

## Emotion recognition through integrating EEG and peripheral physiological signals

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## Emotion Recognition through Integrating EEG and Peripheral Physiological Signals

- Motivation
- Method
- Experiments
- Conclusion

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**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 <sup>4</sup> hidden nodes;





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





$$E(V^{E}, V^{P}, h|\theta) = \sum_{i=1}^{D^{E}} \frac{(v_{i}^{E} - b_{i}^{E})^{2}}{2(\sigma_{i}^{E})^{2}} + \sum_{i=1}^{D^{P}} \frac{(v_{i}^{P} - b_{i}^{P})^{2}}{2(\sigma_{i}^{P})^{2}} - \sum_{i=1}^{D^{E}} \sum_{j=1}^{nhidden} \frac{v_{i}^{E}}{\sigma_{i}^{E}} W_{ij}^{E} h_{j} - \sum_{i=1}^{D^{P}} \sum_{j=1}^{nhidden} \frac{v_{i}^{P}}{\sigma_{i}^{P}} W_{ij}^{P} h_{j} - \sum_{j=1}^{nhidden} b_{j}^{h} h_{j}$$
(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  $W^E$  and  $W^P$ 

$$\frac{1}{N}\sum_{n=1}^{N}\frac{\partial log P(V_{n}^{E}, V_{n}^{P}; \theta)}{\partial W_{ij}^{E}} = E_{P_{data}} \begin{bmatrix} v_{i}^{E}\\ \sigma_{i}^{E} h_{j} \end{bmatrix} - E_{P_{model}} \begin{bmatrix} v_{i}^{E}\\ \sigma_{i}^{E} h_{j} \end{bmatrix}$$
(3)
$$\frac{1}{N}\sum_{n=1}^{N}\frac{\partial log P(V_{n}^{E}, V_{n}^{P}; \theta)}{\partial W_{ij}^{P}} = E_{P_{data}} \begin{bmatrix} v_{i}^{P}\\ \sigma_{i}^{P} h_{j} \end{bmatrix} - E_{P_{model}} \begin{bmatrix} v_{i}^{P}\\ \sigma_{i}^{P} h_{j} \end{bmatrix}$$
(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



 $\diamond$ Learning RBM using complete data

Fine tuning RBM using both incomplete data and complete data

 $\diamond$  The missing values are treated as the same way as the model parameters to be updated each time

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

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

Algorithm 1 Training RBM with incomplete data

**Require:** training data  $(v^E, v^P)$ , learning rate  $\lambda$  **Ensure:** the parameters  $\theta = {\mathbf{b}, \sigma, \mathbf{W^E}, \mathbf{W^P}}$ . Initialize the parameters  $\theta$  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  $\theta$  with Eq.3

for each missing value  $v_i$  do

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

end for until Convergence

## Emotion Recognition through Integrating EEG and Peripheral Physiological Signals

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### Experiments: Experimental Conditions



#### 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	1 г		Pand anarry ratio avarage respiration				
EMG	Energy, mean and variance	1Hz	1		Band energy ratio, average respiration				
	HRV, root mean square of the mean		1		signal, mean of the derivative, standard				
	squared difference of successive beats,			RSP	derivation, range of greatest breath,	0.45Hz			
	standard deviation of beat interval		10 spectral powers within 0-2.4Hz.						
ECG	change per respiratory cycle, 14 spectral				average and median peak to peak time				
	power in the bands from [0, 1.5]Hz, low	1Hz			Mean mean of the derivative encetral				
	frequency [0.01, 0.08]Hz, medium			TEMP	Mean, mean of the derivative, spectral	3Hz			
	frequency [0.08, 0.15]Hz and high				powers in 0-0.1 Hz and 0.1-0.2 Hz				
	frequency [0.15, 0.5]Hz components of		ΙΓ		Average and standard derivation of HRV				
	HRV power spectrum, Poincare analysis				and inter-beat intervals energy ratio				
ļ	features(2 features)[1]				between 0.04.0.15 Hz and 0.15.0.5 Hz				
	Mean, mean of the derivative, mean of			PLET	between 0.04-0.15 Hz and 0.15-0.5 Hz,	0.45Hz			
COD	the positive derivatives, proportion of	211-			spectral power in 0.1-0.2 Hz, 0.2-0.3 Hz,				
GSK	negatives in the derivative, number of	3HZ			0.3-0.4 Hz, 0.01-0.08 Hz, 0.08-0.15 Hz				
	0.2 4Uz				and 0.15-0.5 Hz components of HRV				
	0-2.4HZ		JL		and one one the components of the				

#### Experiments: Experimental Conditions



#### $\diamond$ 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



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

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

	Valence								Arousal							
	RBM +SVM	RBM +SVM	Our	SVM	SVM Paripharal	SVM feature-level	SVM decision-level	RBM +SVM	RBM +SVM	Our	SVM	SVM Paripharal	SVM feature-level	SVM decision-level		
	EEG	Peripheral	moder	EEU	renpiierai	fusion	fusion	EEG	Peripheral	moder	EEU	Feripiteral	fusion	fusion		
Accuracy	58.3%	51.8%	59.1%	52.9%	46.5%	57.4%	52.9%	65.3%	58.5%	65.9%	58.9%	56.3%	64.0%	58.9%		
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

#### **Experimental Results for Complete data**



		Tab	<del>le 1.</del> E	motio	n recogn	ition res	ults on the	e DEAl	P databa	se with	com	olete data	1	
				Val	ence						Are	ousal		
	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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	1		Table	2. Er	notion re	cognitio	n results (	on the I	MAHNO	B-HC	data	base		
	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
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- **RBM+SVM outperforms SVM**, further suggesting good  $\diamond$ representation of RBM

#### Experimental Results for Complete data



		Tal	le 1. l	Emotio	n recogr	ition resu	ults on the	DEA	P databa	se with	n comp	plete data	1	
				Vale	ence						Arc	ousal		
	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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			Tabl	e 2. Er	notion re	cognition	n results of	n the l	MAHNO	B-HC	I data	base		
	RBM	RBM	Tabl	e 2. Er Valo	notion re	cognition	n results o	n the 1		B-HC	I datal	Dase	SVM	SVM
	RBM +SVM EEG	RBM +SVM Peripheral	Tabl Our model	e 2. Er Vak SVM EEG	notion re ence SVM Peripheral	SVM feature-level fusion	n results of SVM decision-level fusion	n the 1 RBM +SVM EEG	RBM +SVM Peripheral	B-HC Our model	I datal	DASE pusal SVM Peripheral	SVM feature-level fusion	SVM decision-level fusion
Accuracy	RBM +SVM EEG 58.3%	RBM +SVM Peripheral 51.8%	Our model 59.1%	e 2. Er Vak SVM EEG 52.9%	notion re ence SVM Peripheral 46.5%	SVM feature-level fusion 57.4%	n results of SVM decision-level fusion 52.9%	n the 1 RBM +SVM EEG 65.3%	RBM +SVM Peripheral 58.5%	B-HC Our model 65.9%	I datal Arc SVM EEG 58.9%	Dase pusal SVM Peripheral 56.3%	SVM feature-level fusion 64.0%	SVM decision-level fusion 58.9%
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- Among three fusion methods, our method performs best, demonstrates 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



**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.

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



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