Detection of Mood Disorder Using Speech Emotion Profiles and LSTM

Tsung-Hsien Yang, **Chung-Hsien Wu**, Kun-Yi Huang, and Ming-Hsiang Su

Department of Computer Science and Information Engineering National Cheng Kung University, Taiwan

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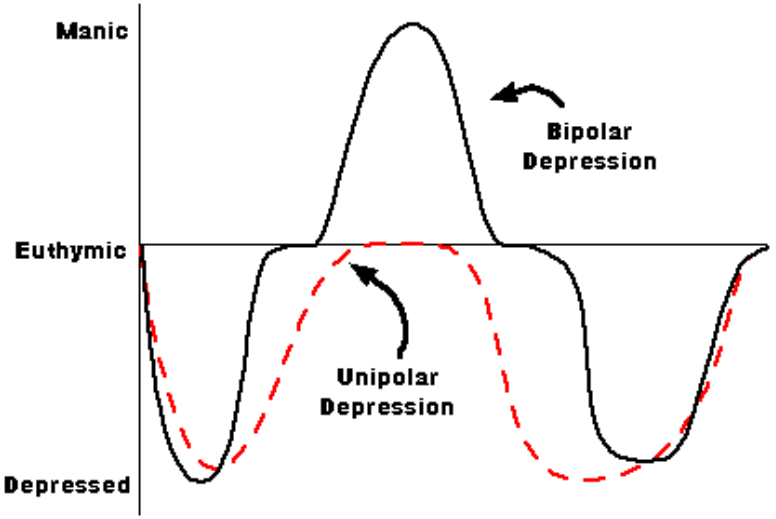
- Experimental results
- Conclusions

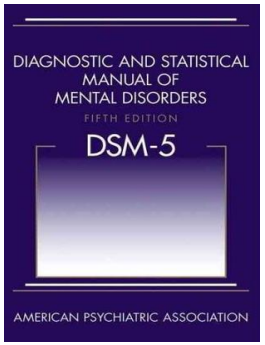
Introduction

- Mood disorder contains Unipolar Depression (UD) and Bipolar Disorder(BD), which are mental illness.
- BD experiences two opposite and extreme emotional states: mania (high) and depression (low) through euthymia, which are different from UD.



Motivation

- The doctors are likely to misdiagnose the patients in low mood of bipolar disorder as unipolar depression.
  - According to the statistics, around 40% misdiagnosis leads to patients not receiving appropriate treatment.
- Correct diagnosis, using DSM-5 as diagnostic criteria, needs a long-term tracking.
- Developing a system for mood disorder detection based on physiological signals or audio-visual signals can help doctor to correctly diagnose mood disorder.



Goal

- Among these signals, speech is the most natural way to express emotion and the simplest way to collect data.
- How to develop a mood disorder detection system for short-term detection becomes an important issue.

CHI-MEI Mood Database Collection

- In a closed environment room.

