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Cross-Day EEG-Based Emotion Recognition Using Transfer Component Analysis

Zhongyang He [1], Ning Zhuang [2], Guangcheng Bao [1], Ying Zeng [1] and Bin Yan [1,*]

[1] Henan Key Laboratory of Imaging and Intelligent Processing, PLA Strategic Support Force Information Engineering University, Zhengzhou 450001, China; zhongyanghe@foxmail.com (Z.H.); baogch001@163.com (G.B.); yingzeng@uestc.edu.cn (Y.Z.)
[2] Troops 73616 of PLA, Shanghai 201100, China; zhuangningyu12@163.com
* Correspondence: ybspace@hotmail.com

Abstract: EEG-based emotion recognition can help achieve more natural human-computer interaction, but the temporal non-stationarity of EEG signals affects the robustness of EEG-based emotion recognition models. Most existing studies use the emotional EEG data collected in the same trial to train and test models, once this kind of model is applied to the data collected at different times of the same subject, its recognition accuracy will decrease significantly. To address the problem of EEG-based cross-day emotion recognition, this paper has constructed a database of emotional EEG signals collected over six days for each subject using the Chinese Affective Video System and self-built video library stimuli materials, and the database is the largest number of days collected for a single subject so far. To study the neural patterns of emotions based on EEG signals cross-day, the brain topography has been analyzed in this paper, which show there is a stable neural pattern of emotions cross-day. Then, Transfer Component Analysis (TCA) algorithm is used to adaptively determine the optimal dimensionality of the TCA transformation and match domains of the best correlated motion features in multiple time domains by using EEG signals from different time (days). The experimental results show that the TCA-based domain adaptation strategy can effectively improve the accuracy of cross-day emotion recognition by 3.55% and 2.34%, respectively, in the classification of joy-sadness and joy-anger emotions. The emotion recognition model and brain topography in this paper, verify that the database can provide a reliable data basis for emotion recognition across different time domains. This EEG database will be open to more researchers to promote the practical application of emotion recognition.

Keywords: EEG signals; emotion recognition; cross-day; Transfer Component Analysis (TCA); domain adaptation

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1. Introduction

Emotions are an important part of human psychological structure, and as the human-computer interaction technology develops, emotional perception computing [1,2] has established a harmonious human-computer environment by enabling computers to perceive, recognize, understand, express, and adapt to human emotions, and allows computers to have a higher and more comprehensive intelligence, which is an important symbol of the naturalization and intelligibility of human-computer interaction [3–5].

One of the important prerequisites for conducting emotion research is to elicit objective, stable and reliable emotions. Researchers use a variety of emotion stimuli, such as images [6,7], sounds and videos [8,9], to induce emotions. Video materials of different emotions are widely used by researchers as through visual and auditory stimuli, subjects may feel personally on the scene. Existing publicly available EEG databases based on emotion video stimuli include DEAP [10], MAHNOB-HCI [11], and SEED [12], etc.

Based on the above publicly available EEG datasets, various emotion feature extraction methods have been developed and used to recognize emotions from EEG signals. These feature extraction methods include (1) time-domain features: Non-linear features such as statistical features [13], fractal dimensions [14,15], sample entropy [16], and non-stationary indices [17], Hjorth features [18], and higher-order crossover features [19]; (2) time-frequency analysis features: The energy, power, power spectral density and differential entropy (DE) [20] of a certain frequency band are extracted as features after the short-time Fourier transform (STFT) [21,22], Hilbert-Huang transform [23,24] or discrete wavelet transform [25–27] of the EEG signals, and in some cases, t for high-frequency bands, such as Beta (16–32 Hz) and Gamma (32–64 Hz) bands, the emotion recognition achieves better results [10,28]; (3) features based on the empirical mode decomposition (EMD) [29,30]: The EMD is used to decompose the EEG signal into multiple intrinsic mode functions (IMFs), and then extract the waveform difference, phase difference, and normalized energy of the IMFs as features for emotion recognition. As the deep learning techniques develop, neural networks are gradually being used in emotion recognition. Zheng et al. [31] extracted DE features with different frequency bands and channels as inputs, and then used deep belief networks (DBN) to classify positive, neutral, and negative emotions. Yang [32] and Zhang et al. [33] all used the extracted neural network structure with DE as the input feature to recognize positive, neutral, and negative emotions from the SEED database. Li et al. [34] formed a two-dimensional matrix of DE features and the HCNN was used to perform emotion recognition based on the SEED database. Xing et al. [35] used the power spectral density of the five frequency bands as the feature to recognize emotions based on DEAP database using LSTM-RNN. Many studies choose DE as the feature and acquire effective recognition accuracy. Therefore, we choose DE as the main feature of emotion recognition in this paper.

Most of the above-mentioned studies have employed the traditional machine learning methods or neural networks for emotion recognition, and have obtained fairly satisfactory recognition accuracy. However, most of those studies have focused on time-specific emotion recognition, and the emotion recognition accuracy of the model developed under such condition will significantly decrease once applied to a complex real-world environment, since the temporal non-stationarity of the EEG signal is a major factor affecting the robustness of the EEG-based emotion recognition model. It is well known that hormone levels, external environment, and diet and sleep can all lead to differences in physiological signals [36], therefore, even for the same emotional state, the EEG signals cross-day also vary. However, in practical applications, there is bound to be a time lag between constructing emotion recognition models and recognizing the emotional states, so the study of emotion recognition cross-day is crucial, which serves as a necessary step from the laboratory to practical applications.

