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Emotion recognition through integrating EEG and peripheral physiological signals

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- Motivation
- Method
- Experiments
- Conclusion

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Motivation

Focus: The inherent dependencies among multiple physiological signals are crucial for multimodal emotion recognition.

Current approaches:

✧ Feature-level fusion — concatenating features from multiple physiological signals into one feature vector

✧ Decision-level fusion — combine emotion classifiers from each modality through decision strategies

Our method:

✧ We propose to use restricted Boltzmann machine (RBM) to model the inherent dependencies among multiple physiological signals.

Why use RBM?

high-order dependencies among visible variables by introducing hidden nodes;

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Assumption: all channels of data are always available.

In fact, physiological signals are often corrupted due to artifacts.

Our method:

Other than discarding all the data instances containing invalid modalities, which results in a substantial amount of unusable data, we use all the complete and incomplete instances by treat the missing data in the same way as the other parameters.

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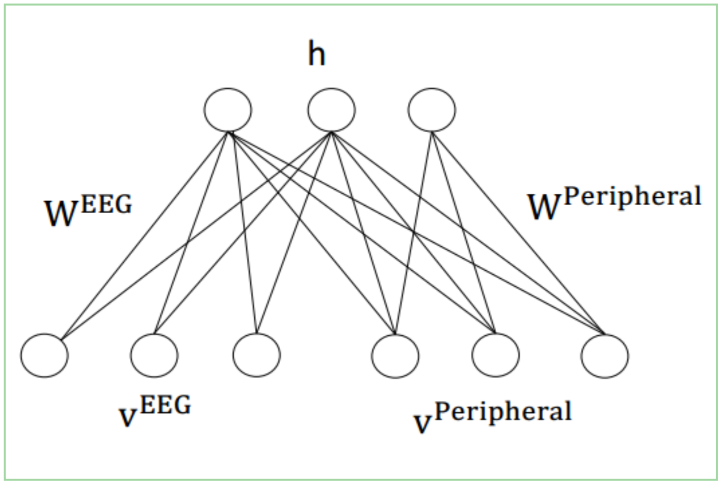
Method: Relation Modeling using a multimodal RBM for complete data



Energy Function:

$$E(V^E, V^P, h|\theta) = \sum_{i=1}^{D^E} \frac{(v_i^E - b_i^E)^2}{2(\sigma_i^E)^2} + \sum_{i=1}^{D^P} \frac{(v_i^P - b_i^P)^2}{2(\sigma_i^P)^2}$$
$$- \sum_{i=1}^{D^E} \sum_{j=1}^{nhidden} \frac{v_i^E}{\sigma_i^E} W_{ij}^E h_j - \sum_{i=1}^{D^P} \sum_{j=1}^{nhidden} \frac{v_i^P}{\sigma_i^P} W_{ij}^P h_j - \sum_{j=1}^{nhidden} b_j^h h_j \quad (1)$$

Joint distribution over visible units:

$$P(V^E, V^P|\theta) = \frac{1}{Z(\theta)} \sum_H exp(-E(V^E, V^P, h|\theta)), \quad (2)$$

Derivative of the log-likelihood respect to $\mathbf{W^E}$ and $\mathbf{W^P}$

$$\frac{1}{N} \sum_{n=1}^{N} \frac{\partial log P(V_n^E, V_n^P; \theta)}{\partial W_{ij}^E} = E_{P_{data}} \left[\frac{v_i^E}{\sigma_i^E} h_j \right] - E_{P_{model}} \left[\frac{v_i^E}{\sigma_i^E} h_j \right] \quad (3)$$

$$\frac{1}{N} \sum_{n=1}^{N} \frac{\partial log P(V_n^E, V_n^P; \theta)}{\partial W_{ij}^P} = E_{P_{data}} \left[\frac{v_i^P}{\sigma_i^P} h_j \right] - E_{P_{model}} \left[\frac{v_i^P}{\sigma_i^P} h_j \right] \quad (4)$$

✧Contractive divergence is adopted for parameter learning.

✧Hidden layer is feature representations, and the input of SVM classifier

Method: Relation Modeling using a multimodal RBM for incomplete data

- ✧Learning RBM using complete data
- ✧Fine tuning RBM using both incomplete data and complete data
- ✧The missing values are treated as the same way as the model parameters to be updated each time

$$v_i^t = v_i^{t-1} + \Delta v_i^t = v_i^{t-1} + \epsilon\left(\frac{\partial F}{\partial \hat{v}_i^{t-1}} - \frac{\partial F}{\partial v_i^{t-1}}\right) \tag{5}$$