The clinician leading the experiment

The subject for evaluation

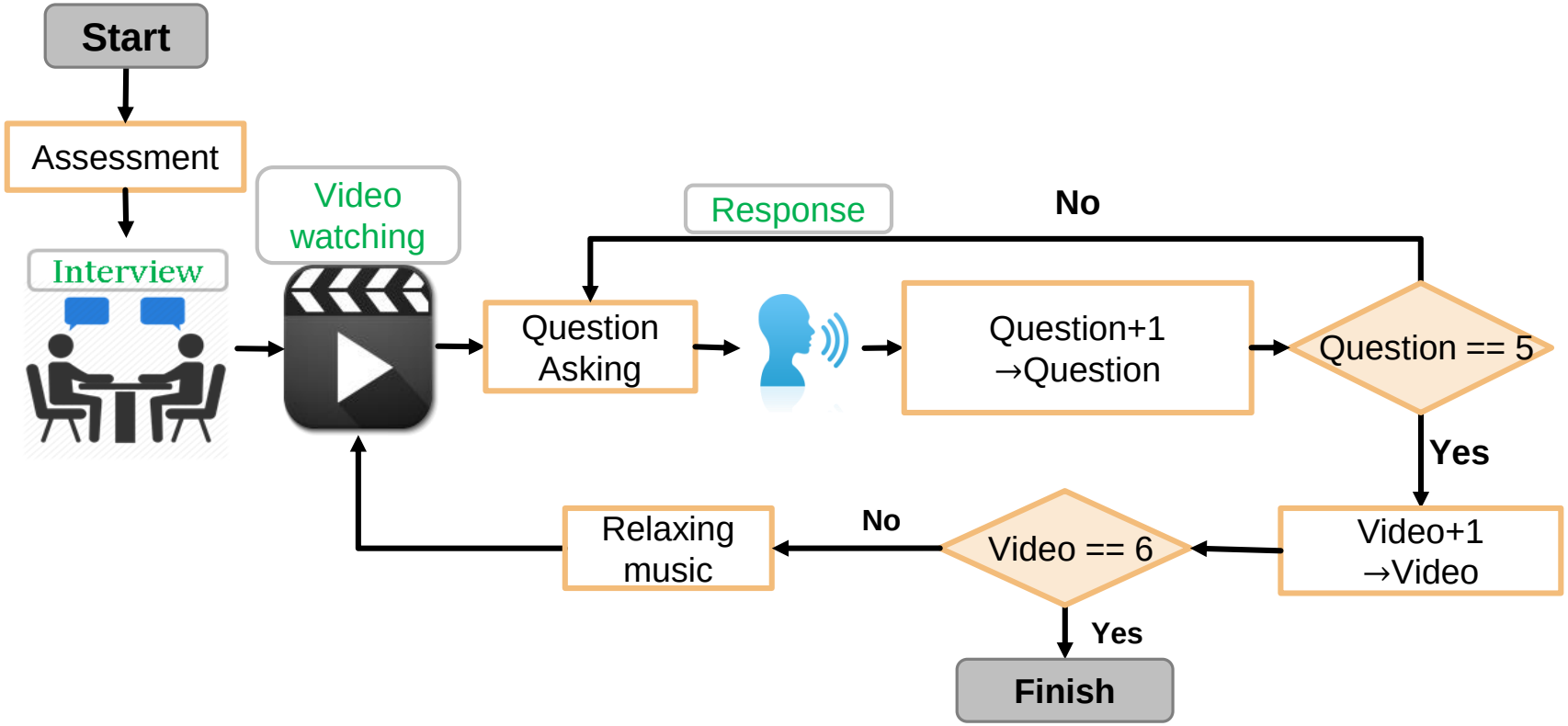
- Only when the subject is in a stable mood-state, the evaluation could be conducted.

Assessment	DSSS	MDQ-C	YMRS	SAS	BARS	CGI-S
Criterion	Scale < 9	Scale < 6	Scale < 3	Scale < 1	Scale < 1	Scale < 4

CHI-MEI Mood Database Collection

- 39 subjects (27 females and 12 males) from 3 different categories (13 BDs, 13 healthy controls (Cs) and 13 UDs) participated in the data collection process.
- All of the subjects watched 6 eliciting video clips with emotions of happiness, fear, surprise, anger, sadness and disgust and answered the following 5 questions.
  - 1. What do you think about the above video? (happy, sad, angry, disgusting, fearful and surprised)
  - 2. How intense is it? (ranging from 1 to 5)
  - 3. Which scene in the movie is impressive? Why?
  - 4. Do you have any similar experience like that scene?
  - 5. Are you feeling sick after watching above film
- Totally 1170 responses segments were collected

