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

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1. Introduction

Motivation

- Identify emotions directly from raw data (spectrograms), getting rid of feature engineering
- Extract discriminative features with larger inter-class variance and smaller intra-class variance to improve performance

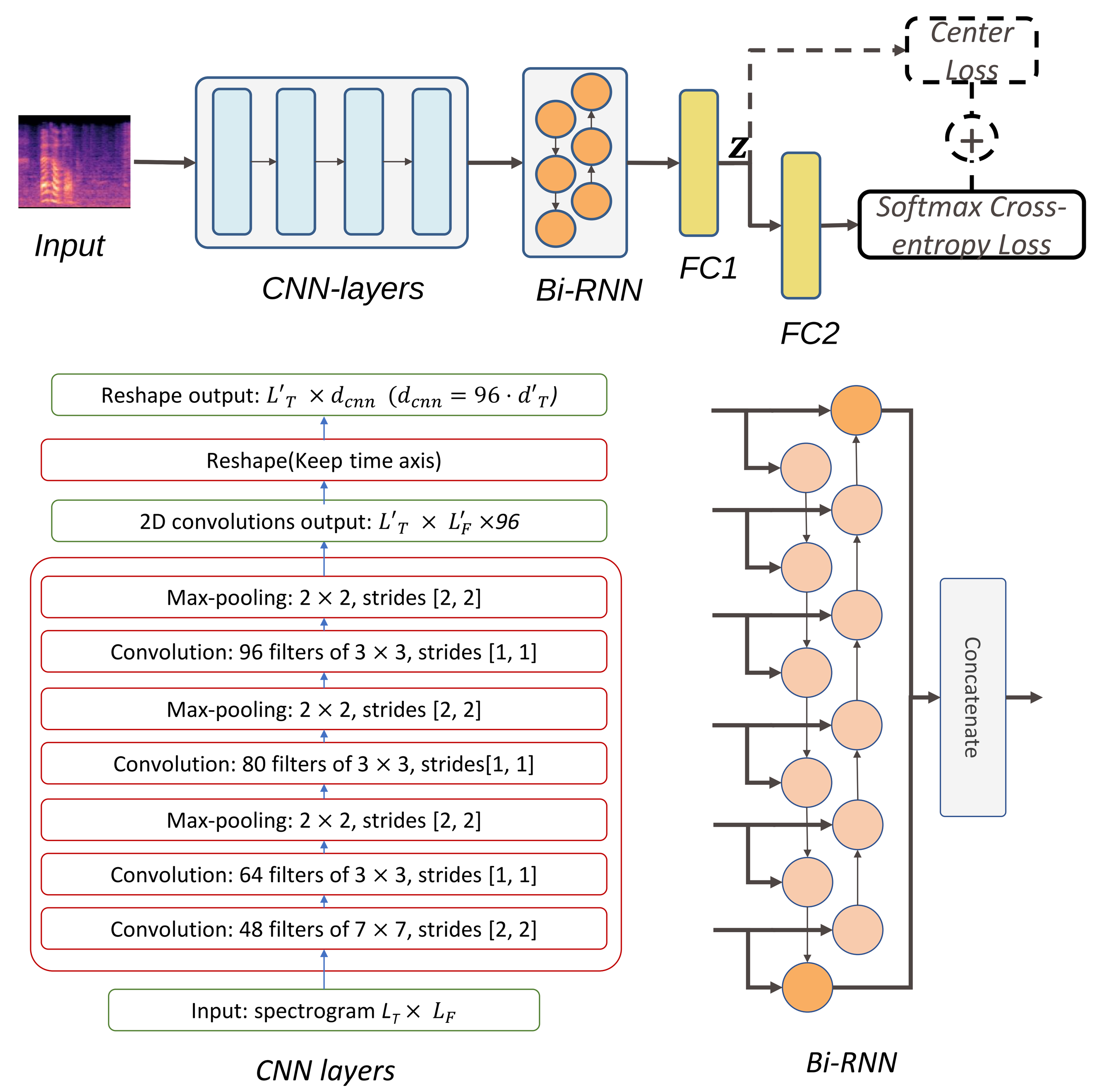
Challenge

- Design suitable model architecture processing variable length spectrograms
- Adopt appropriate methods to extract discriminative features

