Learning Discriminative Features from Spectrograms using Center Loss for Speech Emotion Recognition

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1. Introduction

Motivation

- Extract valid features from raw data for emotion recognition

Speech → Features → Emotion

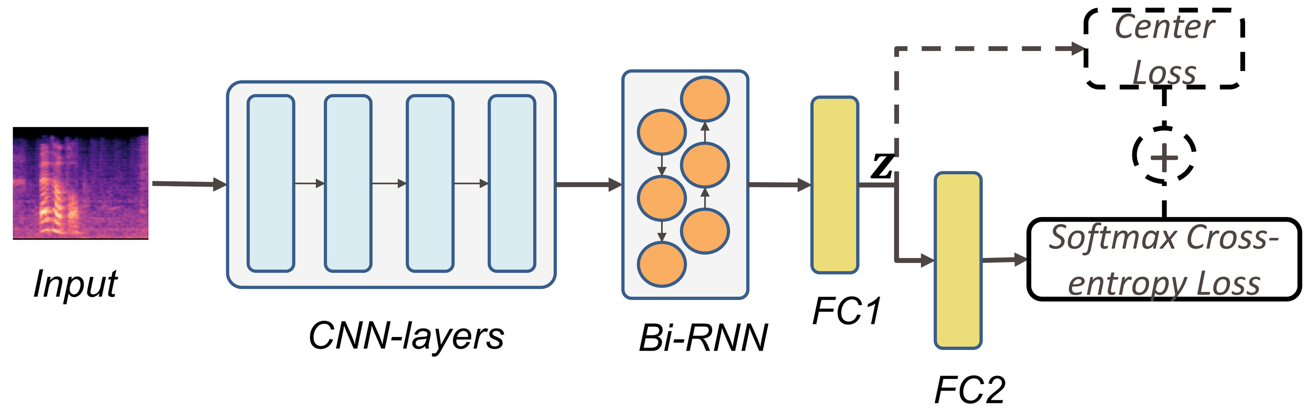
Challenge

- How to design a suitable model processing directly on raw data
- Emotions are naturally ambiguous

Contribution

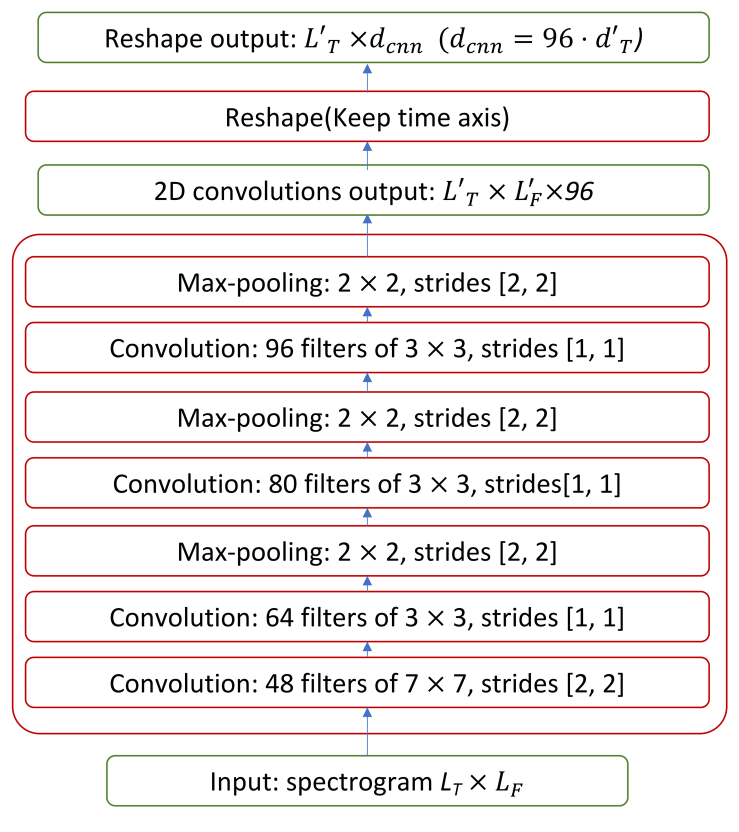
- Extract features and identify emotions directly from spectrograms
- Introduce center loss together with softmax corss-entropy loss in SER task to learn discriminative features
  - Separable inter-class features
  - More compact intra-class features