$$e^{-F(V^E, V^P|\theta)} = \sum_h e^{-E(V^E, V^P, h|\theta)} \tag{6}$$

Algorithm 1 Training RBM with incomplete data

Require: training data (v^E, v^P), learning rate λ
Ensure: the parameters $\theta = \{\mathbf{b}, \sigma, \mathbf{W^E}, \mathbf{W^P}\}$.
Initialize the parameters θ with complete data
Initialize the missing value randomly
repeat
  for each training instance (v^E, v^P) **do**
    $\hat{h}_j \leftarrow g(\sum_{i=1}^{D^E} W_{ij}^E \frac{v_i^E}{\sigma_i^E} + \sum_{i=1}^{D^P} W_{ij}^{(P)} \frac{v_i^P}{\sigma_i^P} + b_j^h)$
    $h_j \sim g(\sum_{i=1}^{D^E} W_{ij}^E \frac{v_i^E}{\sigma_i^E} + \sum_{i=1}^{D^P} W_{ij}^{(P)} \frac{v_i^P}{\sigma_i^P} + b_j^h)$
    $\hat{v}^E \leftarrow P(v^E|h)$
    $\hat{v}^P \leftarrow P(v^P|h)$
  end for
  update θ with Eq.3
  for each missing value v_i **do**
    $v_i^t = v_i^{t-1} + \Delta v_i^t = v_i^{t-1} + \epsilon(\frac{\partial F}{\partial \hat{v}_i^{t-1}} - \frac{\partial F}{\partial v_i^{t-1}})$
  end for
until Convergence

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Experiments: Experimental Conditions

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Databases

✧ MAHNOB-HCI database: 533

Five physiological signals: EEG, ECG, GSR, RESP, TEMP

Valence: 289 positive, 244 negative

Arousal: 268 positive, 265 negative

✧ DEAP database: 1216

Seven physiological signals: EEG, EOG, EMG, ECG, GSR, RESP, TEMP and PLET,

Valence: 672 positive, 544 negative

Arousal: 726 positive, 490 negative

Experiments: Experimental Conditions

Features

- EEG features
  - Power spectrum
  - Power spectrum asymmetry between pairs of electrodes.

- Peripheral features

Signal	Extracted features	filters
EOG	Energy, mean and variance	0.4Hz
EMG	Energy, mean and variance	1Hz
ECG	HRV, root mean square of the mean squared difference of successive beats, standard deviation of beat interval change per respiratory cycle, 14 spectral power in the bands from [0, 1.5]Hz, low frequency [0.01, 0.08]Hz, medium frequency [0.08, 0.15]Hz and high frequency [0.15, 0.5]Hz components of HRV power spectrum, Poincare analysis features(2 features)[1]	1Hz
GSR	Mean, mean of the derivative, mean of the positive derivatives, proportion of negatives in the derivative, number of local minima, 10 spectral powers within 0-2.4Hz	3Hz

RSP	Band energy ratio, average respiration signal, mean of the derivative, standard derivation, range of greatest breath, 10 spectral powers within 0-2.4Hz, average and median peak to peak time	0.45Hz
TEMP	Mean, mean of the derivative, spectral powers in 0-0.1 Hz and 0.1-0.2 Hz	3Hz
PLET	Average and standard derivation of HRV and inter-beat intervals, energy ratio between 0.04-0.15 Hz and 0.15-0.5 Hz, spectral power in 0.1-0.2 Hz, 0.2-0.3 Hz, 0.3-0.4 Hz, 0.01-0.08 Hz, 0.08-0.15 Hz and 0.15-0.5 Hz components of HRV	0.45Hz

Experiments:
Experimental Conditions

- For complete data:
  - Emotion recognition from peripheral signals: RBM+SVM+peripheral, SVM+peripheral
  - Emotion recognition from EEG signals: SVM+EEG, RBM+SVM+EEG
  - Feature-level fusion using SVM
  - Decision-level fusion using SVM
  - Our method
- For incomplete data:
  - Discarding data with missing part
  - Our method

Experimental Results for Complete data

Table 1. Emotion recognition results on the DEAP database with complete data

	Valence							Arousal						
	RBM +SVM EEG	RBM +SVM Peripheral	Our model	SVM EEG	SVM Peripheral	SVM feature-level fusion	SVM decision-level fusion	RBM +SVM EEG	RBM +SVM Peripheral	Our model	SVM EEG	SVM Peripheral	SVM feature-level fusion	SVM decision-level fusion
Accuracy	59.5%	56.3%	**60.7%**	58.0%	51.6%	58.9%	58.0%	60.3%	54.9%	**64.6%**	61.7%	58.1%	62.8%	61.7%
F1 score	0.535	0.510	**0.541**	0.522	0.464	0.527	0.522	**0.532**	0.508	0.512	0.511	0.480	0.521	0.511
Kappa	0.177	0.114	**0.199**	0.147	0.024	0.192	0.147	0.216	0.103	**0.240**	0.196	0.130	0.218	0.196

Table 2. Emotion recognition results on the MAHNOB-HCI database

	Valence							Arousal						
	RBM +SVM EEG	RBM +SVM Peripheral	Our model	SVM EEG	SVM Peripheral	SVM feature-level fusion	SVM decision-level fusion	RBM +SVM EEG	RBM +SVM Peripheral	Our model	SVM EEG	SVM Peripheral	SVM feature-level fusion	SVM decision-level fusion
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F1 score	0.539	0.505	0.542	**0.569**	0.504	0.608	**0.569**	0.646	0.588	**0.654**	0.588	0.574	0.642	0.588
Kappa	0.159	0.038	**0.173**	0.050	0.076	0.142	0.050	0.306	0.171	**0.317**	0.178	0.125	0.280	0.178