Contribution

- Apply CNN + Bi-RNN to extract features directly from spectrograms with variable length
- Introduce center loss together with softmax cross-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
- **CNN layers**: extract spatial information from input, and produce a variable length feature map sequence
- **Bi-RNN**: compresses the variable length sequence down to a fixed-length vector, by concatenating the last output of forward RNN and backward RNN
- **FC1**: outputs $z \in R^d$ as the learned feature, from which center loss is calculated
- **FC2**: outputs posterior class probabilities, from which softmax cross-entropy loss is computed
- **Softmax Cross-entropy Loss:** enables the network to learn separable features
- **Center Loss**: pulls the features belonging to the same emotion category to their center

Center Loss

$$L_c = \frac{1}{\sum_{i=1}^{m} \omega_{y_i}} \sum_{i=1}^{m} \omega_{y_i} ||z_i - c_{y_i}||^2, \quad \dot{c}_j = \frac{\sum_{i=1}^{m} \delta(y_i = j) z_i}{\sum_{i=1}^{m} \delta(y_i = j)}$$

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

- c_j: the global class center of features corresponding to the j-th emotion class, 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

Softmax Cross-entropy Loss

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

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

Joint Loss

$$L = L_s + \lambda L_c$$

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

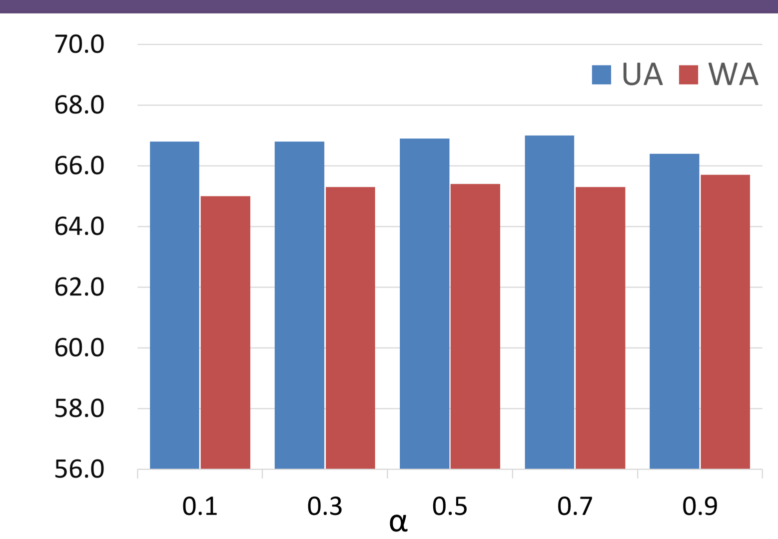
3. Experiments and Results

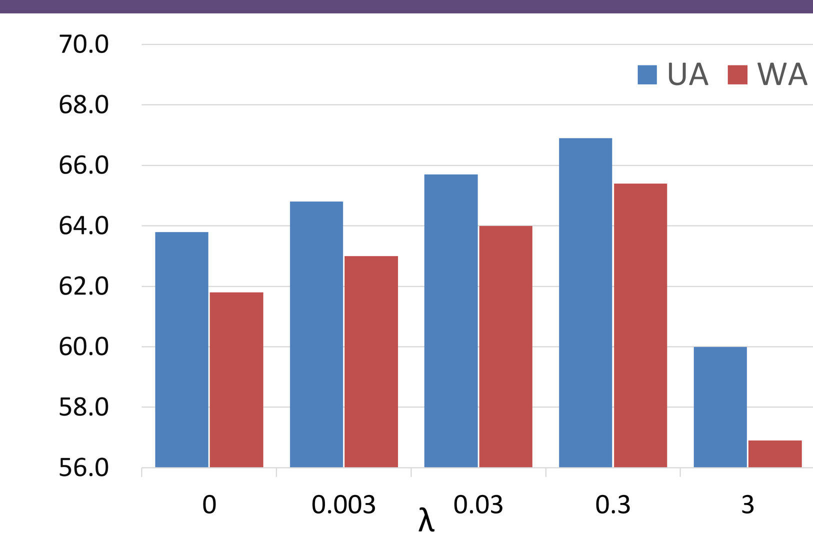
Experimental Setup

- Dataset: IEMOCAP
  - ✓ 4 emotion categories: neutral, angry, happy and sad (happy and excited merged as happy)
  - ✓ 5 subsets
