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# Multimodal Emotion Recognition Using Multimodal Deep Learning

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## Abstract

To enhance the performance of affective models and reduce the cost of acquiring physiological signals for real-world applications, we adopt multimodal deep learning approach to construct affective models from multiple physiological signals. For unimodal enhancement task, we indicate that the best recognition accuracy of 82.11% on SEED dataset is achieved with shared representations generated by Deep AutoEncoder (DAE) model. For multimodal facilitation tasks, we demonstrate that the Bimodal Deep AutoEncoder (BDAE) achieves the mean accuracies of 91.01% and 83.25% on SEED and DEAP datasets, respectively, which are much superior to the state-of-the-art approaches. For cross-modal learning task, our experimental results demonstrate that the mean accuracy of 66.34% is achieved on SEED dataset through shared representations generated by EEG-based DAE as training samples and shared representations generated by eye-based DAE as testing sample, and vice versa.

## 1 Introduction

For human-machine interface (HMI), emotion recognition is becoming more and more important. Emotion recognition could be done through texts, pictures and physiological signals. Bravo-Marquez *et al.* learned an expanded opinion (positive, neutral and negative) lexicon from emoticon annotated tweets [Bravo-Marquez *et al.*, 2015]. Wang and Pal used constraint optimization framework to discover user' emotions from social media content [Wang and Pal, 2015].

Recently, many researchers studied emotion recognition from EEG. Liu *et al.* used fractal dimension based algorithm to recognize and visualize emotions in real time [Liu *et al.*, 2010]. Murugappan *et al.* employed discrete wavelet transform to extract frequency features from EEG signals and two classifiers are used to classify the features [Murugappan *et al.*, 2010]. Duan *et al.* found that differential entropy features are more suited for emotion recognition tasks [Duan *et al.*, 2013]. Zheng and Lu employed

deep neural network to classify EEG signals and examined critical bands and channels of EEG for emotion recognition [Zheng and Lu, 2015].

Besides EEG signals, eye movement data can be used to find out what is attracting users' attention and observe users' unconscious behaviors. It is widely believed that when people are in different emotions, the paradigm of eye movements and pupil diameters will be different. Nelson *et al.* studied the relationship between attentional bias to threat and anxiety by recording eye movement signals in different situations [Nelson *et al.*, 2015]. Bradley and Lang recorded eye movement signals to study the relationship between memory, emotion and pupil diameters [Bradley and Lang, 2015].

To deal with information from different modalities, Yang *et al.* proposed an auxiliary information regularized machine which treats different modalities with different strategies [Yang *et al.*, 2015]. Zhang *et al.* proposed a multimodal ranking aggregation framework for fusion of multiple visual tracking algorithms [Zhang *et al.*, 2015]. In [Ngiam *et al.*, 2011], the authors built a single modal deep autoencoder and a bimodal deep autoencoder to generate shared representations of images and audios. Srivastava and Salakhutdinov extended the methods developed by [Ngiam *et al.*, 2011] to bimodal deep Boltzmann machines to handle multimodal deep learning problems [Srivastava and Salakhutdinov, 2014].

As for multimodal emotion recognition, Verma and Tiwary carried out emotion classification experiments with EEG signals and peripheral physiological signals [Verma and Tiwary, 2014]. Lu *et al.* used two different fusion strategies for combining EEG and eye movement data: feature level fusion and decision level fusion [Lu *et al.*, 2015]. Their experimental results indicated that the best recognition accuracy was achieved by using fuzzy integral method in decision level fusion. Vinola and Vimaladevi gave a detailed survey on human emotion recognition and listed many other multimodal datasets and methods [Vinola and Vimaladevi, 2015].