Currently, there are few studies on cross-day emotion recognition. Zheng et al. [12] investigate the important brain regions and electrodes in emotion recognition based on EEG over time. Lin et al. [37] proposed a robust principal component analysis (RPCA)-based signal filtering strategy and validated it on a binary emotion classification task (happiness vs. sadness) using a five-day EEG dataset of 12 subjects. Liu et al. [38] collected EEG data for days and found that emotion recognition performance can be improved by adding EEG data of different days. However, the problem of how to effectively and adaptively select emotion features cross-day with intrinsically implicit associations has not been well addressed. The robustness of emotion recognition across time domain is worth studying. In this paper, we constructed an EEG database, with collection of six days EEG signals from 12 subjects. Based on the EEG database, we first analyzed the difference in emotion recognition performance between intra-day and cross-day cases. Then, we applied TCA algorithm as a domain adaption method, and showed the effectiveness of enhancing cross-day emotion recognition tasks. At last, we analyzed the brain topography, which showed there was a stable neural pattern of emotions cross-day.

2. Materials and Methods

EEG-based emotion recognition mainly includes the following steps: emotion induction, EEG signal collection, EEG signal pre-processing, extraction and analysis of emotion-related EEG features, emotion computational modeling, and detection and recognition of emotional states, as shown in Figure 1.

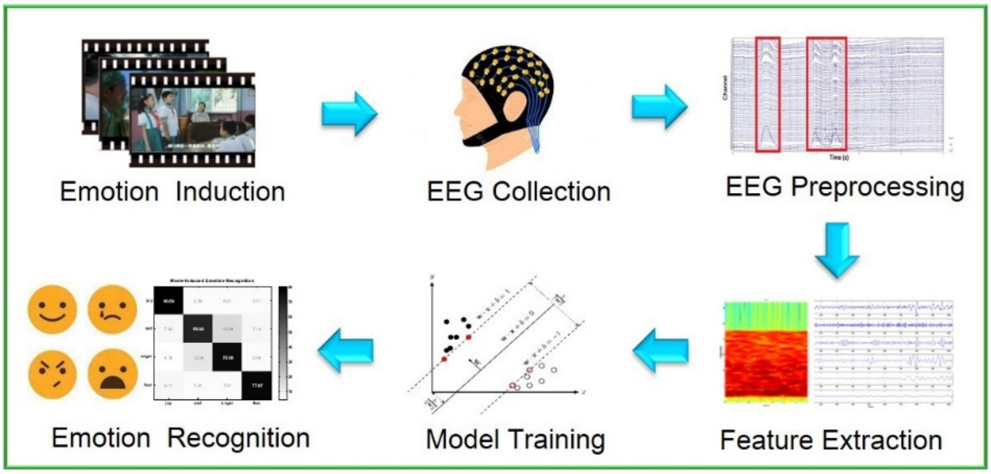

Figure 1. The process of emotion recognition based on EEG signals.

2.1. Experimental Design

Due to the non-stationarity of EEG, EEG signals from different days can be considered as signals from different time domains under the same cognitive emotion recognition task. In order to address the problem of emotion recognition based on EEG signals from different time domains (across different days), this study has designed EEG experiments [39] for studying emotions cross-day, which allows us to collect sufficient emotional samples for deep neural network studies, and investigate the properties of EEG signals cross-day. We have chosen video materials of emotions for the experiment since they can give both visual and auditory stimuli to the subjects, making them feel as if they were in a real-life situation.

A total of 36 video clips of the four emotion types of joy, sadness, anger and fear have been selected from the Chinese Affective Video System [9] and the self-built affective video library for the experiment. The self-built affective video library is a standardized multi-sensory material library of emotional stimuli based on psychological methods provided by the partner Peking University. It includes various domestic and foreign comedies, romance, crime, war, documentary, and horror films, etc. The clips are selected according to such principles as clear content meaning, clear picture, good sound quality, and clear subtitles, and they are tested by the elicitation validity of the stimulus material.

The experiment will be conducted in three parts, namely A, B and C, with each part containing 12 clips of 4 emotions. As shown in Tables A1–A3 of the Appendix A, there are three clips for each emotion type, and the duration of the video clips range from 50 s to 335 s. Videos named with initial uppercase letters are selected from the affective video library of Peking University, and those named with initial lowercase letters are selected from the Chinese Affective Video System.

The experiment is divided into the three parts of A, B, and C, each at a time, as shown in Figure 2. The order of the experiment is randomly balanced to avoid the effects of the fixed-order A-B-C experiments, and the interval between each two experiments is one week. Each subject is to perform the experiment in Figure 2 twice, with an interval of six months between the two experiments, so for each participating subject, a total of six days' EEG data will be collected.

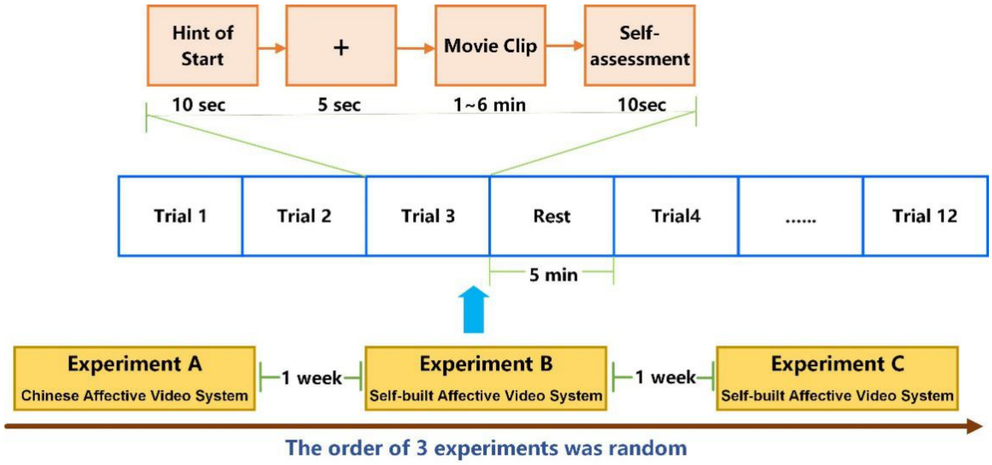

Figure 2. The experiment paradigm for the EEG-based emotion recognition cross-day.

Part A, B, and C of the experiment each contains 12 films of four discrete emotion categories. Each category of emotions is played as a block, and the four blocks corresponding to the four categories of films are played randomly, and the films within each block are also played at random. The 12 film clips are divided into 12 trials, and the flow of each trial is as follows.

