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

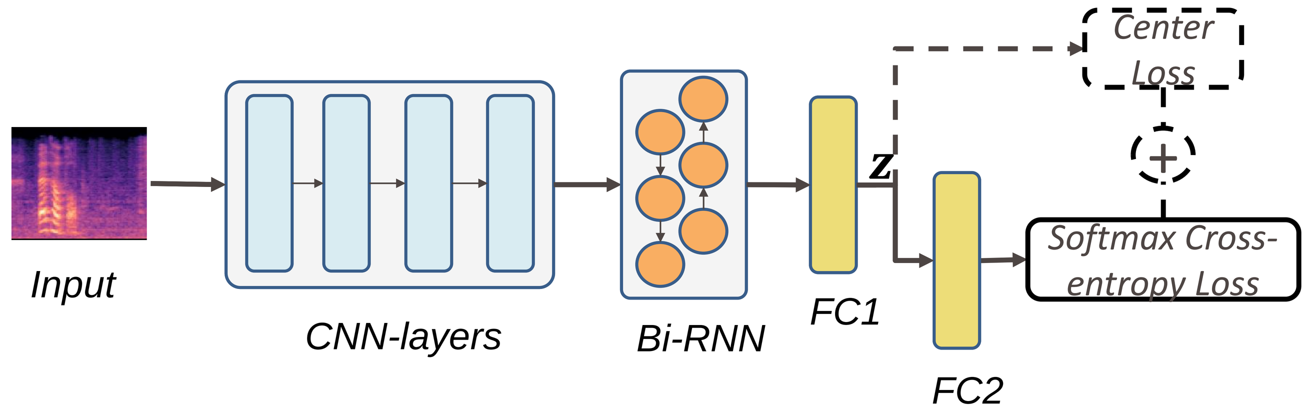
Challenge

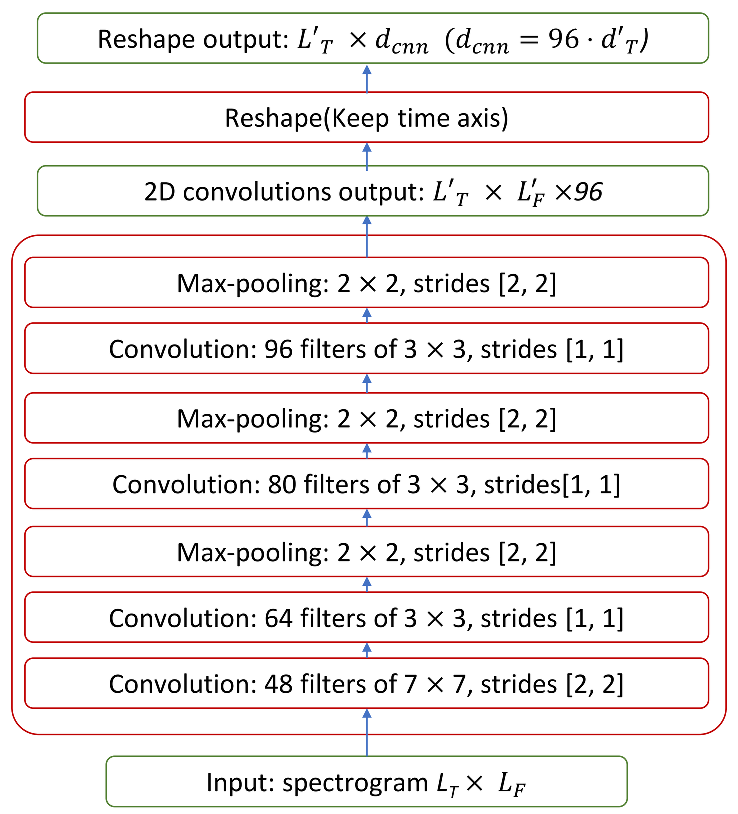
- How to design suitable model processing variable length spectrograms
- How to propose an appropriate method to extract discriminative features

