

MIT COMPUTER SCIENCE AND ARTIFICIAL INTELLIGENCE LABORATORY

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Introduction

- The CMU-MIT System for RC2014 has four parts:
- 1. Speaker tracking to determine speech *direction of arrival*;
- 2. Beamforming to enhance speech from microphone array;
- 3. Speaker clustering to group utterances for speaker adaptation;



- 4. An FST-based speech recognition engine.
- Our system reduced WER from 39.9% with a single array channel to 14.5% with eight channels.



Cluster division stopped for BIC improvement below a threshold.

Table: Speaker Clustering Results on Dev Set

	Simulated D	ata	Real Data			
Threshold T	No. of clusters	WER	No.of clusters	WER		
30	71	19.4	19	17.12		
50	45	18.8	15	16.80		
100	11	20.5	10	16.63		
180	5	19.4	5	17.35		

Experiments

- Speech features were extracted with MVDR cepstral analysis [4].
- Final features obtained by concatenation of 15 successive cepstral frames and performing LDA to reduce feature size to 10.
- The speech recognition engine was based on fast on-the-fly composition of weighted finite-state transducers [5].

Method

Speaker Tracking: see Section 10.2 in [1].

- Four passes of recognition were performed with increasing levels of speaker adaptation.
- Unsupervised speaker adaptation was based on word lattices from the prior pass.

	Simulated Data							Real Data		
	Room 1		Room 2		Room 3			Room 1		
System	Near	Far	Near	Far	Near	Far	Ave.	Near	Far	Ave.
Primary	12.89	14.71	14.09	19.38	16.62	31.45	18.68	16.26	16.54	16.46
Contrast A	8.40	10.27	14.1	30.54	17.11	44.65	20.85	38.38	41.41	39.90
Contrast B	8.12	8.93	9.60	12.99	9.73	20.18	11.80	14.76	14.18	14.50
Contrast C	8.17	9.23	10.10	15.00	15.00	29.04	14.42	18.80	11.04	15.95
Contrast D	6.81	6.81	7.59	7.59	7.08	7.08	7.16	7.98	7.36	7.67

Primary: Our official REVERB Challenge 2014 system Contrast A: Single Array Channel, using true speaker labels Contrast B: Maximum Negentropy Beamforming, using true speaker labels Contrast C: Super Directive Beamforming, using true speaker labels Contrast D: Close Talking Microphone, using true speaker labels

Conclusions and Future Work

- Only experiments on *real* data provide results that reliably predict performance in real environments.
- Maximum negentropy beamforming is more effective than MVDR



II. Maximum negentropy beamforming: see Kumatani et al. [2].



beamforming for DSR applications.

• Future work:

Couple our array processing techniques with a DNN recognizer.
Incorporate more speech knowledge into beamforming.

 $\circ\,$ Release our array processing tools into the public domain.

References

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