Multimodal Emotion Recognition Model using Physiological Signals

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Abstract

As an important field of research in Human-Machine Interactions, emotion recognition based on physiological signals has become research hotspots. Motivated by the outstanding performance of deep learning approaches in recognition tasks, we proposed a Multimodal Emotion Recognition Model that consists of a 3D convolutional neural network model, a 1D convolutional neural network model and a biologically inspired multimodal fusion model which integrates multimodal information on the decision level for emotion recognition. We use this model to classify four emotional regions from the arousal valence plane, i.e., low arousal and low valence (LALV), high arousal and low valence (HALV), low arousal and high valence (LAHV) and high arousal and high valence (HAHV) in the DEAP and AMIGOS dataset. The 3D CNN model and 1D CNN model are used for emotion recognition based on electroencephalogram (EEG) signals and peripheral physiological signals respectively, and get the accuracy of 93.53% and 95.86% with the original EEG signals in these two datasets. Compared with the single-modal recognition, the multimodal fusion model improves the accuracy of emotion recognition by 5%~25%, and the fusion result of EEG signals (decomposed into four frequency bands) and peripheral physiological signals get the accuracy of 95.77%, 97.27% and 91.07%, 99.74% in these two datasets respectively. Integrated EEG signals and peripheral physiological signals, this model could reach the highest accuracy about 99% in both datasets which shows that our proposed method demonstrates certain advantages in solving the emotion recognition tasks.

1 Introduction

Emotion recognition plays a crucial role in human-machine interaction and health care. The recognition method based on physiological signals has become a research hotspot because the signals could represent the inner emotional states and cannot be controlled subjectively compared with other signals as facial expressions or speech.

The traditional machine learning approaches use well-designed classifiers with hand-crafted features have been studied for many years. The most common features\cite{17,39} contains Time Domain Features: Event Related Potentials (ERP)\cite{8}, Statistics of Signal\cite{28} (Power, Mean, Standard deviation, 1st difference, 2nd difference et al.), Higher Order Crossings (HOC)\cite{28} et al; Frequency Domain Features: Power Spectra Density (PSD)\cite{39}, Higher Order Spectra (HOS)\cite{15} et al; Time Frequency Domain Features: Hilbert-Huang Spectrum (HHS)\cite{12}, Magnitude Squared Coherence Estimate (MSCE)\cite{18} et al. A traditional approach which could achieve a high emotion recognition accuracy mostly depended on the well-designed hand-crafted features. So the new and effective feature extraction methods based on phase space reconstruction\cite{38,37} and flexible analytic wavelet transform (FAWT)\cite{11} make a good performance in the emotion recognition task. Soroush\cite{37} made the EEG signals reconstructed in phase space and then in angle space, then extracted features from angle variability and length variability, and used Dempster-Shafer theory for emotion recognition, final used ten-fold cross validation to evaluate their model. To our best knowledge, their method achieved the best performance in traditional machine learning approaches - classification accuracy was about 90% on average classified into four classes in DEAP dataset.

The well-designed hand-crafted features based on comprehensive domain knowledge which may be an obstacle for non-domain experts, on the other hand, the domain knowledge may limit the performance of the model. Deep learning approaches make a great success in pattern recognition domain, motivated by the outstanding performance of deep learning many researchers used it in emotion recognition tasks, such as the pre-trained deep learning model\cite{23,10}, the 2D Convolutional Neural Network Model\cite{13,22}, the 3D Convolutional Neural Network Model\cite{27,34}, the combined model of 2D CNN and LSTM\cite{35} and other models base on deep learning methods\cite{2,29,14}. Deep learning approaches make a good performance in the emotion recognition task based on physiological signals. A 3D CNN Model used to emotion recognition based on EEG signals which we proposed in a previous work gets the accuracy of 93.53% in four classification task of DEAP dataset.

Multimodal information be collected to using for emotion recognition task, such as the electrocardiogram (ECG) signals, electromyogram (EMG) signals, electrooculogram (EOG) signals, galvanic skin resistance (GSR) signals, respiration amplitude signals, blood volume signals and skin temperature in peripheral physiological signals and electroencephalogram (EEG) signals. Integrate multimodal information to improve the model performance attracts many re-
searchers, most of the multimodal information fusion techniques integrate different information on feature level [32, 22, 14] and intermediate level [30, 36], less on decision level [3]. Compared with the feature level fusion and intermediate level, the decision level fusion more easily because the decisions resulting from multiple modalities usually have the same form of data and every modality can utilize its best suitable classifier or model to learn its features [25].