2. Proposed Method

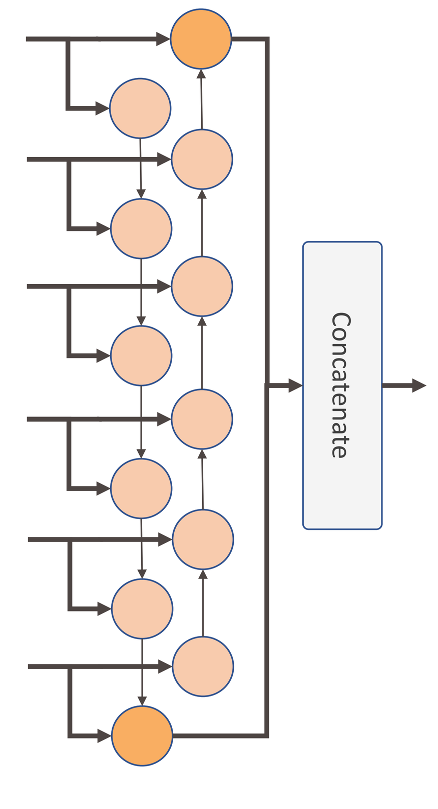


Model Architecture

- Input: variable length spectrograms (STFT or Mel-spectrograms)
- CNN layers: extract spatial information
- Bi-RNN: compresses the variable length sequence down to a fixed-length vector
- FC1: output $z \in R^d$ as the learned feature and calculate center loss according to z
- FC2: outputs posterior class probabilities, used to calculate softmax cross-entropy loss
- Softmax Cross-enctropy Loss: enables the network to learn separable features
- Center Loss: pulls the features belonging to the same emotion category to their center



CNN layers



Bi-RNN

Softmax Cross-entropy Loss

$$L_s = -\frac{1}{\sum_{i=1}^{m} \omega_{y_i}} \sum_{i=1}^{m} \omega_{y_i} log(\frac{e^{W_{y_i}^{\mathrm{T}} z_i + b_{y_i}}}{\sum_{j=1}^{n} e^{W_j^{\mathrm{T}} z_i + b_j}})$$

- ω_j: in inverse proportion to the sample number of the j-th class in training set

Center Loss

$$L_c = \frac{1}{\sum_{i=1}^{m} \omega_{y_i}} \sum_{i=1}^{m} \omega_{y_i} ||z_i - c_{y_i}||^2$$

$$c_j^{t+1} = \begin{cases} (1-\alpha)c_j^t + \alpha \dot{c}_j^t & \sum_{i=1}^{m} \delta(y_i = j) > 0 \\ c_j^t & \sum_{i=1}^{m} \delta(y_i = j) = 0 \end{cases}$$

$$\dot{c}_j = \frac{\sum_{i=1}^{m} \delta(y_i = j) z_i}{\sum_{i=1}^{m} \delta(y_i = j)}$$

- L_c: center loss
- c_j: the global class center of features corresponding to the j-th emotion, updated per mini-batch iteration
- $\dot{c}_j$: the j-th class center of features from a mini-batch
- α: controls the update rate of c_j

Joint Loss

$$L = L_s + \lambda L_c$$

- λ: trades off center loss against softmax cross-entropy loss.

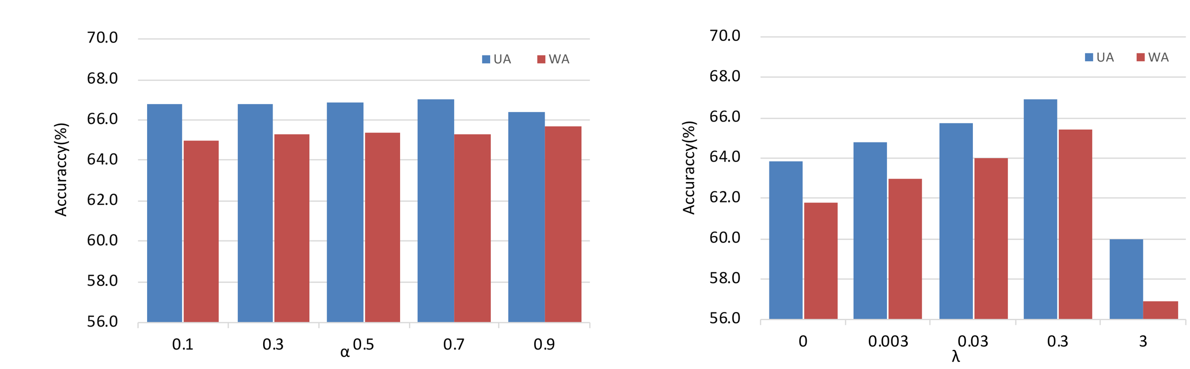
3. Experiments and Results

Experimental Setup

- Data
  - Dataset: IEMOCAP
  - Neutral, angry, happy, sad and excited (merges happy and excited as happy, 5531 utterances)
  - 5 subsets (keep the emotion distribution), 4 subsets for training, half of the last subset as development set and half as test set
- Settings of spectrograms
  - Model input: log scale STFT spectrogram or Mel-spectrogram
  - Hamming window
  - Window size: 40msec
  - Window Shift: 10msec
  - Sample rate: 16KHz
  - DTF length: 1024
  - The number of Mel bands: 128
- Metrics
  - The unweighted accuracy: UA, the mean value of the recall for each class
  - The weighed accuracy: WA, the number of correctly classified samples divided by the total amount of samples

Experiments

- The effect of hyperparameter α and λ on Mel-spectrogram
  - *(left)* fixing $\lambda = 0.3$, *(right)* fixing $\alpha = 0.5$
  - not sensitive to α
  - can be significantly improved with proper value of λ