1. Before the movie clip starts, there will be a 10-s hint to inform the subject of the number of the current movie clip.
2. Present the white fixation cross on a black background for 5 s.
3. Play the emotion stimulus movie clips.
4. The subject will self-assess the valence and arousal of the movie clips with reference to the Self-Assessment Manikin (SAM) scale. The valence scale ranges from 1(extremely unpleasant) to 9(extremely pleasant); and the arousal scale ranges from 1 (calm) to 9 (extremely excited), and the subject will click the corresponding numbers on the keyboard to directly input the ratings.

While switching categories of emotion, the subject will have a 5-min rest to fully eliminate the effect of the previous category of emotion on the current one.

2.2. Data Collection

Before the experiment, we selected subjects through questionnaire and interviews based on the Beck anxiety inventory (BAI) [40], Hamilton anxiety rating scale (HARS) [41], and the Hamilton depression scale (HAMD) [42] to exclude subjects with anxiety and depression mood, mental and physical abnormalities which means a physical disease or a physical defect, and those using sedative agents and psychotropic drugs. In this case, 14 subjects (8 males, 6 females) with normal visual acuity or corrected visual acuity had been selected for the experiment from our current students. Prior to the experiment, all subjects were informed in detail of the content of the experiment, and they filled out an information registration form, and signed an informed consent form.

We used the 64 channel HIamp active electrode EEG cap of g.tec company of Austria to collect EEG signals. Among the 64 channels, the reference electricity was on the right earlobe, and AFz was connected to GND, and Fz was used for internal calculation of the equipment. Therefore, the remaining effective EEG channels were 61 channels. We used E-Prime to play the experimental stimulus, which is a professional psychological stimulus presentation software.

2.3. Data Preprocessing

For all subjects, the 61-channel EEG data were pre-processed as follows.

1. Data extraction. Extracted the EEG data corresponding to the film clips being played (Pre-stimulus duration was 5 s, and post-stimulus duration was that of the video stimulus material).
2. Bad channel averaging. Checked for corrupted channels where no EEG data had been collected, and replaced the data from the corrupted channel with the average data from the adjacent channels.
3. Artifact removal. EEG was decomposed into independent components using ICA algorithm to remove artifacts such as EOG, EMG, and ECG, and then reconstructed to obtain an artifact-free EEG signal.
4. Re-reference calculation. The data were re-referenced and calculated according to the reference electrode standardization technique (REST) proposed by Yao et al. [43,44]. Which used Three-concentric-sphere model as the head model.
5. Signal filtering. The signal passed through a bandpass filter of 0.1–64 Hz.
6. Baseline correction. The baseline correction was performed 5 s before watching the movie stimulus.

Among all the participants, 12 subjects' (8 males, 4 females, with an average age of 22.50 and the standard deviation for age being 1.98) EEG signals were qualified, and two subjects' EEG signals were unqualified. Since one subject's signal had severe drift and the other subject's signal could not be used because there was too much movement during two of the collection sessions. In removing the artifacts, this paper used the FastICA [45] algorithm to decompose the independent components of the EEG signal, one of the remaining 12 subjects removed two artifact components after ICA decomposition, and the other 11 subjects all removed one artifact component. After selecting and removing the artifact components, the EEG signal without artifact interference was reconstructed.

Since the lengths of the film videos range from 50 s to 180 s, and for all videos, the emotion elicitation was the most intense at the end of the film and therefore most effective. To ensure that the EEG signal lengths were consistent with each other for all emotion types, the last 50 s of all videos had been captured for analysis. Considering the application in studies of real-time emotion recognition, the segmentation of EEG signal was performed with reference to [46], taking 2 s of the EEG signal length as one sample, slid the EEG signal window forward for 1 s each time, with an overlap of 1 s for the two adjacent samples, as shown in Figure 3. Thus, the 50 s-length EEG signal could be divided into 49 samples.

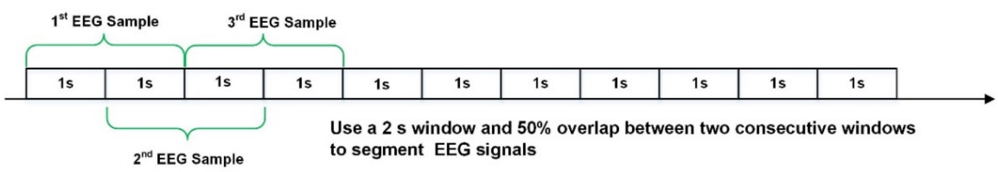

Figure 3. Segmentation of EEG signals. EEG data are segmented using a window of 2 s with 50% overlap between two consecutive windows.

For each sample, the differential entropy (DE) of Delta (1–4 Hz), Theta (4–8 Hz), Alpha (8–12 Hz), Beta (12–30 Hz) and Gamma (30–64 Hz) frequency bands had been extracted. For an EEG signal of 2 s length (sample rate of 512 Hz and sample points of 1024). A 128-point Hann window was selected with 50% overlap of windows, and the short-time Fourier transform was implemented by Matlab's spectrogram function, and then the differential entropy was calculated for each of the five frequency bands. Since the number of effective EEG channels was 61, the number of features corresponding to each EEG sample of 2 s was $61 \times 5 = 305$ features.

In the future, we were willing to disclose this EEG database, including original EEG signals and preprocessed EEG signals, for use by more researchers, to promote the development of emotion recognition technology based on EEG signals.