Here we proposed a 3D and 1D convolutional neural network model for single modal emotion recognition based on EEG signals and various peripheral physiological signals respectively and could achieve a high accuracy especially used the EEG signals. Furthermore, we proposed a biologically inspired multimodal fusion model that integrates multimodal information on the decision level to improve the performance of the model.

The remainder of this paper is organized as follows: Section 2 provides a review of research about the deep learning approaches and the multimodal information fusion techniques used in emotion recognition tasks. Section 3 describes the method of data pre-processing, and the 3D and 1D convolutional neural network model used for single-modal, and the biologically inspired multimodal fusion model. Section 4 presents the description of the DEAP and AMIGOS dataset which used in the experiment and the result to verify the performance of the proposed model. In Section 5, we conclude our work.

2 Related work

Deep learning approaches make a great success in the emotion recognition task, in particular, the deep learning approaches using EEG signals attracted a lot of researchers. Lin [23] and Liu [10] converted the EEG signals into 2D image format and used the pre-trained deep learning model AlexNet and ResNets to extract depth level features respectively, then combine the hand-crafted features which extract from peripheral physiological signals in Lin and EEG signals in Liu for classification, and achieve the accuracy of 87.3%/85.5% (two-category emotion based on the threshold of arousal and valence respectively) in Liu, and 89.06%/90.39% (two-category emotion), 86.05% (four-category emotion based on the threshold of arousal and valence) in Liu. Mei [13] and Kwon [22] used 2D Convolutional Neural Network Model for feature extraction and classification and achieve the accuracy of 73.1% and 73.43% in four-category emotion recognition task respectively. These 2D conventional methods ignore the spatial characteristics of EEG signals, so the spatial-temporal features extraction methods had been proposed. Salama [27] proposed a 3D Convolutional Neural Network Model for spatial-temporal features extraction and classification in EEG signals and achieve the accuracy of 88.49% for arousal, 87.44% for valence in two-category emotion recognition task respectively. Wang [34] converted the EEG channels into 2D electrode topological plate which could include topological position information and used the 3D CNN Model for spatial-temporal features extraction and classification and found that compared with the 2D CNN Model used unconverted data, the 3D CNN Model made a better performance with the accuracy of 73.3% and 72.1% in two-category emotion recognition task. Yang [35] implemented the 2D CNN module and LSTM module extract spatial and temporal features respectively and combined the features for classification, and achieved a high accuracy rate of 91.03% and 90.8% in two-category emotion recognition task. The research of emotion recognition based on peripheral physiological signals is relatively few, especially using deep learning approaches. Machot [2] proposed a 2D CNN architecture for emotion recognition in four-category emotion based on Electrodermal Activity (EDA) signals, and achieve the accuracy of 85% in DEAP dataset. Granados [29] proposed a 1D Convolutional Neural Network Model model using electrocardiogram and galvanic skin response signals in four-category emotion recognition tasks in AMIGOS dataset, and achieve an accuracy of 65.25%.