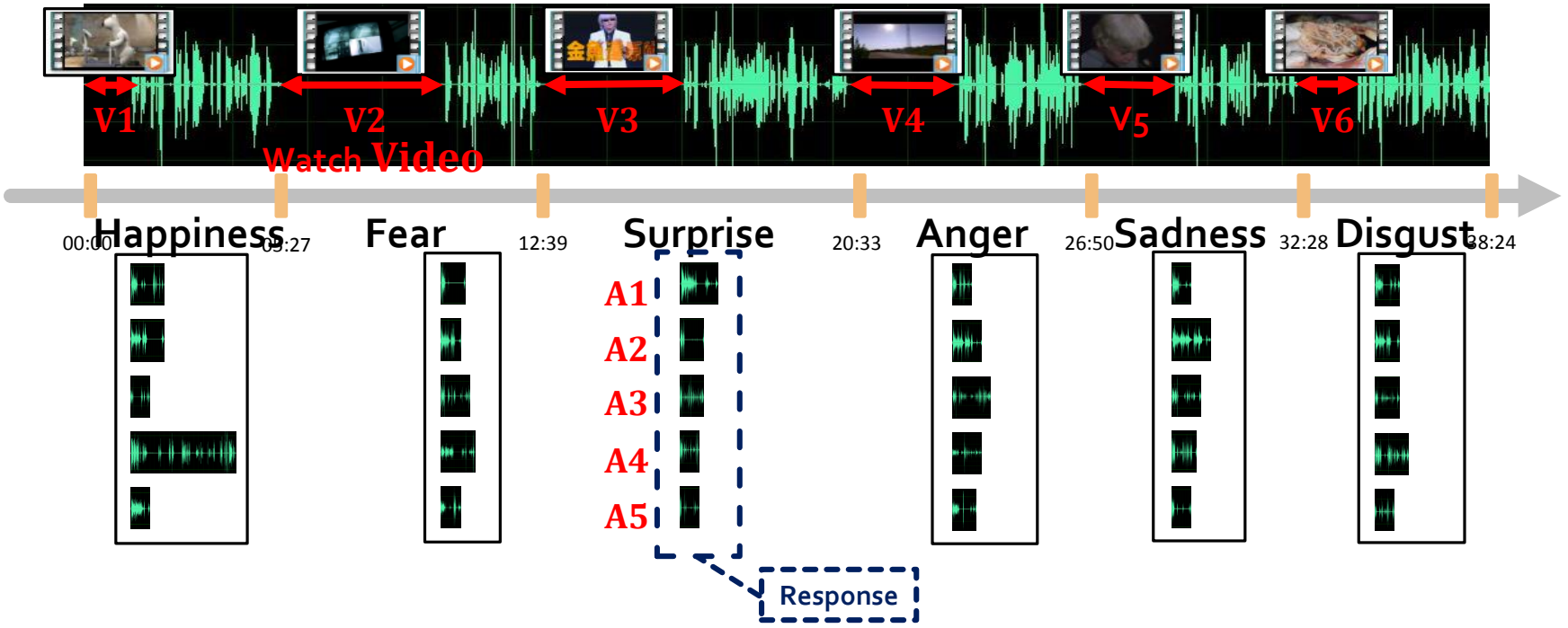
CHI-MEI Mood Database Collection



- The whole process takes about 30 to 40 minutes.