To our best knowledge, there is no research work reported in the literature dealing with emotion recognition from multiple physiological signals using multimodal deep learning algorithms. In this paper, we propose a novel multimodal emotion recognition method using multimodal deep learning techniques. In Section 2, we will introduce the unimodal deep au-

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toencoder and bimodal deep autoencoder. Section 3 contains contents about data pre-processing, feature extraction and experiment settings. The experiment results are described in Section 4. Following discusses in Section 5, conclusions and future work are represented in Section 6.

## 2 Multimodal Deep Learning

### 2.1 Restricted Boltzmann Machine

A restricted Boltzmann machine (RBM) is an undirected graph model, which has a visible layer and a hidden layer. Connections exist only between visible layer and hidden layer and there is no connection either in visible layer or in hidden layer. Assuming visible variables  $\mathbf{v} \in \{0, 1\}^M$  and hidden variables  $\mathbf{h} \in \{0, 1\}^N$ , we have the following energy function  $E$ :

$$E(\mathbf{v}, \mathbf{h}; \theta) = - \sum_{i=1}^M \sum_{j=1}^N W_{ij} v_i h_j - \sum_{i=1}^M b_i v_i - \sum_{j=1}^N a_j h_j \quad (1)$$

where  $\theta = \{\mathbf{a}, \mathbf{b}, \mathbf{W}\}$  are parameters,  $W_{ij}$  is the symmetric weight between visible unit  $i$  and hidden unit  $j$ ,  $b_i, a_j$  are bias terms of visible unit and hidden unit, respectively. With energy function, we can get the joint distribution over the visible and hidden units:

$$p(\mathbf{v}, \mathbf{h}; \theta) = \frac{1}{\mathcal{Z}(\theta)} \exp(E(\mathbf{v}, \mathbf{h}; \theta)) \quad (2)$$

$$\mathcal{Z}(\theta) = \sum_{\mathbf{v}} \sum_{\mathbf{h}} \exp(E(\mathbf{v}, \mathbf{h}; \theta))$$

where  $\mathcal{Z}(\theta)$  is the normalization constant. From Eqs. (1) and (2), we can derive the conditional distribution over hidden units  $\mathbf{h}$  and visible units  $\mathbf{v}$  as follows:

$$p(\mathbf{h}|\mathbf{v}; \theta) = \prod_{j=1}^N p(h_j|\mathbf{v})$$

$$p(\mathbf{v}|\mathbf{h}; \theta) = \prod_{i=1}^M p(v_i|\mathbf{h})$$

with

$$p(h_j = 1|\mathbf{v}; \theta) = g\left(\sum_{i=1}^M W_{ij} v_i + a_j\right)$$

$$p(v_j = 1|\mathbf{h}; \theta) = g\left(\sum_{i=1}^N W_{ij} h_i + b_i\right)$$

$$g(x) = 1/(1 + \exp(-x))$$

Given a set of visible variables  $\{\mathbf{v}_n\}_{n=1}^N$ , the derivative of log-likelihood with respect to weight  $\mathbf{W}$  can be calculated from Eq. (2):

$$\frac{1}{N} \sum_{i=1}^N \frac{\partial \log P(\mathbf{v}_n; \theta)}{\partial W_{ij}} = \mathbb{E}_{P_{data}}[v_i h_j] - \mathbb{E}_{P_{model}}[v_i h_j]$$

In this paper, we use Contrastive Divergence (CD) algorithm [Hinton, 2002] or Persistent CD algorithm [Tieleman, 2008] to train a RBM.

### 2.2 Model construction

To enhance emotion recognition accuracy by combining EEG and eye movement data, we adopt a Bimodal Deep autoencoder (BDAE) to extract shared representations of EEG and eye movement data. When only one modality is available, the unimodal deep autoencoder (DAE) is applied to extract shared representations. These two kinds of deep autoencoder models are depicted in Figure 1.