Multimodal information fusion techniques used to improve the performance of the system by integrating different information on feature level [32, 22, 14], intermediate level [30, 36], and decision level [3]. The feature fusion is most widely used compared with the others in emotion recognition tasks based on physiological signals. Verma [32] proposed a multimodal fusion approach at feature level, they extracted 25 features from EEG and peripheral signals by Discrete Wavelet Transform, and they got the average accuracy of 81.45% by Support Vector Machine (SVM) classifier for thirteen emotions classification in DEAP dataset. Shu [30] proposed a fusion method to model the high-order dependencies among multiple physiological signals by Restricted Boltzmann Machine (RBM), the new feature representation generated from the features of EEG signals and peripheral physiological signals by RBM, then they used Support Vector Machine (SVM) classifier to emotion recognition and got the accuracy of 64.6% and 60.7% in arousal and valence respectively in DEAP dataset. Yin [36] proposed a multiple-fusion-layer based ensemble classifier of stacked auto-encoder (MESAE) for emotion recognition, they extracted 425 salient physiological features from EEG signals and peripheral physiological signals and the features split into non-overlapped physiological feature subsets, then get the abstraction fusion features by the SAE, and used Bayesian model to classification, the model got the accuracy of 84.18% and 83.04% in arousal and valence respectively in DEAP dataset. Kwon [22] proposed a preprocessing method of EEG signals which using a wavelet transform while considering time and frequency simultaneously, then extracted the EEG feature convolution neural networks (CNN) model and combined them with the features extracted from galvanic skin response (GSR) signals, and got the accuracy of 73.43% in four class classification task of DEAP Dataset. Bagherzadeh [3] extracted spectral, time and nonlinear features from peripheral and EEG signals, then used multiple stacked autoencoders in a parallel form (PSAE) to primary classification, the final decision about classification was performed using the majority voting method, and they
got the accuracy of 93.6% in four class classification task of DEAP Dataset. Hassan [14] applied unsupervised deep belief network (DBN) for depth level feature extraction from partial peripheral signals and combined them in a feature fusion vector, then used the Fine Gaussian Support Vector Machine (FGSVM) to classification, they got the accuracy of 84.44% in five class classification task of DEAP Dataset.

3 Methods

Here we propose a Multimodal Emotion Recognition Model that consists of a 3D convolutional neural network model, a 1D convolutional neural network model and a biologically inspired multimodal fusion model on decision level for multimodal emotion recognition.

3.1 Pre-processing

A pre-processing method with baseline signals - the signals be recorded when the participant under no stimulus - which first elaborated by Yang [35] is an effective way to improve recognition accuracy. They reported that the pre-processing method can increase recognition accuracy by 32% approximately in the emotion recognition task. The pre-processing method contains: extract the baseline signals from all channels C and cut it in N segments with fixed length L, get N segments C x L matrixes; calculate the mean value of the baseline signals with segmented data, get the baseline signals mean value M, a C x L matrixes; cut the EEG and Physiological signals which without baseline signals with length L and minus the baseline signals mean value M, get the pre-processed signals.

The raw EEG signals in the dataset lost the topological position information of the electrodes. To solve this problem, the electrodes used in the dataset are relocated to the 2D electrode topological structure based on the 10-20 system positioning. For each time sample point, the EEG signals are mapped into a 9x9 matrixes. The unused electrodes are filled with zero. Z-score normalization is used in each transformation.

3.2 3D Convolutional Neural Network Model

The 3D convolutional neural network model is used for emotion recognition based on EEG signals. The architecture of the 3D convolutional neural network model contains two convolution layers, each followed by a max-pooling layer, and a fully-connected layer. A detailed illustration of the architecture is shown in Fig. 1. The input size is 9x9x128, the 9x9 is the 2D electrode topological structure and the 128 is the number of the consecutive time sample point processed at once. The kernel size of the convolution layer is 3x3x4, which means the spatial-temporal features are generated based on a local topology of 3x3 and a time period of 4-time sample points. To prevent missing information of input data, the zero-padding be used in each convolutional layers. The RELU activation function is used after the convolution operation. The pooling size of a max-pooling layer is 1x1x2 which used to reduce the data size in the temporal dimension and improve the robustness of extracted features. The numbers of feature maps in the first and second convolutional layers are 32 and 64 respectively. Before passing the 64 resulting feature maps to the fully-connected layer, the output feature maps are reshaped in a vector. The fully-connected layer maps the feature maps into a final feature vector of 1024. And a dropout regularization after fully connected layers used to avoid overfitting. The N in the output layer means the numbers of the label in the task.

3.3 1D Convolutional Neural Network Model

The 1D convolutional neural network model is used for emotion recognition based on physiological signals. The architecture of the 1D convolutional neural network model contains two convolution layers, each followed by a max-pooling layer, and a fully-connected layer. A detailed illustration of the architecture is shown in Fig. 2. The input size is 128x1 which represents a 128 consecutive time sample point of physiological signals in each channel. The kernel size of the convolution layer is 3x1. To prevent missing information of input data, the zero-padding be used in each convolutional layers. The RELU activation function is used after the convolution operation. The pooling size of a max-pooling layer is 2x1 which used to reduce the data size in the temporal dimension and improve the robustness of extracted features. The numbers of feature maps in the first and second convolutional layers are 16 and 32 respectively. Before passing the 32 resulting feature maps to the fully-connected layer, the output feature maps are reshaped in a vector. The fully-connected layer maps the feature maps into a final feature vector of 256. And a dropout regularization after fully connected layers used to avoid overfitting. The N in the output layer means the numbers of the label in the task.