- Experiments with different λ on Mel and STFT

	Setting1	Setting2	Setting3	Setting4
λ, α	λ=0	λ=0.3, α=0.5	λ=0	λ=0.3, α=0.5
Input	Mel	Mel	STFT	STFT

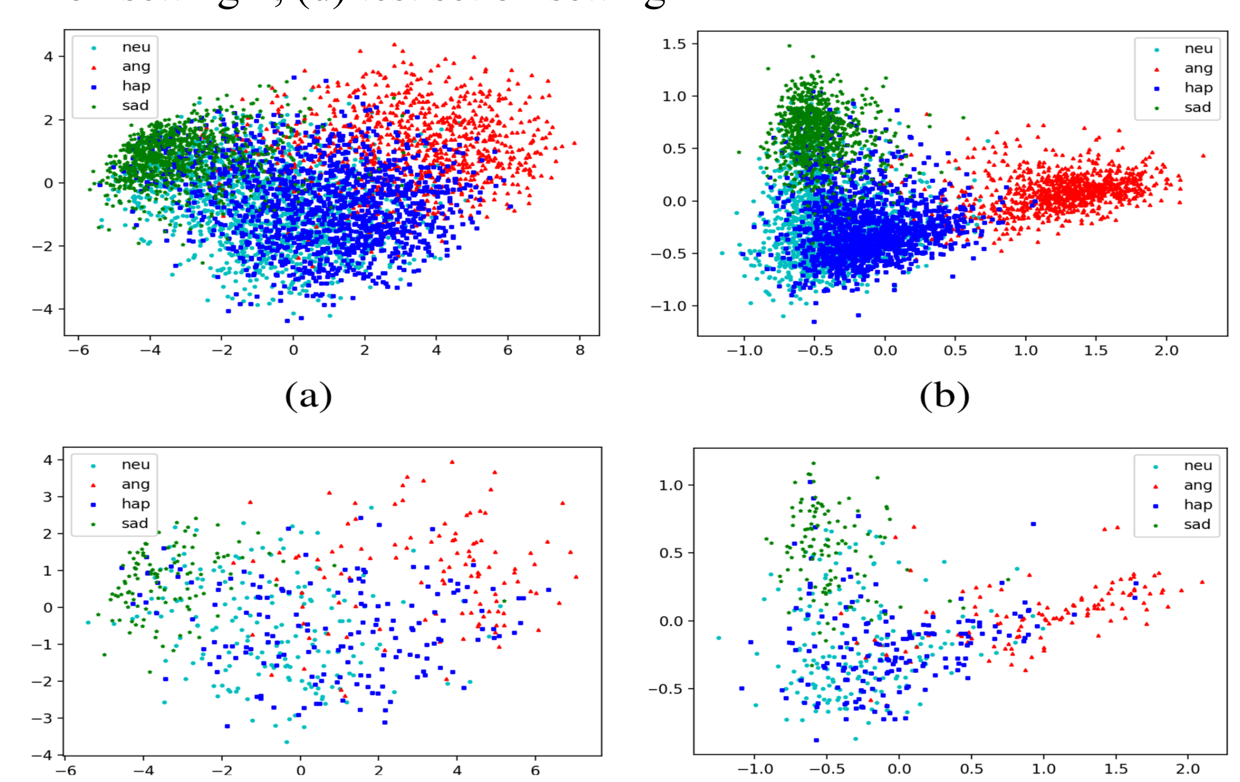
- The UA and WA on setting 1 ~ setting 4

	Setting1	Setting2	Setting3	Setting4
UA(%)	63.80	66.86	60.97	65.13
WA(%)	61.83	65.40	58.93	62.96

- Confusion matrix on setting1/setting2/setting3/setting4(%)

	neutral	*angry*	*happy*	*sad*
neutral	57.5/63.7/54.4/57.3	9.5/6.7/9.3/7.3	16.4/16.7/18.5/19.6	16.6/12.7/17.7/15.7
angry	11.9/10.8/12.7/10.3	69.1/70.5/68.1/72.0	15.5/16.7/16.7/15.3	3.5/2.0/2.5/2.2
happy	21.1/21.9/21.6/20.5	16.2/13.1/18.6/16.1	51.1/55.6/47.6/51.8	11.5/9.4/12.2/11.4
sad	13.8/12.8/16.1/12.5	2.6/2.5/3.9/2.8	6.0/7.0/6.2/5.3	77.6/77.7/73.7/79.3

- PCA embedding of feature z
  - (a) training set on setting 1, (b) training set on setting 2, (c) test set on setting 1, (d) test set on setting 2



(a) (b) (c) (d)

4. Conclusion

Conclusion

- Introducing center loss with proper λ could effectively improve the SER performance on bath STFT spectrogram and Mel-spectrogram input
- Mel-spectrogram input, reducing the dimension based on human hearing characteristics, over performs STFT spectrogram input
- The 2-D PCA embedding illustrates the discriminative power when using center loss, which enables the neural network to learn more effective features for SER

5. Acknowledgment

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