#### BDAE training

To train BDAE, we first trained two RBMs for EEG signals and eye movement data, respectively, i.e., the first two layers in Figure 1(b). After training respective RBMs, two hidden layers indicated by  $h_{\text{EEG}}$  and  $h_{\text{Eye}}$  were linked together directly and we treated the joint hidden layer as the visible layer of an upper RBM. When unfolding the stacked RBMs into a bimodal deep autoencoder, we kept the weights tied. From Figure 1(b), we can see that  $W_1, W_2, W_3$  and  $W_1^T, W_2^T, W_3^T$  were tied weights. At last, we used unsupervised back-propagation algorithm to finely tune the weights and bias.

#### DAE training

A similar method was used when training DAE. Only one RBM was constructed for EEG features or eye tracking features, and the hidden layer of the first RBM was treated as the visible layer of the upper RBM. However, when unfolding the stacked RBMs, we only kept the weights of first EEG (or eye) layer and top EEG (or eye) layer tied. From Figure 1(a), we can see that  $W_1$  and  $W_1^T$  were tied weights while other weights were not. Other weights and bias could be trained with CD algorithm or Persistent CD algorithm. Unsupervised back-propagation was also needed to finely tune the parameters.

There are three steps in total. The first step is to train the DAE network or the BDAE network. It is worth noting that both modality information is needed when training those autoencoders. We will call this step feature selection. The second step is supervised training. After training autoencoders, we can use them to generate shared representations and these shared representations can then be used to train a classifier. And the last step is a testing process, from which the recognition results are produced.

## 3 Experiment settings

### 3.1 Dataset

Two public datasets, the SEED dataset<sup>1</sup> and the DEAP dataset<sup>2</sup>, were used in this paper. The SEED dataset was first introduced in [Zheng and Lu, 2015]. This dataset contains EEG signals and eye movement signals from 15 subjects during watching emotional movie clips. The dataset contains 15 movie clips and each clip lasts about 4 minutes long. The EEG signals are of 62 channels at a sampling rate of 1000 Hz and the eye movement signals contain information about blink, saccade fixation and so on. In order to compare our proposed method with [Lu *et al.*, 2015], we use the same data

<sup>1</sup><http://bcmi.sjtu.edu.cn/~seed/index.html>

<sup>2</sup><http://www.eecs.qmul.ac.uk/nmv/datasets/deap/readme.html>

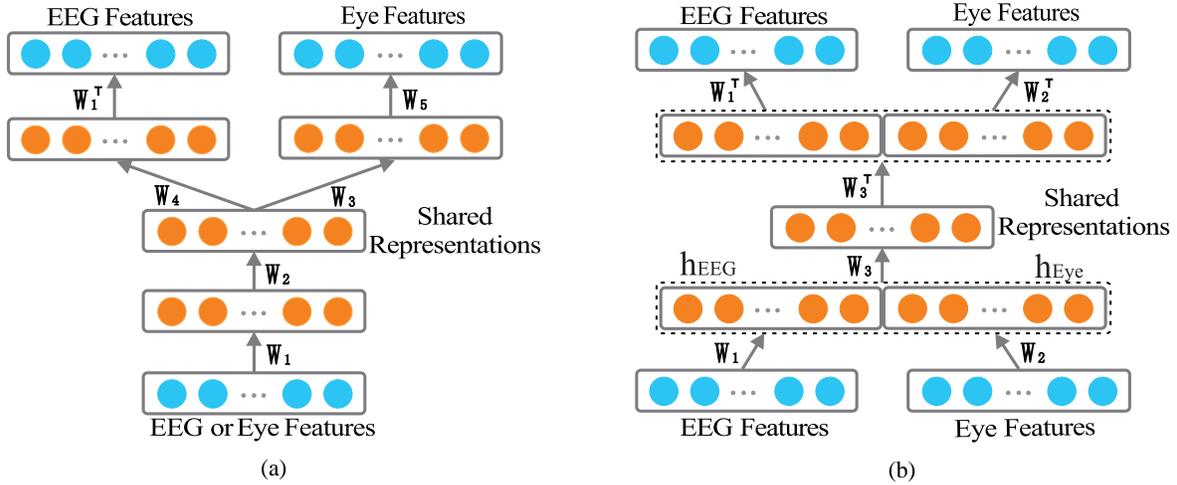


Figure 1: Deep autoencoder models adopted in this paper. Figures 1(a) and 1(b) depict the structure of unimodal DAE and the structure of BDAE, respectively. For DAE model, the inputs are EEG features or eye movement features. For BDAE model, the inputs are both EEG features and eye movement features. The middle layers in both networks are shared representations.