3.4 Multimodal Fusion Model

The multisensory integration has been widely studied in neuroscience and psychophysical [6]. A Bayes-optimal cue integration model been proposed and has been proved its successful in visual and haptic information integration [5], visual and proprioceptive information integration [31], visual and vestibular information integration [7, 9], visual and auditory information integration [19, 4], stereo and texture or texture and motion information integration in vision research [20, 16]. This model estimates the result by weighting the cues in proportion to their relative reliability which proportional to the inverse variance. Take a spatial localization estimate by visual and auditory information integration as an example as shown in Fig 3, this model could describe as follows:

The direction of an event is s, the estimate spatial location by visual (x_v) and auditory (x_a) will inconsistent with the true location because of the noise in transmission and
Figure 1: 3D Convolutional Neural Network Model

Figure 2: 1D Convolutional Neural Network Model

Figure 3: Bayes-optimal combination of multiple sensory cues.

processing. According to Bayes’ theorem and the conditionally independent sources of visual and auditory, it can be described as Equation 1.

\[ p(s|x_v, x_a) \propto p(x_v|s) \cdot p(x_a|s) \cdot p(s) \]  \hspace{1cm} (1)

If assumes that the p(s) is uniform prior distribution and the additional simplifying assumption of Gaussian likelihood function, the average estimate derived from an optimal Bayesian integrator is a weighted average of the average estimates that would be derived from each cue alone, it could be described as Equation 2.

\[ s^* = \omega_v \times x_v + \omega_a \times x_a \]  \hspace{1cm} (2)

where

\[ \omega_v = \frac{1/\sigma_v^2}{1/\sigma_v^2 + 1/\sigma_a^2} \quad \text{and} \quad \omega_a = \frac{1/\sigma_a^2}{1/\sigma_v^2 + 1/\sigma_a^2} \]  \hspace{1cm} (3)

It means that the greater a cue’s reliability, the more it contributes to the final estimate.

In the research of affect, Russell’s valence-arousal scale [26] has been widely used quantitatively describe emotions. After watching a video that could induce the participant’s emotion, the participant rated a self-assessment of arousal and valence on a scale from 1 to 9. In the emotion recognition task, the researchers often divided the dataset into various classes based on the threshold of arousal and valence. So the class labels could mapping in the two-dimensional space by calculated the mean value of the corresponding class labels on Arousal-Valence data. In this way, we can calculate the Euclidean distance between various class labels, then using the standard normal distribution to calculate the classification score reliability of other labels in a certain label based on the Euclidean distance, as shown in Equation 4.

\[ f(d_{ij}) = \frac{1}{\sqrt{2\pi}} e^{-\frac{d_{ij}^2}{2}} \]  \hspace{1cm} (4)

The \( f(d_{ij}) \) is the classification score reliability between label i and label j. For example, the emotion dataset is divided into 4 classes based on the threshold of arousal and valence: LALV (e.g. sad), HALV (e.g. stressed), LAHV (e.g. relaxed), HAHV (e.g. happy). For a certain label HAHV, the distance between HAHV and LALV is the farthest, so the classification score reliability of LALV is lowest, similarly, the classification score reliability of HAHV is lowest for a certain label LALV.