Contribution

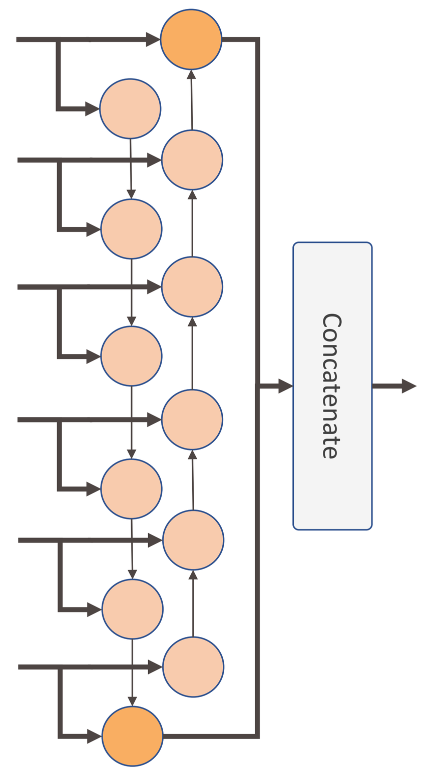
- Apply CNN + Bi-RNN to extract features directly from spectrograms
- Introduce center loss together with softmax cross-entropy loss in SER task to learn discriminative features
  - ✓ Separable inter-class features
  - ✓ More compact intra-class features

2. Proposed Method





CNN layers



Bi-RNN

Model Architecture

- **Input**: variable length spectrograms
- **CNN layers**: extract spatial information from input , outputs a variable length sequence
- **Bi-RNN**: compresses the variable length sequence down to a fixed-length vector, by concatenating the last output of forward RNN and backword 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

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

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

- 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

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

Joint Loss

$$L = L_s + \lambda L_c$$

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

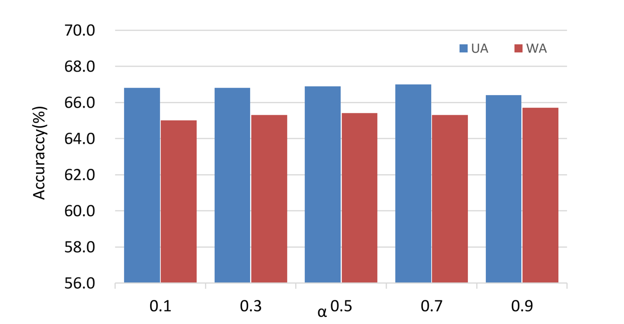
3. Experiments and Results

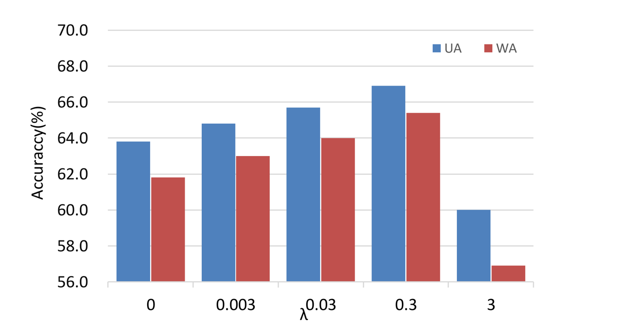
Experimental Setup

- Dataset: IEMOCAP
  - ✓ 4 emotion categories: neutral, angry, happy and sad (happy and excited merged as happy)
  - ✓ 5 subsets
    - Randomly divided the total 5531 utterances, but 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
  - ✓ The number of Mel bands: 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