as in [Lu *et al.*, 2015], that is, 27 data files from 9 subjects. For every data file, the data from the subjects watching the first 9 movie clips are used as training samples and the rest are used as test samples.

The DEAP dataset was first introduced in [Koelstra *et al.*, 2012]. The EEG signals and peripheral physiological signals of 32 participants were recorded when they were watching music videos. The dataset contains 32 channel EEG signals and 8 peripheral physiological signals. The emotional music videos include 40 one-minute long small clips and subjects were asked to do self-assessment by assigning values from 1 to 9 to five different status, namely, valence, arousal, dominance, liking and familiarity. In order to compare the performance of our proposed method with previous results in [Rozgic *et al.*, 2013] and [Li *et al.*, 2015], we did not take familiarity into consideration. We divided the trials into two different classes according to the assigned values. The threshold we chose is 5, and the tasks can be treated as four binary classification problems, namely, high or low valence, arousal, dominance and liking. Among all of the data, 90% samples were used as training data and the rest 10% samples were used as test data.

### 3.2 Feature Extraction

#### SEED dataset

Power Spectral Density (PSD) and Differential Entropy (DE) features were extracted from EEG data. Both two kinds of features contain five frequency bands: delta (1–4Hz), theta (4–8Hz), alpha (8–14Hz), beta (14–31), and gamma (31–50Hz). As for eye movement data, we used the same features as in [Lu *et al.*, 2015], which were listed in Table 1. The extracted EEG features and eye movement features were then scaled between 0 and 1 and the scaled features were used as the visible units of BDAE or DAE network.

Eye movements parameters	Extracted features
Pupil diameter(X and Y)	Mean, standard deviation, DE in four bands (0–0.2Hz, 0.2–0.4Hz, 0.4–0.6Hz, 0.6–1Hz)
Dispersion(X and Y)	Mean, standard deviation
Fixation duration (ms)	Mean, standard deviation
Blink duration (ms)	Mean, standard deviation
Saccade	Mean, standard deviation of saccade duration(ms) and saccade amplitude( $^{\circ}$ )
Event statistics	Blink frequency, fixation frequency, fixation duration maximum, fixation dispersion total, fixation dispersion maximum, saccade frequency, saccade duration average, saccade amplitude average, saccade latency average.

Table 1: The details of the extracted eye movement features.

#### DEAP dataset

Instead of extracting features manually, we used the downloaded preprocessed data directly as the inputs of BDAE network and DAE network to generate shared representations of EEG signals and peripheral physiological signals. First, the EEG signals and peripheral physiological signals were separated and then the signals were segmented into 63 seconds. After segmentation, we combined different channel data of the same time period (one second), forming the input signals of BDAE network. At last, BDAE network generates shared representations.

### 3.3 Classification

The shared representations generated by BDAE network or DAE network were used to train a classifier. In this paper, linear SVM was used. Inspired by [Guo and Guo, 2005], we performed experiments on the following three kinds of emotion recognition tasks to examine the efficiency of our proposed method.

- (1) For unimodal enhancement task, we built a unimodal DAE network for EEG features or eye movement features to reconstruct both modalities. The mid-layer shared representations were extracted to train a classifier. In this task, only SEED dataset was used.
- (2) In multimodal facilitation task, both modalities were needed. The shared representations generated by BDAE network were fed into linear SVM to train a classifier. Both SEED dataset and DEAP dataset were used.
- (3) For cross-modal learning task, we built two unimodal DAEs for EEG features and eye movement features. The mid-layer outputs were extracted as shared representations. Then we used extracted features of one modality as training samples and extracted features of the other modality as testing samples. In this task, only SEED dataset was used.

