# USING NEURAL NETWORK FRONT-ENDS ON FAR FIELD MULTIPLE MICROPHONES BASED SPEECH RECOGNITION

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#### **Abstract**

- Meeting recognition with far-field recordings has been a challenging topic of wide research interest.
- We showed on average 25% relative WER reduction by using bottleneck features in tandem structure compared to using PLP features.
- Direct channel concatenation can outperform standard beamforming in utilizing multiple channel data to train DNN front-end.
- Adding meta-information (e.g. speaker information) in DNN front-end can further improve performance.

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# Meeting Recognition on AMI Corpus

#### **AMI Corpus**

- Meeting corpus with multi-channel recordings: headset (IHM), distant microphones (SDM, MDM).
- Multi-level annotation on meta-information like head and body movement of speakers.
- Baseline using PLP features and HMM-GMMs

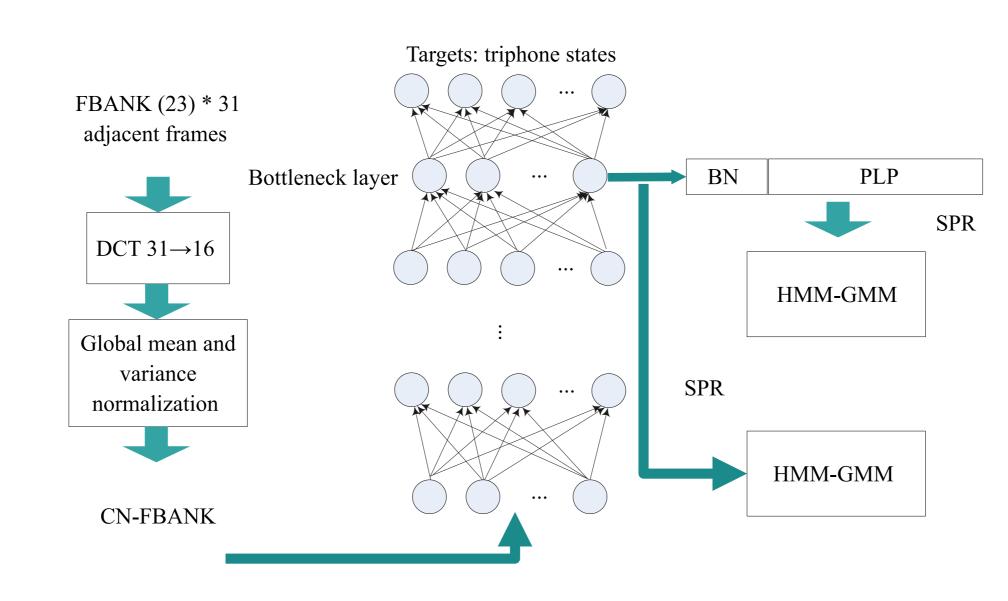
Train	Test	IHM	SDM	2bmit	4bmit	8bmit
00	00	35.6	66.3	61.8	60.5	58.2
~1	00	32.3	61.3	57.1 60.4	56.0	53.8
04	o4	35.4	65.1	60.4	59.8	58.2

o0: non-overlapping speech; o4: overlapping speech from maximally 4 speakers simultaneously. Beamforming is performed with toolkit BeamformIt.

Training and test sets used:

Dataset	Time	#Utt.	#Words	Description
acftrain	87.8h	73173	863726	Full training set (o4).
acntrain	15.8h	12876	152876	o0 from acftrain.
acftest	6.1h	4633	54820	Full test set (o4).
acntest	1.9h	1188	17536	o0 from acftest.