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



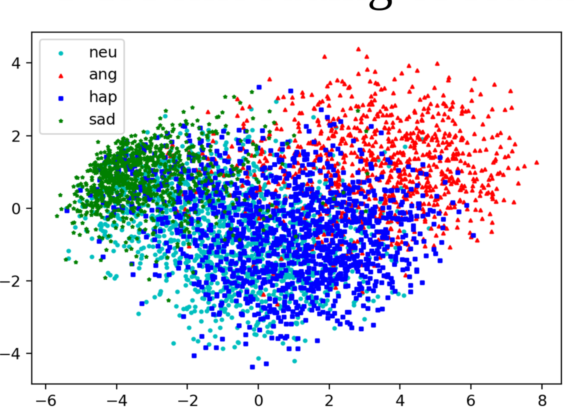


- Experiments with different λ on Mel and STFT
  - ✓ The UA and WA on setting 1 ~ setting 4 (%)
  - ✓ Confusion matrix on setting1|setting2|setting3|setting4 (%)

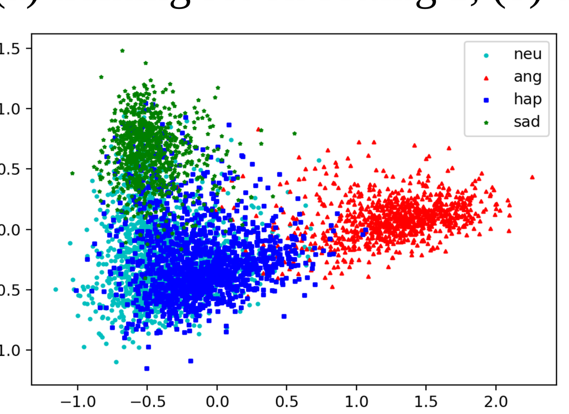
	λ, α	Input	UA	WA
Setting1	λ=0	Mel	63.80	61.83
Setting2	λ=0.3, α=0.5	Mel	66.86	65.40
Setting3	λ=0	STFT	60.97	58.93
Setting4	λ=0.3, α=0.5	STFT	65.13	62.96

	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

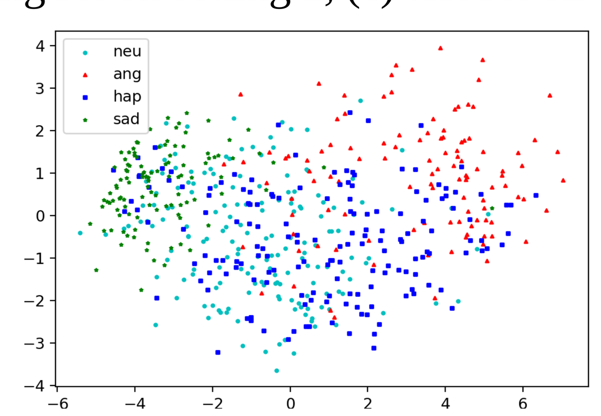
- PCA embedding of feature z: (a) training set on setting 1, (b) training set on setting 2, (c) test set on setting 1, (d) test set on setting 2



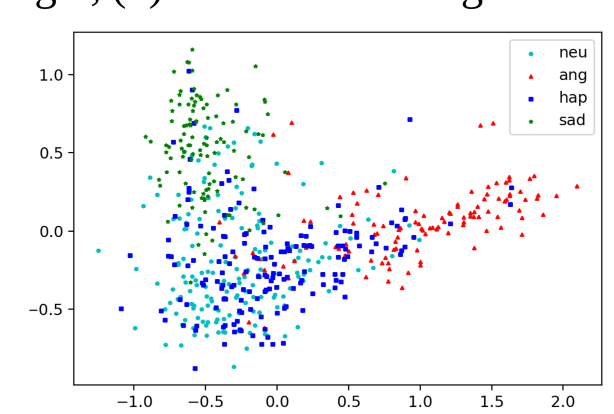
(a)



(b)



(c)



(d)

4. Conclusion

Conclusion

- Introducing center loss with proper λ could effectively improve the SER performance on both STFT spectrogram and Mel-spectrogram input
- Mel-spectrogram input, reducing the dimension based on human hearing characteristics, outperforms STFT spectrogram input
- The 2-D PCA embedding 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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