## 4 Results

### 4.1 Unimodal enhancement

In unimodal enhancement task, we used EEG signals to reconstruct information of two modalities. Once the DAE network was trained, we could use it as a feature selector to generate shared representations, even if only one modality information is available. For eye movement data, the process was the same as when only EEG signals were available.

Figure 2 is the summary of all unimodal enhancement results. We can see from Figure 2 that the DAE model performed best on both EEG features and eye movement features.

For EEG-based unimodal enhancement experiments, we constructed an affective model using EEG features of different frequency bands. The experimental results are shown in Table 2. After that an EEG-based DAE network was built to reconstruct both EEG and eye movement features and the shared representations were used as new features to classify emotions. The EEG-only DAE results are shown in Table 3.

For eye-based unimodal enhancement experiments, the processes were the same. We carried out experiments using eye movement features. We linked all eye movement features listed in Table 1 together to classify different emotions and the recognition accuracy of 79.64% is achieved. Then, eye movement features were used to train the DAE network to reconstruct both EEG and eye movement features. Emotion recognition accuracies, as shown in Table 4, were got with shared representations.

When only EEG features were used, we can see from Tables 2 and 3, the DAE network increased the recognition rate from 77.64% to 81.19% and the standard deviation for the best accuracy is 13.82, which is smaller than 17.19. We also compared our results with [Lu *et al.*, 2015].

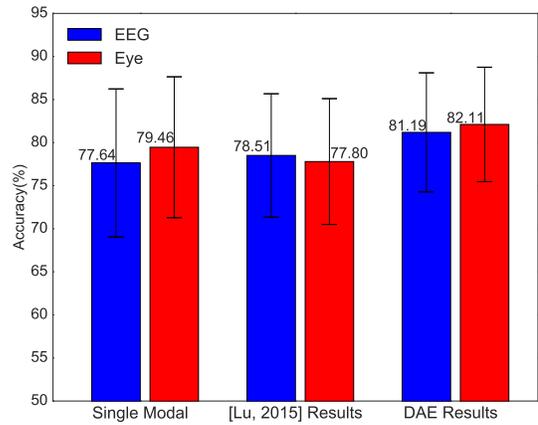


Figure 2: Summary of unimodal enhancement results. Three different models are compared. The left two bars are the results when only EEG features or Eye features are used. The middle bars show the results in [Lu *et al.*, 2015], and the right two bars are the results of our DAE model. It is clear that our model performs best.

Feature	$\delta$	$\theta$	$\alpha$	$\beta$	$\gamma$	All	
PSD	Ave.	73.81	62.91	67.47	71.96	72.62	<b>77.54</b>
	Std.	14.88	14.02	17.06	15.77	17.89	<b>12.62</b>
DE	Ave.	70.97	67.98	71.91	75.47	<b>77.64</b>	76.44
	Std.	15.35	15.64	16.32	15.57	17.19	<b>13.32</b>

Table 2: Recognition accuracy obtained by using EEG signal only. Here ‘All’ represents the direct concatenation of all features from five frequency bands.

Feature	$\delta$	$\theta$	$\alpha$	$\beta$	$\gamma$	All	
PSD	Ave.	<b>73.92</b>	70.00	70.93	69.64	73.12	73.49
	Std.	15.42	14.02	18.53	15.62	<b>11.12</b>	16.51
DE	Ave.	78.02	72.32	71.24	74.96	78.64	<b>81.19</b>
	Std.	12.55	15.52	14.58	13.91	<b>12.09</b>	13.82

Table 3: DAE–EEG features unimodal enhancement results. We used EEG data from different frequency bands to reconstruct both EEG and eye movement features.