CHI-MEI Mood Database Collection

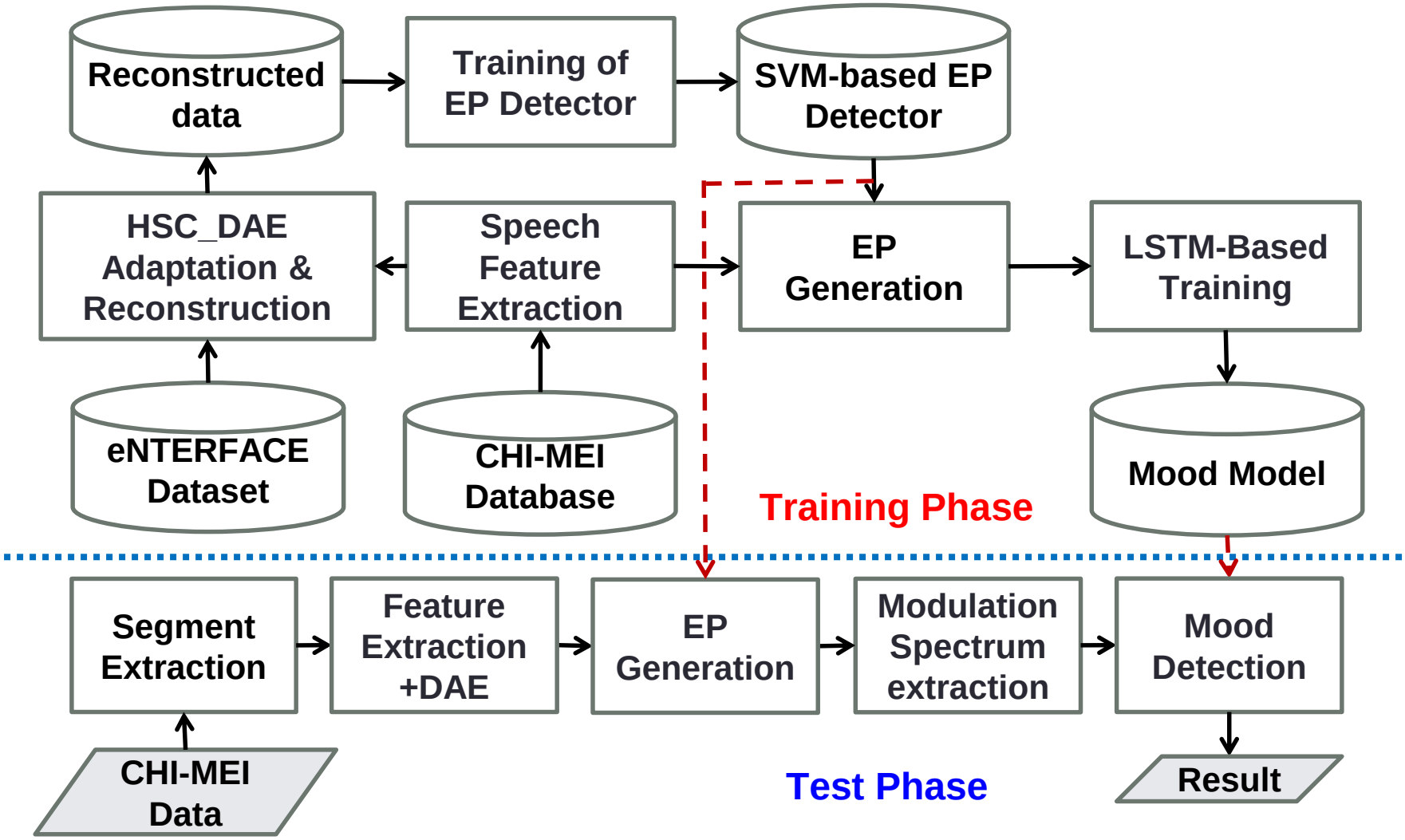
- Each participant provides six responses.
- Each response contains 5 answers with respect to 5 questions.



CHI-MEI Mood Database Collection

- Because labeling the sentence with emotion tags is difficult and tedious, the CHI-MEI mood database is not labeled.
- The eNTERFACE database is selected as the adaptation database of the emotion detector
  - Because this database contains six emotional expressions the same as CHI-MEI mood database
- The eNTERFACE database
  - were provided by 42 subjects (18 females and 24 males) from 14 different nationalities
  - Each subject was recorded for 6 emotions, and there were 5 different sentences for each emotion