- Among three fusion methods, our method performs best, demonstrating that the proposed fusion method can successfully capture the dependencies among multiple physiological signals, and result in good performance
- RBM+SVM outperforms SVM, further suggesting good representation of RBM

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Experimental Results for Incomplete data

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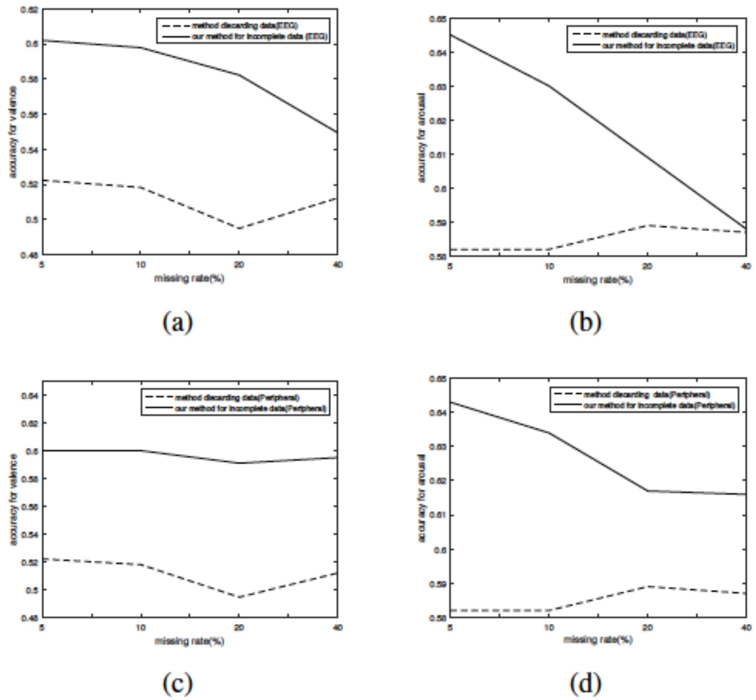

Fig. 2. Experimental results for incomplete data on the DEAP database

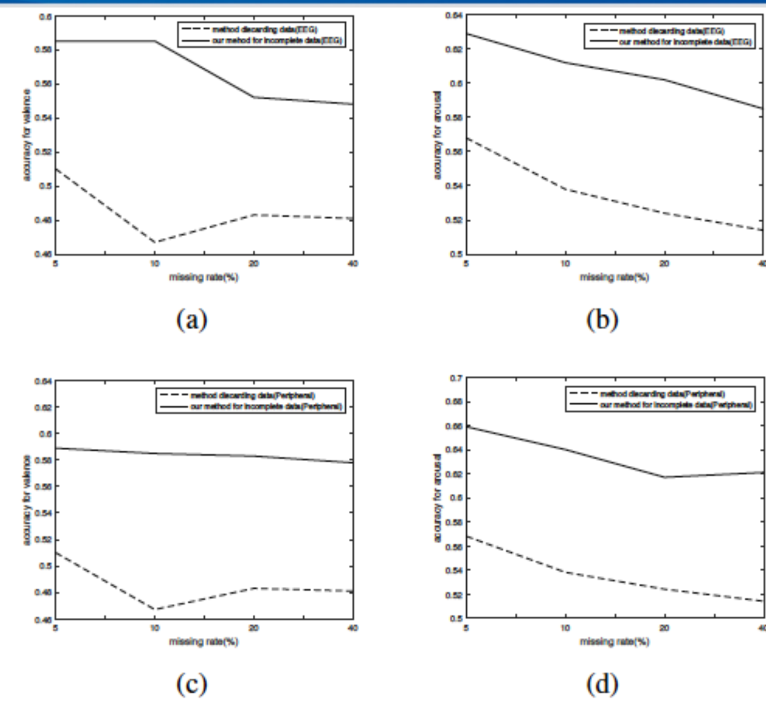

Fig. 3. Experimental results for incomplete data on the MAHNOB-HCI database

✧Our method outperforms the method which discards the whole data with missing part, demonstrating our method successfully exploit all available data for emotion recognition.

✧With the increase of missing rate, emotion recognition performance decrease, since less physiological signals provide less information.

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Conclusion

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- Propose RBM model capturing relations between EEG and peripheral physiological signals for multimodal emotion recognition.
- Other than discarding samples with missing part, our model take full advantage of all available data for multimodal emotion recognition.

- Experimental results on two benchmark databases demonstrate that with complete data, our model can combine EEG and peripheral physiological signals to construct a better feature space for emotion recognition, with incomplete data, our model can exploit all available data to achieve better performance.

Thanks!

Any question?