Feature	Re- $\delta$	Re- $\theta$	Re- $\alpha$	Re- $\beta$	Re- $\gamma$	Re-All	
PSD	Ave.	81.21	79.81	79.61	80.34	80.01	<b>82.11</b>
	Std.	13.30	13.61	13.35	14.24	<b>12.28</b>	13.29
DE	Ave.	81.19	81.00	<b>82.08</b>	81.93	80.71	81.51
	Std.	<b>11.69</b>	13.66	12.25	13.05	14.83	12.78

Table 4: DAE–Eye movement features unimodal enhancement results. The prefix ‘Re’ denotes reconstruct. Eye movement features were used to reconstruct EEG features and eye movement features.

In [Lu *et al.*, 2015], the best result achieved when only EEG signal used was 78.51% and the standard deviation for its best accuracy was 14.32. It is clear that the DAE network is supe-

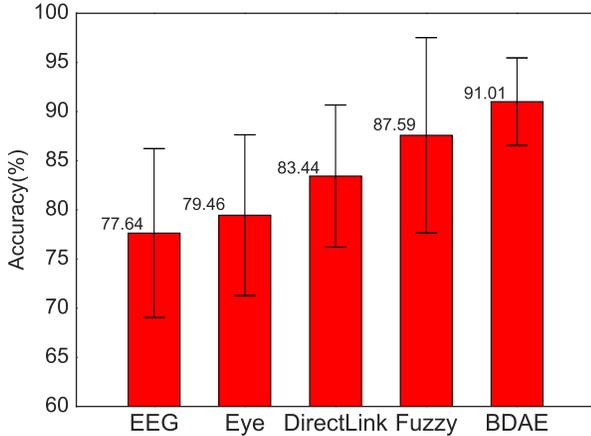


Figure 3: Multimodal facilitation results. The first two bars denote single modality. The rest bars denote multimodal with different fusion strategies. The fourth Fuzzy bar denotes the best result in [Lu *et al.*, 2015].

rior to the state-of-the-art approach.

When only eye movement data were available, the DAE network achieved the highest accuracy of 82.11% (in Table 4) in comparison with the state-of-the-art approach [Lu *et al.*, 2015] (77.80%) and directly using eye movement features (79.46%).

## 4.2 Multimodal Facilitation

We performed two kinds of different experiments to compare our BDAE network with other models.

- (1) Only single modality is available.
- (2) When both modalities are available, the shared representations are obtained by linking the features directly.

### SEED results

Figure 3 shows the summary of multimodal facilitation experiment results. We can see from Figure 3 that our BDAE model has the best performance (91.01%). Besides, the standard deviation of our BDAE model is also the smallest. This indicates that the BDAE model has a good robustness. Table 5 shows the results when we linked the features extracted from EEG signals and eye movement data directly. The last column of Table 5 means that we linked both five frequency bands of EEG signals and eye movement data features directly.

Compared with Table 2, we can see that when linking different modalities together, the emotion recognition accuracy increased in almost all frequency bands, and the standard deviation becomes smaller.

The experimental results using the BDAE model are shown in Table 6. We examined the BDAE model three times and the recognition accuracies shown in Table 6 were average. We can see that the BDAE model achieved the best accuracy of 91.01%, which is higher than those of single modality and directly linking strategy. And the standard deviation of the BDAE model is 8.91, which is the smallest among three different approaches.