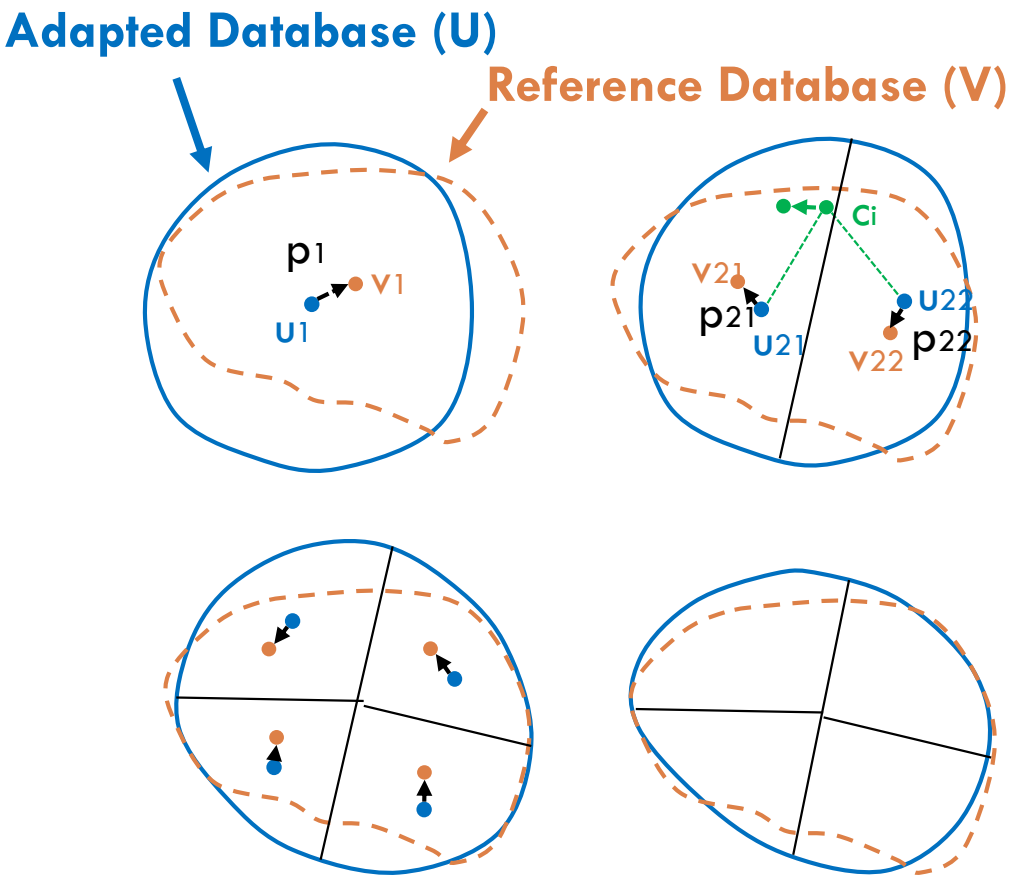
System Framework



Database Adaptation

- OpenSMILE is employed to extract the acoustic features of 384 dimensions
- Training data: the eNTERFACE databases with emotion labels (source domain)
- Test data: the CHI-MEI Mood database (target domain)
- A domain adaptation method, Hierarchical Spectral Clustering (HSC), is adopted to adapt the eNTERFACE databases to fit the CHI-MEI mood database