2.4. Transfer Component Analysis

Due to individual differences and the non-stationary nature of EEG signals, it is difficult to promote the classification model across different domains. There is a method called Transfer Learning in machine learning, which can be used to reduce differences distribution between different domains. Domain adaptation as one of the methods of transfer learning, solves a learning problem in a target domain by utilizing the training data in a different but related source domain, which can be used to reduce differences in EEG data distribution between different domains. Based on this, the research team of Professor Yang Qiang at Hong Kong University of Science and Technology had proposed the Transfer Component Analysis (TCA) algorithm [47], which was a feature-based transfer learning method. When the source and target domains had different data distribution in the issue of domain adaptation, TCA would be used to map the data in the two domains to a high-dimensional Reproducing Kernel Hilbert Space (RKHS), where the maximum mean discrepancy (MMD) of the source and target would be minimized, while their respective internal properties were preserved to the largest extent possible. TCA was currently the most widely used domain adaptation method, with good generalization capabilities in multiple domains.

It has shown that, under the cross-day case, there is a more stable neural pattern of EEG signals from the same subject under different emotional conditions. Therefore, there are implicit common correlations between the EEG signals of the same subject in different time domains, and due to such correlations, there may be some implicit features of the categorical information inherent in the representational data. Thus, if one knew the abstract common feature representation $\phi(X)$ in the implicit feature space for both the training set X_{train} and the test set X_{test}, the difference in probability distributions of $P(\phi(X_{train}))$ and $P(\phi(X_{test}))$ between the data domains would greatly reduce. Therefore, in this paper TCA will be used to EEG emotion recognition under cross-day case.

2.5. Emotion Recognition

In this paper, the EEG data of 6 days had been collected for each subject and 5 cases had been given here.

- Intra-day case

Classified data for each subject within each experiment. There were 3 video clips for each emotion under each experiment, and 3-fold cross-validation was performed between videos to ensure that the training and test sets are uncorrelated.

- Cross-day case

Emotion recognition cross-day included four cases, namely train1_ V1_ Test4, Train2_ V1_ Test3, Train3_ V1_ Test2, Train4_ V1_ Test1. For instance, Train1_V1_Test4: Data of days 1 and 2 were for training, where one day's data were selected as the validation set and the other day's as the training set, with a total of 2 combinations and data of day 3 to day 6 are for testing, and the final emotion recognition accuracy was the average of the two combinations. In this case, the number of training samples for each emotion type was 147 (There were 3 movies for each category of emotion in one day's EEG data, and the number of samples corresponding to each movie was 49, so the number of movie samples for each emotion type was $49 \times 3 = 147$).

According to Train1_V1_Test4, the remaining three cases, Train2_ V1_ Test3, Train3_ V1_ Test2 and Train4_ V1_ Test1, correspond to that the data of 3 days, 2 days and 1 day were randomly selected from the 6 days as the test set, and the other days are used as the training set and verification set. The number of training samples for each emotion type respective ware 147×2, 147×3, 147×4.

Since the experimental stimuli were four discrete emotion types of joy, sadness, anger, and fear, the emotion recognition in this paper was also performed for discrete emotions. A binary classification of positive-negative, joy-sadness, joy-anger, and joy-fear emotions was performed in five cases, Intra-days, Train1_V1_Test4, Train2_V1_Test3, Train3_V1_Test2, and Train4_V1_Test1, respectively. For the positive-negative classification of emotions, the emotion of joy would be presented as the positive emotion and sadness, anger, and fear emotions would be presented as negative emotions. Under the positive-negative emotion classification, the negative emotion samples were more than those of the positive emotion; the three classification tasks of joy-sadness, joy-anger, and joy-fear were all performed with a balanced training sample.

Firstly, for the above five cases, this paper utilizes SVM to recognize emotions, which was implemented by LIBSVM with linear kernel functions. Parameter optimization of the nuclear function was performed on the training and validation sets, and the optimal value of parameter C was searched with a stride of 1 within the range from 2^{-8} to 2^{8}. The classification in this paper was based on a subject-dependent system, and the final classification accuracy was the average of recognition accuracies for all subjects.

Then, this paper employs TCA to perform adaptive matching of the EEG features across time domains. The original feature dimension was 305, and the optimal transformed dimensionality L_{opt} via TCA would be searched with a stride of 20 in the range form 10 to300 for the training and validation sets. After determining optimal transformed dimensionality L_{opt} via TCA, the training and validation sets were merged into a new training set $X'_{train} = [X_{train}\ X_{validate}]^T$, and then the new training set X'_{train} and the test set X_{test} would be analyzed using TCA algorithm under the parameters of L_{opt} and the features obtained after the transfer component analysis would be used for emotion recognition.

Such classification as above mentioned had two advantages, first, the overlap of data from the training and the test sets could be avoided as they were from different days; second, the EEG data were increasing cross-day to validate the practicability and robustness of the domain adaptive algorithm for emotion recognition cross-day.

3. Results

3.1. Cross-Day and Intra-Day Emotion Recognition

This paper utilizes SVM to recognize emotions, and Figure 4 gives the average classification accuracy for all the subjects under the four classification tasks in different cases. For the intra-day emotion recognition, the average recognition accuracies for positive-negative, joy-sadness, joy-anger, and joy-fear are 90.18%, 86.38%, 88.12%, and 85.13%, respectively. As time goes on, the accuracy of emotion recognition decreases significantly in the four cases of Train1_V1_Test4, Train2_V1_Test3, Train3_V1_Test2, and Train4_V1_Test1, indicating that the EEG signals of the subjects will change cross-day. In case of the Train1_V1_Test4 with the shortest training days, the average recognition accuracies for positive-negative, joy-sadness, joy-anger, and joy-fear are 76.06%, 69.23%, 68.90%, and 63.66%, respectively. In addition, the recognition accuracy rates also show that the classification accuracy rates can be effectively improved if training models are built using EEG signals from different days, as shown in Figure 4, where the accuracy rates for Train3_V1_Test2 and Train4_V1_Test1 are higher than those for Train1_V1_Test4, and Train2_V1_Test3. When the training data of 4 days are used (Train4_V1_Test1), the average recognition accuracies for positive-negative, joy-sadness, joy-anger, and joy-fear are 81.31%, 72.15%, 71.57%, and 72.38%, respectively.