In each channel, we calculate the final classification score through classification probability from CNN model and classification score reliability as shown in Equation 5, the \( NL \) is the number of labels, and the \( PR_{c,i} \) represents the classification probability of label i in channel c, the \( GauPR_{c,j} \) is the final classification score of label j in channel c with classification score reliability. Considering the difference between the biological system and the machine systems, the classification probability from the CNN model with Softmax Regression and the sum of all the classification probability is 1, here we use the dispersion of final classification score to represent the corresponding channel reliability, and
the dispersion calculate by the standard deviation as shown in Equation 6, the $S_c$ represents the channel reliability of channel $c$. The more average the final classification scores are, the smaller of the dispersion is, the lower the corresponding channel reliability is. If one of the final classification scores in a channel is high, the corresponding channel reliability is high because of the greater dispersion.

$$GauPR_{c,j} = \sum_{i=1}^{NL} PR_{c,i} \times f(d_{ij})$$ (5)

$$S_c = \left(\frac{1}{NL-1} \sum_{j=1}^{NL} (GauPR_{c,j} - \bar{GauPR}_{c,j})^2 \right)^{\frac{1}{2}}$$ (6)

where

$$\bar{GauPR}_{c,j} = \frac{1}{NL} \sum_{j=1}^{NL} GauPR_{c,j}$$ (7)

Then we calculate the fusion result of label $j$ as shown in Equation 8, the $NC$ represents the number of the channels. Then we use $\arg\max$ to select the final result.

$$F_j = \sum_{c=1}^{NC} GauPR_{c,j} \times S_c$$ (8)

$$R_{\text{label}} = \arg\max(F_j)$$ (9)

4 Result

We test this method in public database DEAP[21] and AMIGOS[24]. The proposed model is implemented by using the Tensorflow framework [1] and deployed on NVIDIA Tesla K40c. The learning rate is set to 1E-3 with Adam Optimizer, and the keep probability of dropout operation is 0.5. The batch size for training and testing is set to 240. We use 10-fold cross-validation to evaluate the performance of our model. The average accuracy of the 10-fold validation processes is taken as the final result.

4.1 DEAP Dataset

The DEAP [21] is an open dataset for researchers to validate their model. This dataset contains 32 channels EEG signals and 8 channels peripheral physiological signals which be collected when 32 participants watched 40 videos each with one-minute duration. The EEG channels contain Fp1, AF3, F3, F7, FC5, FC1, C3, T7, CP5, CP1, P3, P7, PO3, O1, Oz, Pz, Fp2, AF4, Fz, F4, F8, FC6, FC2, Cz, C4, T8, CP6, CP2, P4, P8, PO4 and O2. The peripheral physiological channels contain hEOG, vEOG, zEMG, tEMG, GSR, respiration amplitude, blood volume, and skin temperature. Each trial contains 63s signals and the first 3s are the baseline signals. The baseline signals are recorded when the participant under no stimulus. After watching a minute video, the participants rated a self-assessment of arousal, valence, liking, and dominance on a scale from 1 to 9. A preprocessed version had been provided: The data was down-sampled from 512Hz to 128Hz, and a bandpass frequency filter from 4.0-45.0Hz was applied.

In the process of data pre-processing for one trial signals (40x8064), the baseline signals (40x384) have been cut in 3 segments (3 40x128), and calculate the mean value of the baseline signals (1 40x128). And the data without baseline signals cut in 60 segments (60 40x128) then minus the baseline signals mean value, get the preprocessed signals (40x7680). For each time sample point, the 32 channels EEG signals are mapped into a 9x9 matrixes (as shown in Fig.4), get the 2D electrode topological structure (7680 9x9) with Z-score normalization. Final, the signals are cut into 60 segments with 1s length (60 9x9x128), and the 1s length was reported as the most suitable time window length in [33]. The final data size of EEG signals after processing is 76800 9x9x128. The 8 channels physiological signals cut into 60 segments with 1s length in each channel, and the final data size of physiological signals in each channel after processing is 76800 9x9x128. The 8 channels physiological signals cut into 60 segments with 1s length in each channel, and the final data size of physiological signals in each channel after processing is 76800 9x9x128.

The dataset could be segmented in four classes low arousal low valence (LALV), high arousal low valence (HALV), low arousal high valence (LAHV), high arousal high valence (HAHV) based on the arousal and valence value with the threshold of 5 respectively, and the corresponding instance numbers are shown in Table 1.

Fig 5 shows the distribution of emotion classes in DEAP. The red points are calculated by the mean value of the corre-
Figure 5: Distribution of emotion classes in DEAP, and the red points are the mean value of the corresponding labels on Arousal-Valence data, such as LALV (2.95, 3.51), HALV (6.64, 3.07), LAHV (3.44, 6.42), HAHV (6.58, 7.11).

