End-to-end Multichannel Speaker-Attributed ASR: Speaker Guided Decoder and Input Feature Analysis

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Task

- Transcribe a multichannel multi-speaker meeting

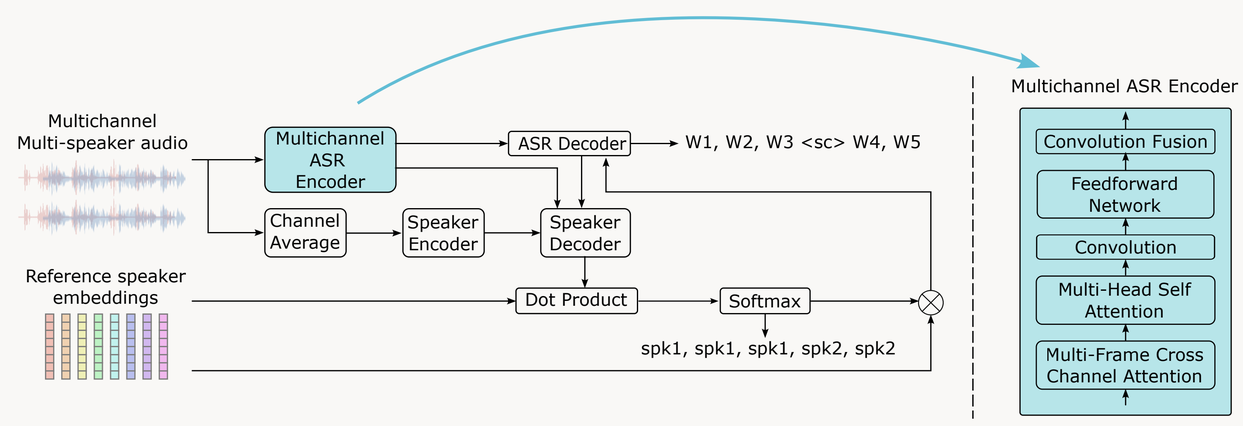
Key challenges

- Complex audio signals containing overlapping speech, noise, and reverberation
- Information sharing between ASR and speaker identification modules
- Design of optimal training losses, regularization, and training schedules of the E2E model

Main contributions

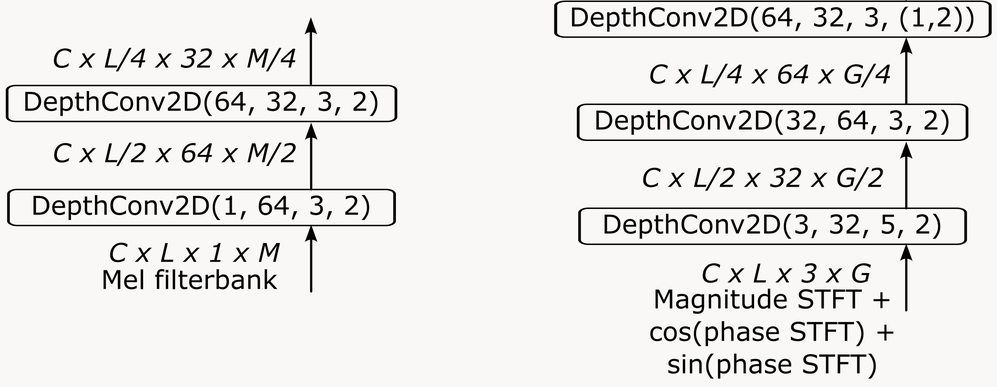
- E2E Multichannel Speaker-Attributed ASR (MC-SA-ASR) system
- Impact of multichannel input features

Proposed methods: MC-SA-ASR



- Proposed MC-SA-ASR combines Conformer-based multichannel Encoder [1] and Transformer-based speaker-wise Decoder [2]
- *W1, W2, W3 <sc> W4, W5* where <sc> indicates speaker change

Proposed methods: Input features



Experiments on LibriSpeech: Data preparation

- Data: LibriSpeech train-960, dev-clean, test-clean
- Preparation for multichannel multi-speaker setting on train-dev-test set: Room Impulse Responses simulated by the gpuRIR toolkit; Dynamic mixing for 2 and 3 speakers without duplication

Experiments on LibriSpeech: Results and discussion

Table: WER (%), sentence-level speaker error rate (SER) (%) on test set.

System	Input	# Ch	1-spk		2-spk mix		3-spk mix		1,2,3-spk mix		#Prm
			WER	SER	WER	SER	WER	SER	WER	SER	
Baseline											
SC-SA-ASR	Mel	1	7.15	1.64	14.68	3.23	20.39	**5.59**	16.81	**3.95**	61.1M
MC-ASR	Mel	2	8.52	-	16.76	-	22.87	-	18.21	-	27.8M
		3	8.29	-	16.54	-	22.01	-	18.03	-	
		4	8.11	-	16.43	-	21.76	-	17.84	-	
Proposed											
MC-SA-ASR	Mel	2	6.64	1.15	14.21	3.19	19.03	5.92	**15.41**	4.34	51.6M
		3	**6.62**	**1.11**	14.24	3.15	18.92	6.11	15.25	4.12	
		4	7.17	1.41	14.09	**3.06**	18.70	6.06	14.77	4.05	
	Mag+phase	2	7.24	1.53	15.42	3.85	20.34	7.06	16.76	4.87	
		3	6.86	1.78	**13.69**	3.72	18.14	6.86	**15.04**	4.08	
		4	6.91	1.86	13.97	3.10	**18.03**	6.69	**14.69**	4.12	

Experiments on AMI: Data preparation

- Data: 100 hours of meeting data with 3–5 participants and 8–16 microphones
- Dividing each meeting (approximately 1 hour) into fixed-size chunks while avoiding speaker overlaps or cutting within a word
- The training and development sets consist of 5 s, 10 s, or 15 s chunks only. The test set comprises 5 s, 10 s, and 15 s chunks

Experiments on AMI: Results and discussion

Table: WER (%) and token-level SER (%) of models adapted to AMI.

System	1-spk		2-spk mix		3-spk mix		4-spk mix	
	WER	SER	WER	SER	WER	SER	WER	SER
SC-SA-ASR								
5 s	28.10	**13.37**	42.03	25.53	54.04	35.65	67.27	43.17
10 s	31.84	17.25	43.93	27.88	54.20	35.82	67.92	43.49
15 s	48.38	32.38	60.73	43.12	64.39	44.53	73.68	49.40
MC-SA-ASR (prop)								
5 s	**27.68**	13.43	**39.54**	**24.83**	**52.76**	35.70	**64.72**	**41.24**
10 s	31.81	17.52	43.77	27.18	53.92	**34.99**	66.54	42.80
15 s	48.69	31.79	60.34	42.48	63.66	44.19	72.69	48.36

Conclusions

- WER reduction up to 16% relative on simulated data
- Phase features perform better on chunks with a larger number of channels and/or with a larger number of speakers

Perspectives

- Improve the speaker count accuracy on real data
- Make effective usage of multichannel phase features for a better localization of speakers

References

- F. Yu, S. Zhang, P. Guo, Y. Liang, Z. Du, Y. Lin, and L. Xie, "MFCCA: Multi-frame cross-channel attention for multi-speaker ASR in multi-party meeting scenario," in *SLT*, 2023.
- N. Kanda, G. Ye, Y. Gaur, X. Wang, Z. Meng, Z. Chen, and T. Yoshioka, "End-to-end speaker-attributed ASR with Transformer," in *INTERSPEECH 2021*, 2021.