If negative emotions can be effectively detected in life, timely intervention and positive regulation can be carried out for people to improve the quality of life and work efficiency. So, the core purpose of emotion classification tend to correct identify negative emotions. We selected sensitivity, specificity, and the receiver operating characteristic (ROC) curves of the positive-negative emotions as evaluation metrics, which can verify the robustness of the classification model.

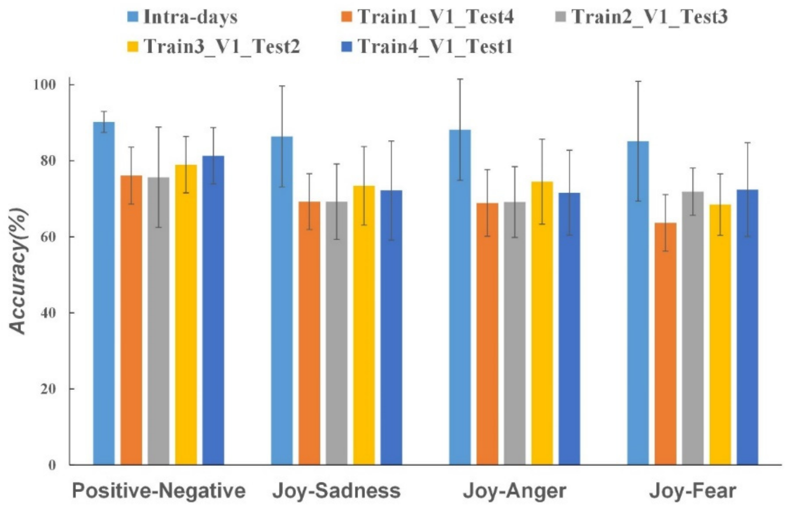

Figure 4. The intra-day and cross-day emotion recognition performance.

Sensitivity reflects the ability of the model to recognize the positive samples, and the formula for computing sensitivity is:

$$\text{Sensitivity} = TP/(TP + FN) \quad (1)$$

where, TP is the number of positive samples predicted to be positive and FN is the number of positive samples predicted to be negative.

Specificity reflects the ability of the model to recognize negative samples and is calculated as follows:

$$\text{Specificity} = TN/(TN + FP) \quad (2)$$

where, TN is the number of negative samples predicted to be negative and FP is the number of negative samples predicted to be positive.

ROC curves typically feature false positive rate (FPR) on the X axis and true positive rate (TPR) on the Y axis. The area under curve (AUC) is a measure of how good the classification model is. Figure 5 presents the ROC curves under five classification tasks, with the intra-day AUC values of 0.9422, 0.7196, 0.7648, 0.7399 and 0.7829 for Train1_V1_Test4, Train2_V1_Test3, Train3_V1_Test2, and Train4_V1_Test1, respectively. A larger AUC value indicates a more robust classification model, and therefore the best classification model in all five cases is the intra-day rather than the cross-day model.

Table 1 gives the actual and predicted values of all the positive and negative samples tested in the five cases, as well as the sensitivity, specificity and accuracy of the model. From the results, it can be seen that the imbalance between positive and negative training samples (with more negative samples) leads to the higher ability of the model to classify the negative samples and the ability to classify the positive samples is weaker than that to classify the negative samples. In the case of cross-day, the value of Specificity becomes higher and higher as the increasing of the training data, which means the performance of negative emotion recognition is becoming better and better. This is consistent with the change of the recognition accuracy.

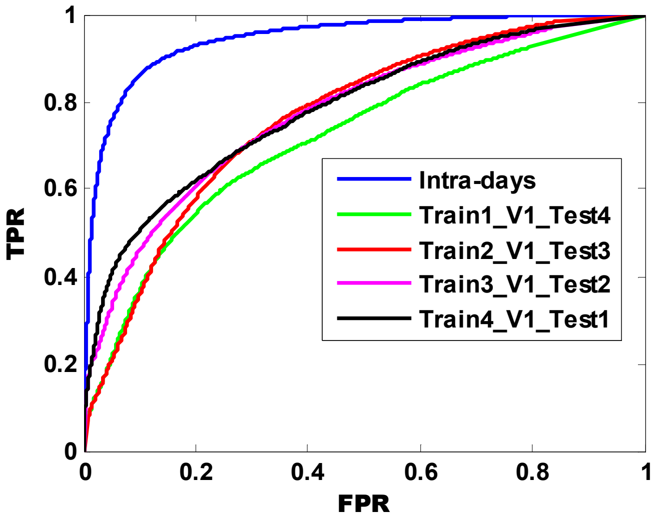

Figure 5. The average ROC curves of all the subjects in the binary classification of positive and negative emotions.

Table 1. Performance of the binary classification of positive-negative emotions on the intra-day and cross-day.

	Intra-Day		Train1_V1_Test4		Train2_V1_Test3		Train3_V1_Test2		Train4_V1_Test1	
Actual Predicted	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**	**Positive**	**Negative**
Positive	8081	1657	8129	7728	6284	5684	6511	4284	3934	1709
Negative	2503	30,095	7747	39,900	7828	36,652	7601	38,052	4886	24,751
Sensitivity (%)	76.35		51.20		44.53		46.14		44.60	
Specificity (%)	94.78		83.77		86.57		89.88		93.54	
Accuracy rate (%)	90.17		75.63		76.06		78.95		81.31	

3.2. Cross-Day Emotion Recognition Based on the Domain Adaption Algorithm

The accuracy of emotion recognition decreases due to the random nature of the EEG signal, which changes cross-day for the same individual being tested. Domain adaptation of features across time domains via TCA algorithm has effectively improved the accuracy of emotion recognition, as shown in Figure 6, in the case of Train4_V1_Test1, the average recognition accuracies of positive-negative, joy-sadness, joy-anger, and joy-fear using the TCA algorithm are 83.03%, 75.70%, 73.91% and 72.79%, with an improvement of 1.72%, 3.55%, 2.34% and 0.41%, respectively, in accuracy compared to using SVM alone, and the use of TCA for domain adaptation strategy has significantly improved the accuracy of emotion recognition in the three classification tasks of positive-negative (t-test, p = 0.046), joy-sadness (t-test, p = 0.039), and joy-anger (t-test, p = 0.042).