Feature	$\delta$ +eye	$\theta$ +eye	$\alpha$ +eye	$\beta$ +eye	$\gamma$ +eye	All+eye	
PSD	Ave.	80.48	77.30	78.46	76.17	78.62	<b>80.88</b>
	Std.	14.08	17.77	15.38	13.78	15.87	<b>13.47</b>
DE	Ave.	83.33	81.79	79.14	82.98	<b>83.44</b>	82.83
	Std.	13.44	13.47	<b>10.02</b>	13.06	14.47	11.88

Table 5: Directly linking EEG and eye movement features. The last column means we link all five frequency bands and eye movement features

Feature	$\delta$ +eye	$\theta$ +eye	$\alpha$ +eye	$\beta$ +eye	$\gamma$ +eye	All+eye	
PSD	Ave.	<b>85.12</b>	83.89	83.18	83.23	82.92	85.10
	Std.	<b>11.09</b>	13.13	12.68	13.65	13.59	11.82
DE	Ave.	85.41	84.64	84.58	86.55	88.01	<b>91.01</b>
	Std.	14.03	11.03	12.78	10.48	10.25	<b>8.91</b>

Table 6: BDAE model results.

In [Lu *et al.*, 2015], the authors employed fuzzy integral method to fuse different modalities. The classification accuracy is 87.59% and the deviation is 19.87%. Compared with [Lu *et al.*, 2015], the BDAE model enhanced the performance of affective model significantly.

### DEAP results

In previous papers, Rozgic *et al.* treated the EEG signals as a sequence of overlapping segments and a novel non-parametric nearest neighbor model was employed to extract response-level feature from these segments [Rozgic *et al.*, 2013]. Li *et al.* used Deep Belief Network (DBN) to automatically extract high-level features from raw EEG signals [Li *et al.*, 2015].

The experimental results on the DEAP dataset are shown in Table 7. We compared the BDAE results with results in [Li *et al.*, 2015] and [Rozgic *et al.*, 2013]. As can be seen from Table 7, the BDAE model improved recognition accuracies in all classification tasks.

	Valence	Arousal	Dominance	liking
[Rozgic <i>et al.</i> , 2013]	76.9	69.1	73.9	75.3
[Li <i>et al.</i> , 2015]	58.4	64.3	65.8	66.9
<b>Our Method</b>	<b>85.2</b>	<b>80.5</b>	<b>84.9</b>	<b>82.4</b>

Table 7: The experimental results on the DEAP dataset.(%)

From the experimental results on the SEED and DEAP datasets, we have demonstrated that the BDAE network can be used to extract shared representations from different modalities and the extracted features have better performance than other features.

## 4.3 Cross-modal learning

The key point of both DAE model and BDAE model is the shared representation. In this section, the cross-modal experiments are carried out to examine whether the shared representations can learn common information between two different modalities.

In traditional machine learning framework, a classifier trained by EEG features are usually considered to generate bad results when testing it on eye movement features.

However, things are different when we use the DAE model. The DAE network is thought to be able to learn something in common between different modalities. We can test this by using shared representations generated by EEG features as training samples and shared representations generated by eye features as testing samples, and vice versa.

Both settings are examined, and the results are shown in Tables 8 and 9. We first trained a classifier with shared representations generated from EEG fed DAE network, and then tested the classifier with eye movement features generated shared representations. The results are shown in Table 8. As we can see from Table 8, both PSD features and DE features in all frequency bands achieved accuracies more than 60%, and the best performance is 66.23%. This is much higher than 33% of random classification of three emotional states.

Then the other experiment setting was tested. We used shared representations generated by eye movement features to train the classifier and the EEG-based shared representations were used as testing samples. Table 9 shows the results. Similar to Table 8, all accuracies are larger than 60%, and the best result is 66.45%. From Tables 8 and 9, we can see that the DAE models are able to learn common features between EEG features and eye movement features. Though we do not know what kind of shared representations they really are, we can take advantage of this to improve emotion recognition accuracy.

Feature		$\delta$	$\theta$	$\alpha$	$\beta$	$\gamma$	All
PSD	Ave.	63.74	65.29	62.42	64.22	62.84	<b>66.23</b>
	Std.	11.97	<b>9.66</b>	11.02	11.25	9.95	9.91
DE	Ave.	63.41	<b>66.08</b>	61.52	64.42	63.33	65.82
	Std.	10.40	11.11	10.59	11.11	10.99	<b>8.32</b>

Table 8: Cross-modal: EEG–training versus Eye–testing.

