DEVELOPING FAR-FIELD SPEAKER SYSTEM VIA TEACHER-STUDENT LEARNING

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1. Introduction

We develop keyword spotting (KWS) and acoustic model (AM) components in a farfield speaker system.

- Use teacher-student (T/S) learning to adapt a *close-talk* well-trained production AM to *far-field* by using parallel close-talk and **simulated** far-field data.
- Use T/S learning to compress a large-size KWS model into a *small-size* one to fit the device computational cost requirement.
- Utilize unlabeled data to boost the model performance in both scenarios.



3. ASR Experiments

- Source training data:
 - 3.4k hours of labeled US-English close-talk Cortana audio.
 - 25k hours of unlabeled US-English close-talk Cortana audio.
 - 300 hours labeled live far-field audio.
- Teacher Model:
 - LSTM-RNN: 4-layer uni-LSTM-P, 1024 memory units and projection layer with 512 nodes. Output layer has 9404 nodes, modeling senones.
 - Singular value decomposition (SVD) and frame skipping are used to reduce cost. •
 - Trained with labeled data with CE and then sequence discriminative training.
- Source training data:
 - 760 hours labeled close-talk Cortana audio, half with "Hey Cortana" and half with
 - 600 hours labeled far-field live data or 940 hours unlabeled far-field live data.
- Large-size model used as teacher (24M parameters):
 - LSTM-RNN-CTC: 5-layer uni-LSTM-P, 1024 memory units and projection layer with nodes. Output layer has 5 nodes, modeling Hey, Cortana, silence, garbage, and b
- Small-size model (0.9M parameters):
 - 3-layer uni-LSTM-P, 256 memory units and projection layer with 128 nodes, with

5. Conclusions

- Simulating far-field data, especially the beamformed one, is very helpful to improving the accuracy of real test data.
- T/S learning effectively used *unlabeled* data to improve the student model.
- The final AM improves the baseline by with 72.60% and 57.16% relative WER reduction on play-back and live far-field data.
- The small-size CTC KWS model trained with unlabeled data using T/S learning has the same performance as the large-size CTC KWS model, but with only 1/27 foot-print.

4. KWS Experiments

2. Teacher-Student (T/S) Learning

T/S model compression

J. Li, R. Zhao, etc. "Learning small-size DNN with output-distribution-based criteria," In Proc. Interspeech, 2014.

$$-\sum_{f}\sum_{i}P_{T}(s_{i}|x_{f})logP_{S}(s_{i}|x_{f})$$

T/S domain adaptation

J. Li, M. Seltzer, etc. "Large-scale domain adaptation via teacher student learning," in Proc. Interspeech, 2017.

$$\sum_{f} \sum_{i} P_T(s_i | x_{src,f}) log P_S(s_i | x_{tgt,f})$$



Source Domain Data

Target Domain Data

Model	WER (%)			
	Playback	Live		
Close-talk	47.34	23.81		
CE (3.4k hours single channel simulation)	21.22	14.30		
T/S (3.4k hours single channel simulation)	18.79	14.19		
T/S (25k hours unlabeled single channel simulation)	16.61	12.98		
T/S (25k hours unlabeled beamformed simulation)	15.26	11.96		
T/S (25k hours unlabeled beamformed simulation) +	12.97	11.20		
3.4k hours simulation sequence training				
T/S (25k hours unlabeled beamformed simulation) +	13.38	10.20		
3.4k hours simulation + 300 hours live sequence training				

nout.	Data Model	simulation	simulation + 600-hour live labeled	simulation + 940-hour live unlabeled	
h 512	large-size CTC	5.39	1.60	-	
lank.	small-size CTC	11.28	1.94	-	
	small-size CTC with T/S	7.61	1.73	1.59	
SVD.	The FA rates (%) of KWS models operating at the 96% CA rate.				