Since the positive and negative samples are not balanced, the sensitivity, specificity, and the receiver operating characteristic (ROC) curves of the positive-negative emotions in the five cases are also presented to verify the robustness of the classification model. Table 2 gives the actual and predicted values for all the positive and negative samples tested in the five cases, as well as the sensitivity, specificity and accuracy of the model. From the results, it can be seen that the imbalance between the positive and negative training samples (with more negative samples) indicates a higher ability of the model to classify the negative samples and the ability to classify the positive samples is weaker than that to classify the negative samples. It can also be seen that the introduction of the TCA algorithm has improved the ability of the model to recognize both positive and negative samples. Figure 7 presents the ROC curves, and the AUC values are 0.7829 and 0.8166 in both cases. The larger the AUC value, the more robust the classification model is.

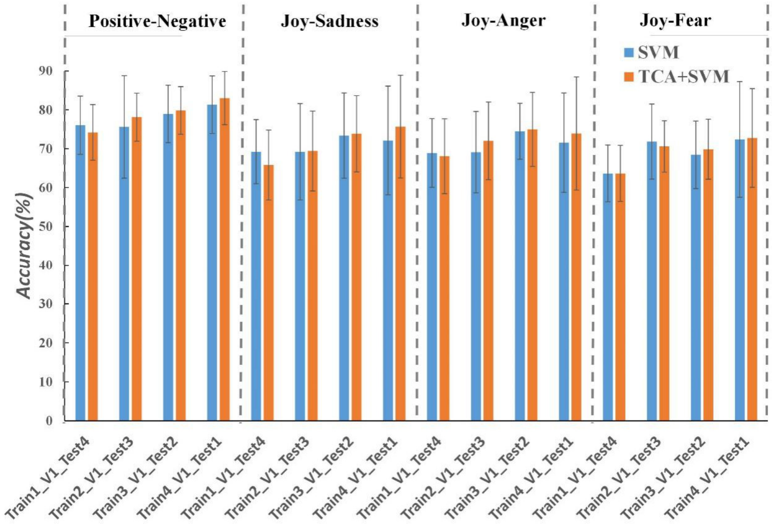

Figure 6. Performance of cross-day emotion recognition using domain adaptation algorithm and SVM, where "Positive-Negative", "Joy-Sadness", "Joy-Anger", "Joy-Fear" indicate the binary classification of the positive and negative emotions: joy and sadness, joy and anger, and joy and fear, respectively. "SVM" represents a short-time Fourier transform of the EEG signals, and then the differential entropy features are extracted for recognition using SVM. "TCA + SVM" represents a short-time Fourier transform of the EEG signals, and then domain adaptive matching via TCA algorithm will be applied to the EEG features and the features transformed will be recognized using SVM.

Table 2. Performance of binary classification of the positive-negative emotions in case of Train4_V1_Test1.

	SVM		TCA + SVM	
Actual Predicted	**Positive**	**Negative**	**Positive**	**Negative**
Positive	3934	1709	4362	1530
Negative	4886	24,751	4458	24,930
Sensitivity (%)	44.60		49.46	
Specificity (%)	93.54		94.22	
Accuracy rate (%)	81.31		83.03	

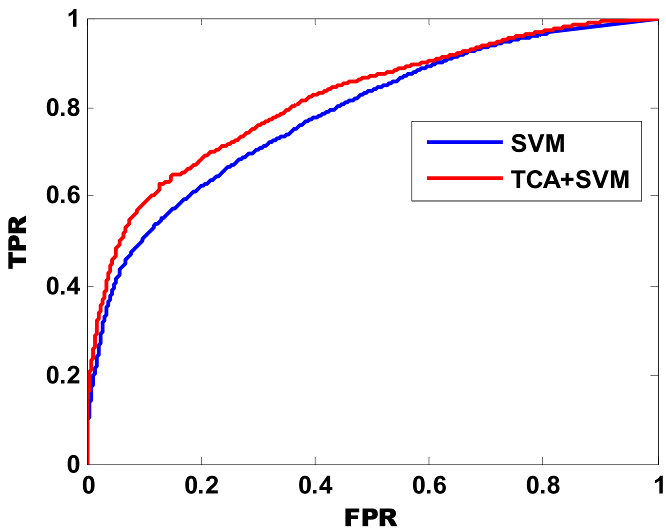

Figure 7. The average ROC curve of all the subjects in the binary classification of positive and negative emotions in case of Train4_V1_Test1.

Figures 8 and 9 present the confusion matrices of SVM and TCA + SVM under the three classification tasks of joy-sadness, joy-anger, and joy-fear. It can be seen from the figures that the TCA algorithm has improved the classification ability for both joy and the three negative emotions.

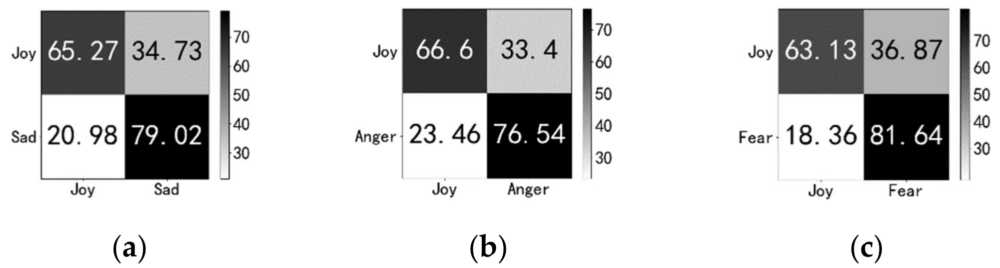

Figure 8. Average confusion matrices for all subjects in the binary classification of emotions using SVM underTrain4_V1_Test1. (**a**) Average confusion matrix for the joy-sadness classification. (**b**) Average confusion matrix for the joy-anger classification (**c**) Average confusion matrix for the joy-fear classification.