#### **DNN Front-end**



- Input features: log filter bank.
- Hidden layers: 1745 neurons in all but the bottleneck layer of 26 neurons.
- TNET toolkit, GTX690 based GPUs.
- Configuration abbreviation

"	Z = T - S	· · ·
Number of hidden layers beside the bottleneck layer	DNN training targets:  • T - 1259 triphone states  • M - 46 monophone	Bottleneck features · S - sigmoidal · L - linear

Performance using bottleneck features in HMM-GMMs

Feature					2bmit		
BN-2TL	00	00	26.6	49.5	46.8	46.3	45.6
PLP+BN-2TS	00	00	26.7	49.9	46.9	46.8	45.3
	о4	00	22.1	43.5	41.8	41.2	39.5
		o4	23.9	48.5	46.8	46.9	45.1

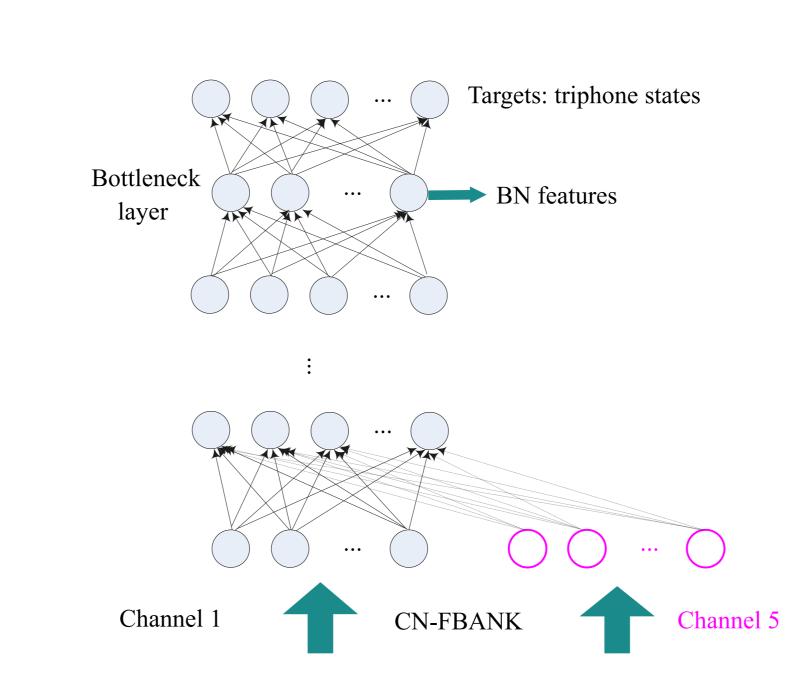
#### **Progress in Channel Concatenation**

• Channel concatenation can achieve equivalent or better performance compared with beamforming in both HMM-GMM system [1] and hybrid system [2].

[1] D. Marino and T. Hain, "An analysis of automatic speech recognition with multiple microphones", in INTERSPEECH 2011.

[2] P. Swietojanski, A. Ghoshal, and S. Renals, "Hybrid acoustic models for distant and multichannel large vocabulary speech recognition", in ASRU 2013.

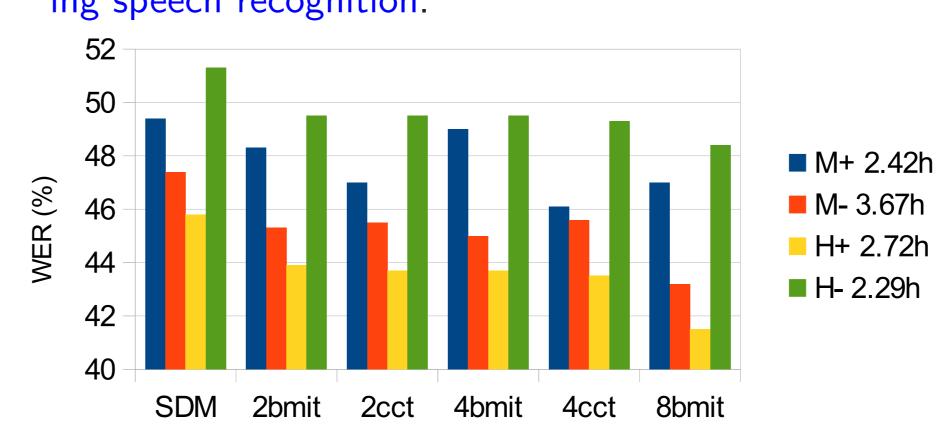
### **Channel Concatenation in DNN**



- Augment the DNN input with features from nonneighbouring multiple channels.
- Performance (%WER)