The 3D CNN model and 1D CNN model are used for emotion recognition based on EEG signals and peripheral physiological signals. To verify the multimodal fusion framework of EEG signals, the signals decomposed into four parts according to the four frequency bands of theta (4-7 Hz), alpha (8-13 Hz), beta (14-30 Hz) and gamma (31-45 Hz). Table 2 shows the accuracy rate of each single-modal and the increment in fusion result. It is easy to see, there is a significant increase of accuracy rate in fusion result compared with the single-modal results.

Fig 6 shows the average accuracy of fusion results in the various numbers of modals, and the average accuracy of the fusion result is proportional to the numbers of the modal.

The accuracy rate will rise further with the fusion between EEG signals and peripheral physiological signals. Table 3 shows the fusion accuracy rate of EEG signals and peripheral physiological signals respectively and the increment in EEG signals + peripheral physiological signals fusion result.

Fig.7 shows the result of emotion recognition in each modal and the fusion results.

4.2 AMIGOS Dataset

The AMIGOS [24] is a new open dataset. This dataset contains 14 channels EEG signals and 3 channels peripheral

| Modality | Single-modal Result | Improvement in Fusion Result |
|----------|----------------------|----------------------------|
| EEG Signals |
| Alpha | 89.01% | 6.76% |
| Beta | 89.69% | 6.08% |
| Gamma | 73.09% | 22.68% |
| Theta | 81.97% | 13.80% |
| Peripheral Physiological Signals |
| hEOG | 72.57% | 24.70% |
| vEOG | 86.45% | 10.82% |
| zEMG | 73.66% | 23.61% |
| tEMG | 83.74% | 13.53% |
| GSR | 74.60% | 22.67% |
| Respiration belt | 66.33% | 30.94% |
| Plethysmograph | 72.94% | 24.33% |
| Temperature | 51.43% | 45.84% |

Table 2: Accuracy improvement in fusion result of EEG signals and peripheral physiological signals compared with the single-modal result (DEAP). The fusion result of four frequency bands EEG signals is 95.77% and the fusion result of 8 multimodal peripheral physiological signals is 97.27%.

Table 3: Accuracy improvement in fusion result of EEG signals + peripheral physiological signals compares with the fusion result of EEG signals and peripheral physiological signals respectively (DEAP). The fusion result of EEG signals + peripheral physiological signals achieves the accuracy rate of 99.17% with the decomposed EEG signals (EEG) and 98.52% with the original EEG signals (EEG*).
physiological signals which be collected when 40 participants watched 20 videos (16 short videos + 4 long videos).

The EEG channels contain AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, and AF4. The peripheral physiological channels contain ECG Right, ECG Left, and GSR. Each trial contains 5s baseline signals in first and the signals depend on the duration of the video. The baseline signals are recorded when the participant under no stimulus. After watching the video, the participants rated a self-assessment of arousal, valence, liking, and dominance on a scale from 1 to 9. A preprocessed version had been provided: The data was down-sampled to 128Hz, and a bandpass frequency filter from 4.0-45.0Hz was applied.

Here we use the signals which were recorded in short videos experiment. The participant ID of 9, 12, 21, 22, 23, 24 and 33 has been removed because there are some invalid data in the preprocessed version. The data pre-processing in the AMIGOS dataset is the same as in the DEAP dataset, and the signals also be segmented with 1s length. The 14 channels EEG signals are mapped into a 9x9 matrixes (as shown in Fig.8). The final data size of EEG signals after processing is 45474 9x9x128. The 3 channels physiological signals cut into 60 segments with 1s length in each channel, and the final data size of physiological signals in each channel after processing is 45474 128x1.

The dataset could be segmented in four classes, i.e. low arousal low valence (LALV), high arousal low valence (HALV), low arousal high valence (LAHV), high arousal high valence (HAHV) based on the arousal and valence value with the threshold of 5 respectively, and the corresponding instance numbers are shown in Table 4.

Fig 9 shows the distribution of emotion classes in AMIGOS, and the labels could be represented as LALV (2.95, 3.51), HALV (6.64, 3.07), LAHV (3.44, 6.42), HAHV (6.58, 7.11) in two-dimensional space. The process of calculating the multimodal information integration result is the same as in DEAP.