    - Randomly divided the total 5531 utterances into 5 subsets, keeping the distribution portion of emotion categories
    - 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: 40ms window length and 10ms shift
  - ✓ Sample rate: 16KHz
  - ✓ DTF length: 1024
  - ✓ Mel bands number: 128
- Evaluation metrics
  - ✓ **Unweighted Accuracy (UA)**: the mean value of the recall for each class
  - ✓ **Weighed Accuracy (WA)**: the number of correctly classified samples divided by the total amount of samples

Experiments

- Effect of hyperparameter α and λ on Mel-spectrogram
  - ✓ *(left)* fixing λ = 0.3, *(right)* fixing α = 0.5
  - ✓ Performance not sensitive to α
  - ✓ Performance can be significantly improved with proper value of λ





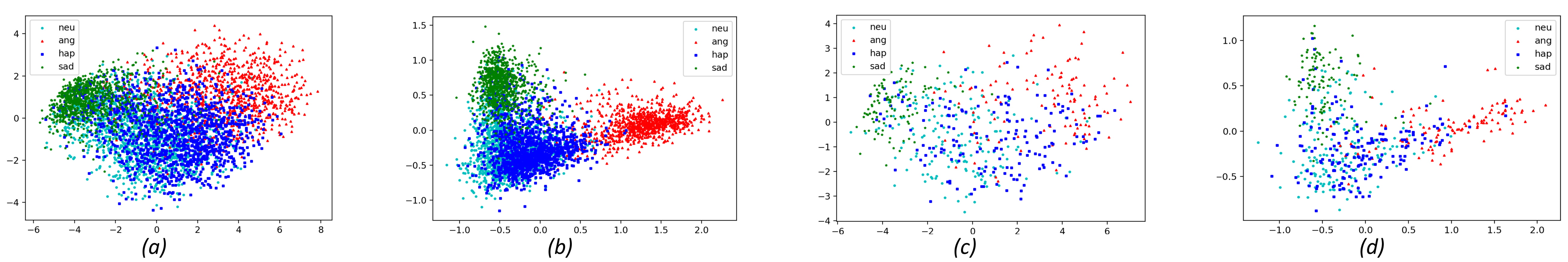
- Experiments with different λ on Mel and STFT
  - ✓ UA and WA (%) on setting 1 ~ 4

	λ, α	Input	UA	WA
Setting1	λ=0	Mel	63.80	61.83
Setting2	λ=0.3, α=0.5	Mel	66.86	65.40
Setting3	λ=0	STFT	60.97	58.93
Setting4	λ=0.3, α=0.5	STFT	65.13	62.96

  - ✓ Confusion matrix (%) on setting1|setting2|setting3|setting4

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

- PCA embedding of z: (a) training set on setting1, (b) training set on setting2, (c) test set on setting1, (d) test set on setting 2



4. Conclusion

Conclusion

- Introducing center loss with proper λ can effectively improve the SER performance on both STFT spectrogram and Mel-spectrogram input
- The Mel-spectrogram input, which reduces the dimension based on the characteristics of human hearing, outperforms the STFT spectrogram input
- The 2-D PCA embedding of the learned features illustrates the discriminative power of using center loss, which enables the neural network to learn more effective features for SER

5. Acknowledgment

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