41)	80.76 (11.56)	79.56 (11.38)
RF* [38]	64.56 (08.32)	65.27 (11.64)	65.67 (13.94)	73.35 (14.35)	74.48 (12.80)
CCA* [39]	55.30 (12.02)	55.75 (10.99)	64.96 (12.05)	69.16 (11.45)	70.67 (14.06)
GSCCA* [111]	63.92 (11.16)	64.64 (10.33)	70.10 (14.76)	76.93 (11.00)	77.98 (10.72)
DBN [13]	64.32 (12.45)	60.77 (10.42)	64.01 (15.97)	78.92 (12.48)	79.19 (14.58)
GRSLR* [12]	63.90 (11.83)	62.61 (10.73)	71.11 (09.04)	81.18 (10.74)	81.91 (10.36)
GCNN [40]	72.75 (10.85)	74.40 (08.23)	73.46 (12.17)	83.24 (09.93)	83.36 (09.43)
DGCNN [14]	74.25 (11.42)	71.52 (05.99)	74.43 (12.16)	83.65 (10.17)	85.73 (10.64)
DANN* [17]	72.13 (11.22)	68.75 (07.40)	70.27 (10.84)	83.35 (11.46)	87.89 (11.35)
BIDANN-R1	71.63 (10.69)	66.79 (08.96)	67.71 (12.49)	85.68 (10.13)	86.93 (09.56)
BIDANN-R2	75.26 (10.95)	71.20 (07.23)	75.40 (14.26)	87.73 (10.58)	86.80 (10.78)
BIDANN	76.97 (10.95)	75.56 (07.88)	81.03 (11.74)	89.65 (09.59)	88.64 (09.46)

* Denotes the experiment results obtained are based on our own implementation.





**THANKS FOR
YOUR ATTENTION**

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