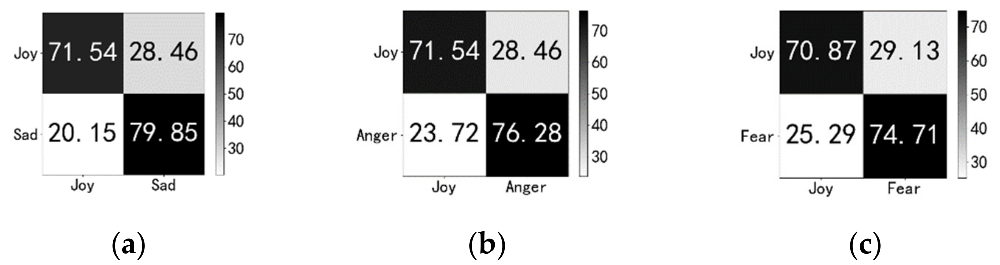

Figure 9. Average confusion matrices for all subjects in the binary classification of emotions using TCA + SVM under Train4_V1_Test1. (**a**) Average confusion matrix for the joy-sadness classification. (**b**) Average confusion matrix for the joy-anger classification (**c**) Average confusion matrix for the joy-fear classification.

3.3. Analysis of Brain Topography

In order to seek the support of cross-day emotion recognition at the theoretical level, we study the neural patterns of emotions based on EEG signals cross-day. We have presented the average brain topography of all subjects at different time during the first three days of the trial. The interval between each two of the trials A, B, and C is one week.

Figure 10 gives the DE features of all subjects in Gamma bands (30–64 Hz) cross-day. The energy in the central regions of the temporal, occipital, and parietal lobes is higher for positive emotions than that for negative emotions, and the energy in the prefrontal lobes for positive emotions is lower than that for negative emotions, which has something to do with the mechanism that negative emotions need more prefrontal cognitive resources for actions such as defense and escape. Negative emotions also have an asymmetry of energy on both sides of the temporal lobe, with higher energy in the left temporal lobe than in the right temporal lobe. This also happens in the three experiments A, B and C at different moments, which indicates that even though there are some superficial changes in the amplitude of the individual's EEG signals, there is still a more stable neural pattern of emotions cross-day. Meanwhile, these further verify that the database can provide a reliable data basis for emotion recognition across different time domains.

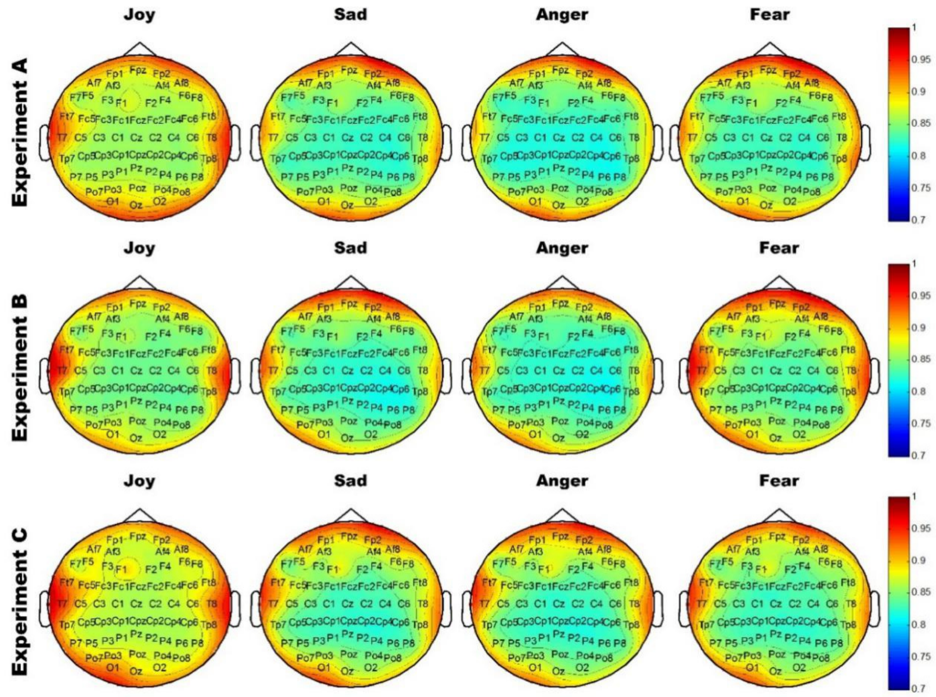

Figure 10. The average brain topography of all subjects under different emotional states, which shows the differential entropy features of all subjects in Gamma bands (30–64 Hz) cross-day.

4. Discussion

This study performs the emotion recognition on 6 days of emotional EEG data collected from each subject and has the following findings.

- The performance of emotion recognition within the same experiment is better than the emotion recognition cross-day.

The time effect of EEG can have impacts on the accuracy of emotion recognition, and a study by Liu et al. [40] has found that the accuracy of emotion recognition decreases significantly when the training and test samples of EEG are from different time domains (different days). Consistent with the results of this study, the performance of cross-day emotion recognition based on EEG signals can be significantly reduced in the four cases, Train1_V1_Test4, Train2_V1_Test3, Train3_V1_Test2, and Train4_V1_Test1, compared to the emotion recognition within a single experiment (Intra-days) (*t*-test. $p < 0.05$).

Though EEG signals will change cross-day, the average brain topography shows that there is still a stable neural pattern cross-day and the accuracy gradually improves as the number of days in the training set samples increases. When data of 4 days are used as for training (Train3_V1_Test2: the number of training samples for each emotion is 147×3), the emotion recognition accuracy has improved by 5.25%, 2.92%, 2.67%, and 8.73%, respectively, under the positive-negative, joy-sadness, joy-anger, and joy-fear classification compared to the case where data of only 1 day is selected for training (Train1_V1_Test4: the number of training samples for each emotion is 147).