Feature		Re- $\delta$	Re- $\theta$	Re- $\alpha$	Re- $\beta$	Re- $\gamma$	Re-All
PSD	Ave.	62.07	65.69	<b>66.14</b>	62.55	63.52	64.85
	Std.	9.71	10.87	<b>8.57</b>	9.83	11.08	10.79
DE	Ave.	64.72	63.48	61.70	62.68	<b>66.45</b>	63.57
	Std.	11.83	10.16	9.77	9.87	<b>7.14</b>	9.94

Table 9: Cross-modal: Eye–training versus EEG–testing.

In the last, we analyzed the confusing matrices. Table 10 shows the confusing matrices based on the experiment results for each individual task. For convenient, we only listed the confusing matrices on the SEED dataset. From Table 10, we can see that negative emotions are the hardest to recognize and positive emotions are easiest to recognize. This might indicate that when people are happy or exciting, brain activities have some common patterns while when people are sad, the patterns are not so obvious or the patterns are changing with time.

	Positive	Neutral	Negative
Positive	<b>99.03%</b>	0.00%	0.97%
Neutral	3.7%	<b>90.26%</b>	6.03%
Negative	11.25%	3.57%	<b>85.19%</b>

(a) Multimodal Facilitation.

	Positive	Neutral	Negative
Positive	<b>80.16%</b>	9.73%	10.11%
Neutral	9.26%	<b>83.33%</b>	7.41%
Negative	9.24%	13.93%	<b>76.83%</b>

(b) Unimodal Enhancement

	Positive	Neutral	Negative
Positive	<b>78.97%</b>	10.61%	10.42%
Neutral	9.64%	<b>67.18%</b>	23.18%
Negative	25.14%	23.17%	<b>51.68%</b>

(c) Crossmodal Learning

Table 10: Confusing matrices of different tasks.

## 5 Discussion

All of three kinds of emotion recognition mentioned tasks above are important for HMI systems in practice. The multimodal facilitation task allows us using different modalities so that HMI systems could have a better recognition accuracy. Besides, the experiments results have indicated that when both modalities were used, the standard deviation became smaller than before. This phenomenon indicates that our system becomes more reliable. Unimodal enhancement results have shown that if we train the DAE network with two modalities, it is feasible to use only one modal in practice. Inspired by this results, EEG signals might be not needed in practice and only some easily-collected signals are used. In the last, cross-modal learning tries to find out the common features between EEG signals and eye movement data. The experiment results have demonstrated that our shared representations do extract some common features between EEG features and eye movement features.

## 6 Conclusions and Future Work

This paper has shown that by fusing EEG features and other features with bimodal deep autoencoders (BDAE), the shared representations are good features to discriminate different emotions. For the SEED dataset, compared with other feature merging strategies, the BDAE model is better than others with the best accuracy of 89.94%. In order to avoid intricacies during acquiring EEG signals, we have adopted unimodal deep autoencoder model (DAE) to extract shared representations even there was only one modality available. The experimental results on the unimodal enhancement task have shown that the DAE model (82.11%) performs better than using single modality directly (78.51% in [Lu *et al.*, 2015]). In addition, the experimental results on the cross-modal learning task demonstrated that the shared representations contain higher level common features between EEG signals and eye movement features. The affective models with the shared representation performed much better than random classification (33.33%) and achieved the best accuracy of 66.45%.

As future work, we will focus on the following issues that we have not covered in this paper. First, we will explore the relationship between unimodal features and shared representations, so that we may find a clear explanation of confusing matrices. Second, we want to go deeper with the performance of the DAE and BDAE networks when parameters change. Besides, more experiments are needed in order to study the stability of the DAE and BDAE networks.

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