Database Adaptation – Hierarchical Spectral Clustering (HSC

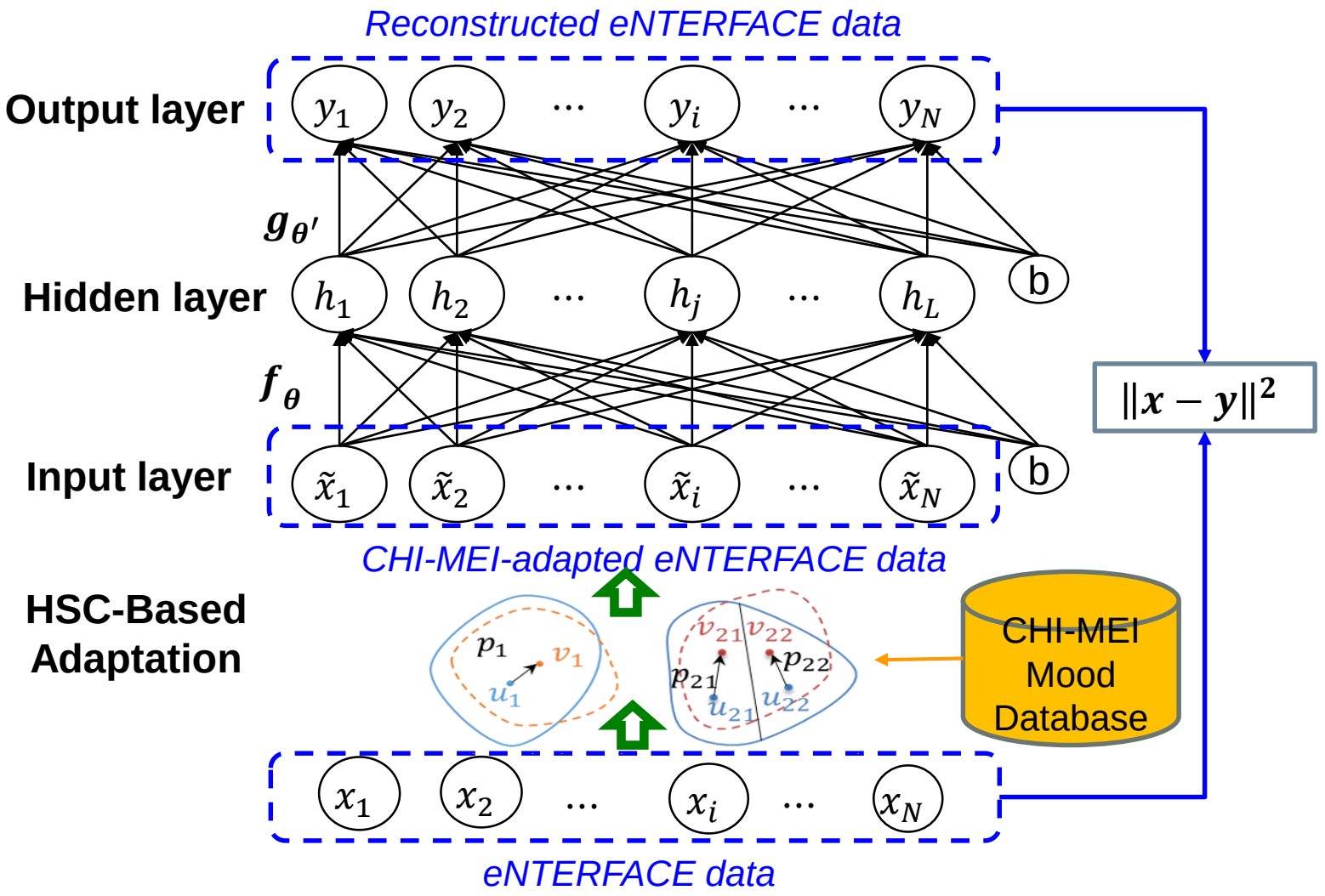


1. u_1 and v_1 are the centroids of U and V
2. Shifted the U by the deviation vector $p_1=u_1-v_1$.
3. Clustering V by k-means.
4. Calculating the centroid of each V_{2i}.
5. All elements in U belong to its nearest V_{2i}.
6. Calculating the centroid of each U_{2i}, and deviation vector between U_{2i} and V_{2i}.
7. Each cluster element c_i in shifted U is shifted as
8. Repeat from step3 to step7