Feature	Train	Test	2cct 4cct 8cct
BN-2TL	00	00	46.0 45.5 -
	00	00	46.8 46.5 47.4
PLP+BN-2TS	04	00	41.1 40.3 41.7 46.4 46.2 47.8
	04	04	46.4 46.2 47.8

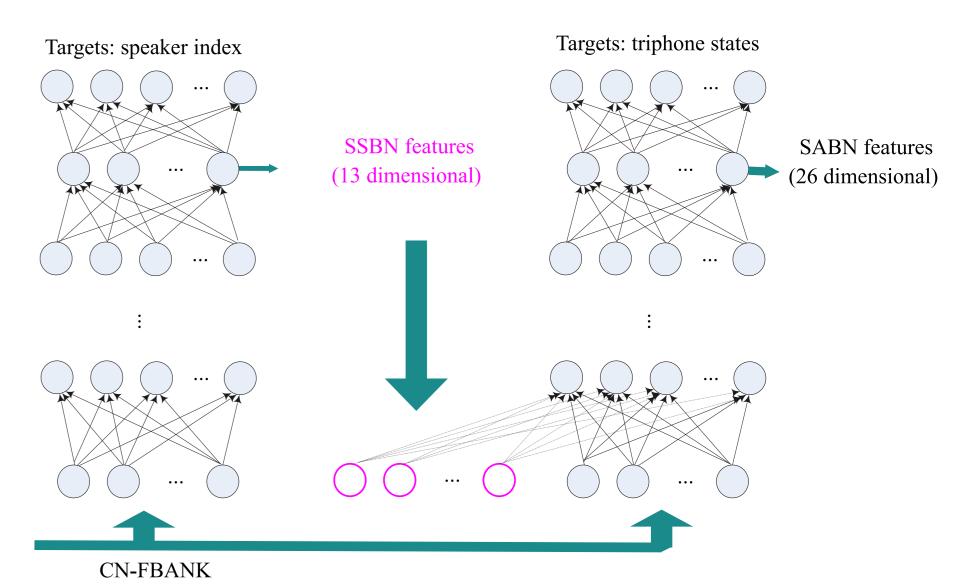
- Direct concatenation of 2 or 4 non-neighbouring distant channels outperforms beamforming, while 8 channel degrades because of large input dimension.
- Analysis
- Distant channels: channel concatenation improved moving speech recognition.



- M+: body moving; M-: body not moving; H+: head moving; H-: head not moving.
- -IHM channel: cognitive load when head moves.

	M+	M-	H+	H-
IHM (%WER)	22.4	24.6	23.3	25.7

# Speaker Awareness Deep Neural Network (SADNN)



- Augment DNN input with 13 dimensional *Speaker Separation Bottleneck* (SSBN) features, to generate the *Speaker Awareness Bottleneck* (SABN) features.
- Performance (%WER, trained and tested on o0)

					,
Feature	IHM	SDM	2bmit	4bmit	8bmit
SABN-2TL	26.5	48.9	47.4	46.0	44.8
PLP+SABN-2TS	26.1	49.8	47.4	46.0	44.7

With channel concatenation (%WER)

Feature	Train	Test	2cct	4cct
SABN-2TL	00	00	45.7	44.8
PLP+SABN-2TS	00	00	46.8	45.5

#### **Adding Other Meta-information**

- Location: Adding TDOA over channel concatenation degraded the performance, to 46.8% WER on 4 channels.
- Global information: Adding PLP based global speaker-GMM means degraded performance substantially.

## Summary

- 2 and 4 channel concatenation in DNN front-end outperforms beamforming in tandem system.
- Adding speaker information with SSBN leads to further WER reduction.
- In total 2.5% relative WER reduction is observed across different channels by using both channel concatenation and SADNN structure.