As the process of emotion recognition in DEAP, the same model be used in AMIGOS. Table 5 shows the accuracy rate of each single-modal and the increment in fusion result. There is a significant increase of accuracy rate in fusion result of four frequency bands EEG signals, but the increment is unobvious in the fusion result of peripheral physiological signals compared with the ECG signals.

Table 6 shows the fusion accuracy rate of EEG signals and peripheral physiological signals respectively and the increment in EEG signals + peripheral physiological signals fusion result. There is a significant increase compared with the EEG modal, but make an unsatisfactory performance compared with the fusion result of peripheral physiological modal.

Fig.10 shows the result of emotion recognition in each modal and the fusion results.

5 Conclusions

In this paper, we have proposed a Multimodal Emotion Recognition Model that consists of the 3D convolutional neural
network model, the 1D convolutional neural network model and the biologically inspired multimodal fusion model for emotion recognition. In the single-modal emotion recognition, the model achieves the highest accuracy rate of 89.69% and 86.45% based on the Beta band of EEG signals and the vEOG of peripheral physiological signals in the DEAP dataset respectively, and achieve the highest accuracy rate of 86.8% and 99.71% based on the Beta band of EEG signals and ECG Right of peripheral physiological signals in AMIGOS dataset respectively. The accuracy rate achieves 93.53% and 95.86% with original EEG signals in DEAP and AMIGOS dataset respectively. The biologically inspired multimodal fusion model improves the recognition accuracy of 5% ˜25% based on the fusion of EEG signals and peripheral physiological signals compared with single-modal, and achieve the accuracy of 95.77%, 97.27% in the DEAP dataset and 91.07%, 99.74% in AMIGOS dataset respectively. Compared with the result of original EEG signals, the fusion result of various bands of EEG signals gets a higher accuracy of 2.24% in the DEAP dataset and a lower accuracy of 4.79% in the AMIGOS dataset. This result proves that the original EEG signals contain enough information and could be used directly for emotion classification, besides, the result of peripheral physiological signals shows that a robust classification of human emotion is possible without EEG signals which signals be collected a little difficult. The fusion result of EEG signals + peripheral physiological signals gets the highest accuracy rate of 99.17% and 99.04% with the EEG signals decomposed into four frequency bands, 98.52% and 99.89% with the original EEG signals in DEAP dataset and AMIGOS dataset respectively. This model makes a good performance in the DEAP dataset and AMIGOS dataset, in the future, we will verify the universality of the model on varied dataset. Furthermore, the biologically inspired multimodal fusion model uses the correlation between various labels and integrates the information on the decision level, the multimodal information fusion method could be used for other multimodal pattern recognition tasks.

Table 5: Accuracy improvement in fusion result of EEG signals and peripheral physiological signals compared with the single-modal result (AMIGOS). The fusion result of four frequency bands EEG signals is 91.07% and the fusion result of 3 multimodal peripheral physiological signals is 99.74%

| Modality                  | Single-modal Result | Improvement in Fusion Result |
|---------------------------|---------------------|-----------------------------|
| EEG Signals              |                     |                             |
| Alpha                    | 79.54%              | 11.53%                      |
| Beta                     | 86.80%              | 4.27%                       |
| Gamma                    | 85.39%              | 5.68%                       |
| Theta                    | 75.88%              | 15.19%                      |
| Peripheral Physiological Signals |         |                             |
| ECG Right                | 99.71%              | 0.03%                       |
| ECG Left                 | 99.30%              | 0.44%                       |
| GSR                      | 84.69%              | 15.05%                      |

Table 6: Accuracy improvement in fusion result of EEG signals + peripheral physiological signals compared with the fusion result of EEG signals and peripheral physiological signals respectively (AMIGOS). The fusion result of EEG signals + peripheral physiological signals achieves the accuracy rate of 99.04% with the decomposed EEG signals (EEG) and 99.89% with the original EEG signals (EEG*).

| Modality             | Result  | EEG Peripheral | EEG* Peripheral |
|----------------------|---------|----------------|-----------------|
| EEG*                 | 95.86%  | 3.18%          | 4.03%           |
| Fusion EEG           | 91.07%  | 7.97%          | 8.82%           |
| Fusion Peripheral    | 99.74%  | -0.70%         | 0.15%           |

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