Reconstruction from Biased (Noisy) Data

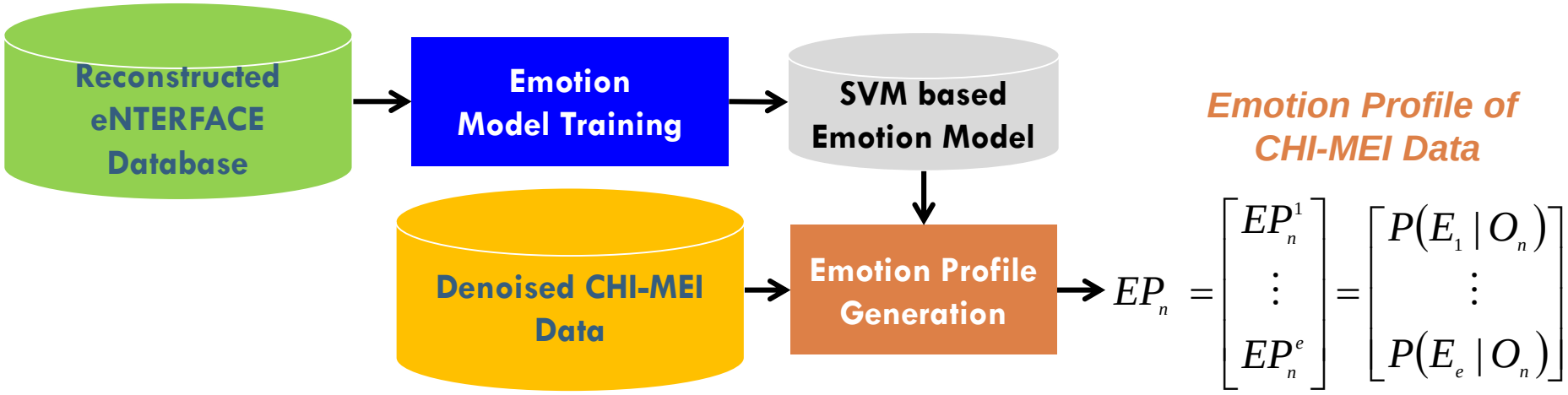
- The adapted data are used as the input to train a denoising autoencoder (DAE)
- The DAE reconstructs the CHI-MEI-adapted eNTERFACE emotional data, which are regarded as the eNTERFACE data with noises due to different environments, participants, expressions, etc. to the original eNTERFACE emotional data.

HSC-based Denoising Autoencoder



Emotion Profile Generation

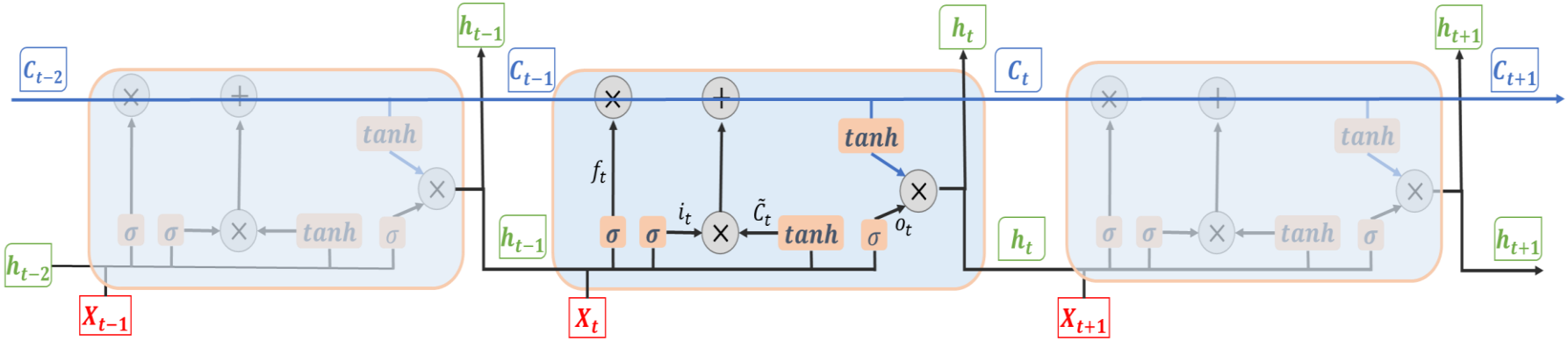
- An SVM-based ***Emotion Profile (EP)*** detector is adopted to provide a quantitative measure for expressing the degree of the presence or absence of a set of basic emotions within an expression. [Mower et al. 2011]



- O_n is the *n*-th input feature sequence.
- e is the *e*-th emotion.