- Domain adaptation algorithm can improve the performance of cross-day emotion recognition

For the cross-day emotion recognition, the TCA algorithm is used for feature matching in different time domains, and by using EEG data from different days as training and validation sets, the optimal transformed dimensionality of TCA will be determined adaptively and the emotion recognition performance will be optimized. In case of the Train4_V1_Test1, the average recognition accuracies of positive-negative, joy-sadness, joy-anger, and joy-fear using the TCA algorithm are 83.03%, 75.70%, 73.91%, and 72.79%, respectively, which has been improved by 1.72%, 3.55%, 2.34%, 2.34% and 0.41%, respectively, compared to using SVM alone. Under the binary classification of discriminating positive from negative emotions, the use of TCA algorithm has improved the recognition performance of both the positive and negative samples, and the robustness of the model has also been improved, with the AUC value increasing from 0.7829 to 0.8166. Under the three classification tasks of positive-negative, joy-sadness, and joy-anger, the use of domain adaptation via TCA has significantly improved the accuracy of emotion recognition (t-test, $p < 0.05$). This paper also discovers that in comparison to using fixed dimensionality, selecting the optimal dimensionality of TCA through the validation set can improve the performance of emotion recognition.

- The EEG database can provide a reliable data basis for emotion recognition across time domains

To study the neural patterns of emotions based on EEG signals cross-day, the brain topography has been analyzed in this paper, which show there is a stable neural pattern of emotions cross-day. The TCA-based emotion recognition model and brain topography in this paper, verify that the database can provide a reliable data basis for emotion recognition across time domains. This EEG database will be open to more researchers to promote the practical application of emotion recognition. Based on the self-built cross -day EEG database, this paper proposes a strategy based on cross-day EEG data to determine the dimension of TCA transform, which can be used to solve the problem of EEG feature matching in different time domains and effectively improve the performance of emotion recognition cross-day. Meanwhile, the experiment result shows that the database can provide a reliable data basis for emotion recognition across time domains. However, there are still some limitations, for example, the rate of emotion recognition can be further improved, TCA algorithm reduces the fear classification performance, and only the binary classification is studied, etc. Thus, on the basis of above research, we will continue to study better robust emotion recognition algorithms, subsequently study multiple classification and fine-grained classification recognition algorithms.

5. Conclusions

In this study, we have constructed a emotional EEG database based on the Chinese Affective Video System and the self-built video stimuli materials, which collected over 6 days of EEG signals for each subject. This database provided a favorable signal foundation for emotion recognition studies across time domains. On the basis of this database, we have proposed the employment of TCA algorithm to match the EEG emotional features in multi-time domain. The EEG data from different days are used as the training and validation sets to adaptively determine the optimal transformed dimensionality of TCA, which has effectively improved the recognition accuracy of joy, sadness, anger, and fear emotions, and has validated the effectiveness of the TCA strategy in improving emotion recognition performance across time domains. In future studies, further use of deep learning methods for emotion recognition cross-day will be investigated.

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Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

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Appendix A

The experiment was conducted in three parts, namely A, B and C, with each part corresponded to a table, namely Tables A1–A3 as follows.

- Part A

Table A1. Number labels of emotion videos.

Category of Emotion	Name of the Video	Label	Time (ms)
Joy	j2.avi Eat Hot Tofu Slowly	1	109,000
	j3.avi A Big Potato	2	142,000
	j5.avi Flirting Scholar	3	112,000
Sadness	s12.avi Roots and Branches	4	146,000
	s14.avi My Beloved	5	137,000
	s15.avi Warm Spring	6	102,000
Anger	a23.avi Fist of Fury (2)	7	66,000
	a24.avi Kang Xi Kingdom	8	94,000
	a25.avi Conman In Tokyo	9	107,000
Fear	f27.avi Save Me	10	50,000
	f28.avi The Game of Killing (1)	11	159,000
	f31.avi Help	12	247,000

- Part B

Table A2. Number labels of emotion videos.

Category of Emotion	Name of the Video	Label	Time (ms)
Joy	H2.avi East Meets West, Hong Qi expressed love to his cousin-sister	1	228,000
	H3.avi A World Without Thieves, the clip of robbing	2	191,000
	H5.avi Chaplin Comedy	3	244,000

Table A2. *Cont.*

Category of Emotion	Name of the Video	Label	Time (ms)
Sadness	S2.avi Darling, Tian Wenjun looked for his sun	4	182,000
	S3.avi Aftershock	5	335,000
	S4.avi Darling, Mom watched her daughter through the window	6	120,000
Anger	A1.avi Yip Man 2, The boxing champion mocked Chinese martial arts	7	172,000
	A2.avi Never Talk to Strangers	8	205,000
	a22.avi Fist of Fury (1)	9	258,000
Fear	F1.avi Lights out, the film clip of shadows after lights out	10	134,000
	F5.avi F_05, Four men lying on the ground at the beginning of the film	11	291,000
	F7.avi The film clip of big snake eating people	12	158,000

- Part C

Table A3. Number labels of emotion videos.

Category of Emotion	Name of the Video	Label	Time (ms)
Joy	H1.avi Lost on Journey, Check-in part	1	281,000
	H6.avi Home with Kids	2	187,000
	j4.avi East Meets West, Hong Qi jumped off the cliff part	3	53,000
Sadness	S5.avi English movie, a man calling in the snow	4	142,000
	S8.avi Echoes of the Rainbow, the part of typhoon blowing	5	241,000
	s13.avi Rob-B-Hood, saving the baby part	6	234,000
Anger	A3.avi The film clip of Japanese invasion	7	96,000
	A4.avi Blind Mountain, villagers stopped the abducted woman from being saved	8	275,000
	A5.avi Wildlife hunt	9	148,000

Table A3. *Cont.*

Category of Emotion	Name of the Video	Label	Time (ms)
Fear	F2.avi Lying in bed and the quilt lifted by itself	10	162,000
	F3.avi Ju-on: The Grudge, Japanese girl watching TV	11	167,000
	F6.avi F_06, A woman hanging around with a gun	12	190,000

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