Long Short-Term Memory (LSTM)

- LSTM-based method considering the temporal evolution is employed to precisely characterize the time-varying signal characteristics.
- X_t is the EP vector at time t

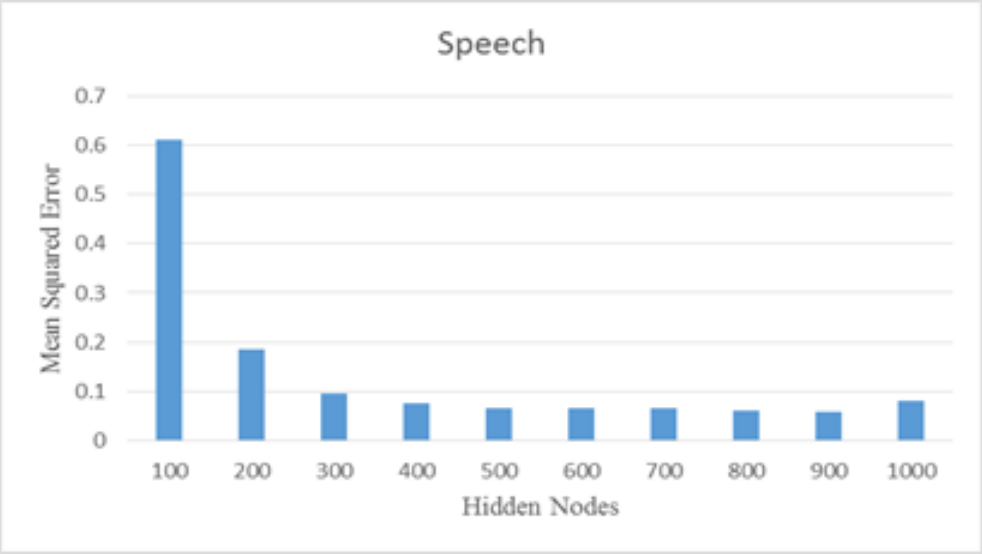


Experimental setup

- The proposed method was evaluated using 13-fold cross validation
- Each fold contains 36 subjects for training and 3 subjects (one of each category, i.e., BDs, Cs, or UDs) for testing
- Linearly scaling each attribute to the range [0, 1] for both training and test data was used

Experimental results (1)

- For optimizing the parameters used in the HSC-DAE, the number of hidden nodes should be determined first
  - X-axis is the number of hidden nodes and Y-axis represents the Mean Squared Error (MSE) of the HSC-DAE
  - We selected the reconstructed data which were trained by 900 hidden nodes



Experimental results (2)

- We compared forward/backward LSTMs and BLSTM to analyze if the past and future contexts could influence mood disorder detection
  - All networks consisted of one hidden layer and each LSTM memory block contained one memory cell
  - The networks were trained on the training set until the cross entropy error did not improve for at least 10 epochs

No. of Hidden Nodes	LSTM (forward)	LSTM (backward)	BLSTM
16	0.6667	0.4615	0.6410
32	0.6667	0.5897	0.6410
64	**0.6923**	**0.7179**	**0.7179**
128	0.6667	**0.7179**	0.6923
256	**0.6923**	0.6410	0.6667

Experimental results (3)

- Motivated by the success of Deep Neural Network, we stacked two LSTMs and two BLSTMs respectively

No. of Hidden Nodes	Stacked LSTM	Stacked BLSTM
16-16	0.7179	**0.7692**
32-32	0.7436	0.7436
64-64	**0.7692**	0.7436
128-128	0.6923	0.7436
256-256	0.7179	0.6923

Experimental results (4)

- Comparison among different classifiers
  - The SVM performed grid search with Radial basis function (RBF) kernel using LibSVM toolkit
  - The MLP was a three-layer topology with 64 hidden nodes which were fine-tuned to achieve the best performance
- The LSTM-based classifiers outperformed SVM and MLP classifiers

Methods	SVM	MLP	LSTM-based
Accuracy	0.4983	0.4197	**0.7692**

Conclusions

- We proposed an LSTM-based approach to modeling the long-range contextual information based on the temporal change of speech responses for mood disorder detection
  - The HSC-DAE method was employed for domain adaptation and data denoising.
  - The LSTM-based method is applied to model the EP sequence for mood disorder detection
- In the future, combining other modalities such as facial expression information is helpful to improve system performance

Questions?