Linear prediction-based dereverberation with advanced speech enhancement and recognition technologies for the REVERB challenge

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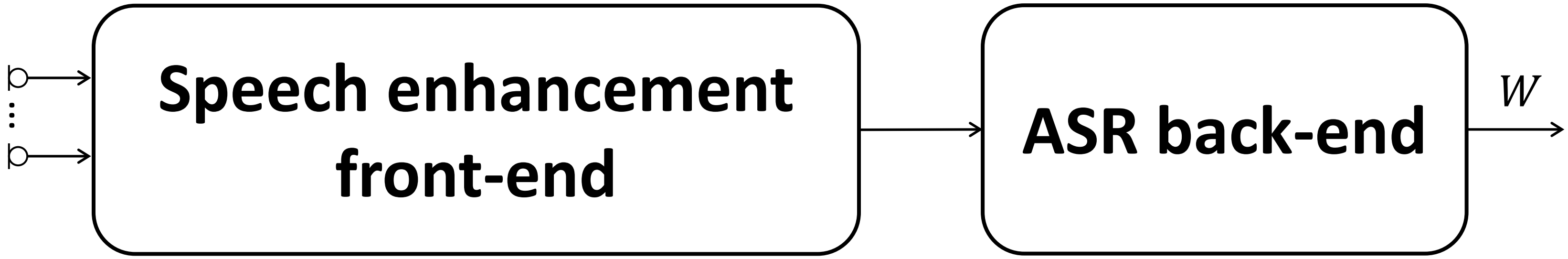
Summary

- Combine state-of-the-art SE and ASR techniques



SE task: 2ch & 8ch

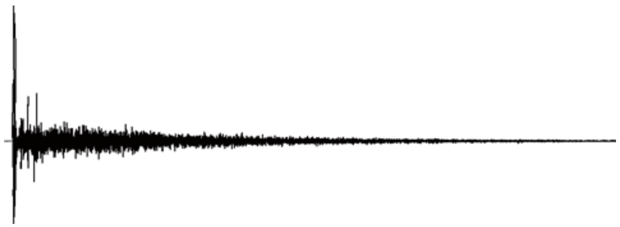
ASR task: 1ch, 2ch & 8ch

- Significant performance improvement:

SE 8ch (FWSegSNR) :	3.62 dB → 10.31 dB
ASR 8ch (WER) :	4.2 % (SimData)
	9.0 % (RealData)

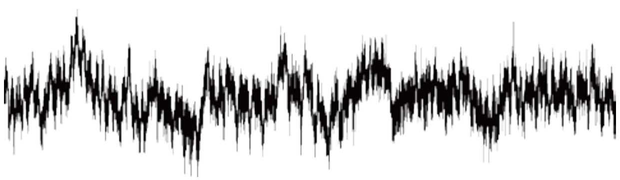
The challenges of the challenge…

1. Severe reverberation



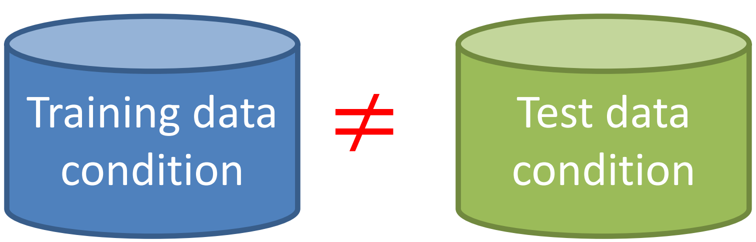
→ Powerful dereverberation

2. Significant amount of noise



→ Noise robust dereverberation
+ additional noise reduction

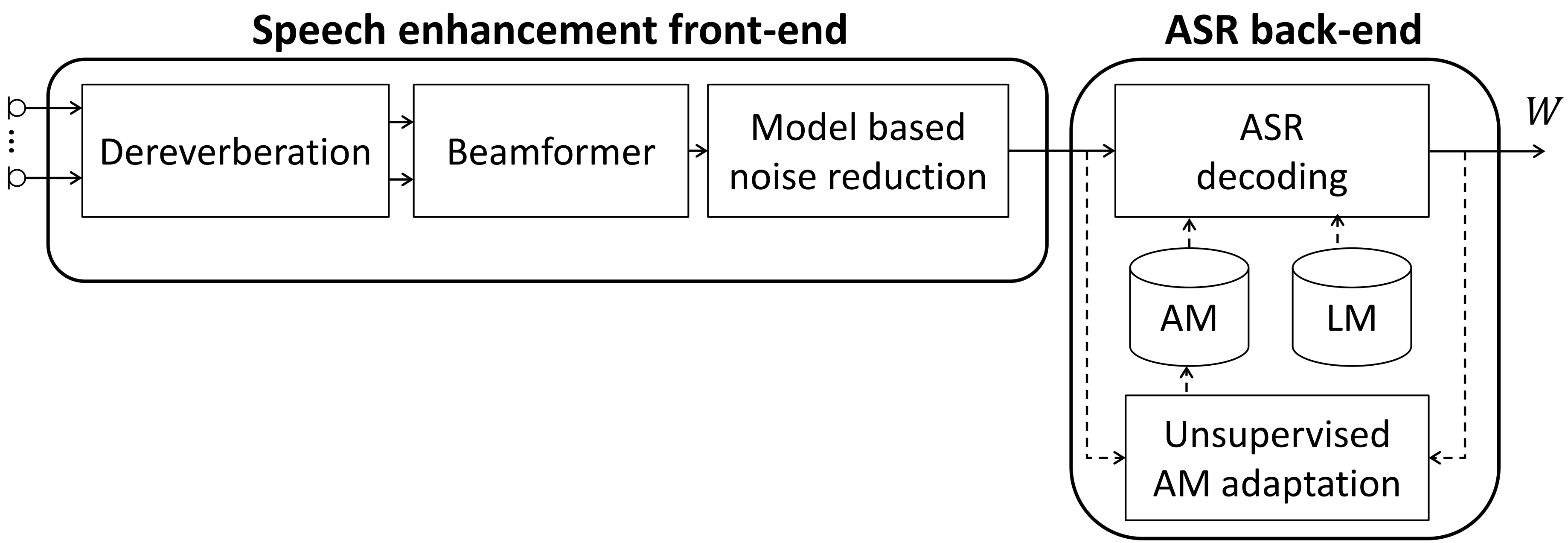
3. Mismatch between training and testing



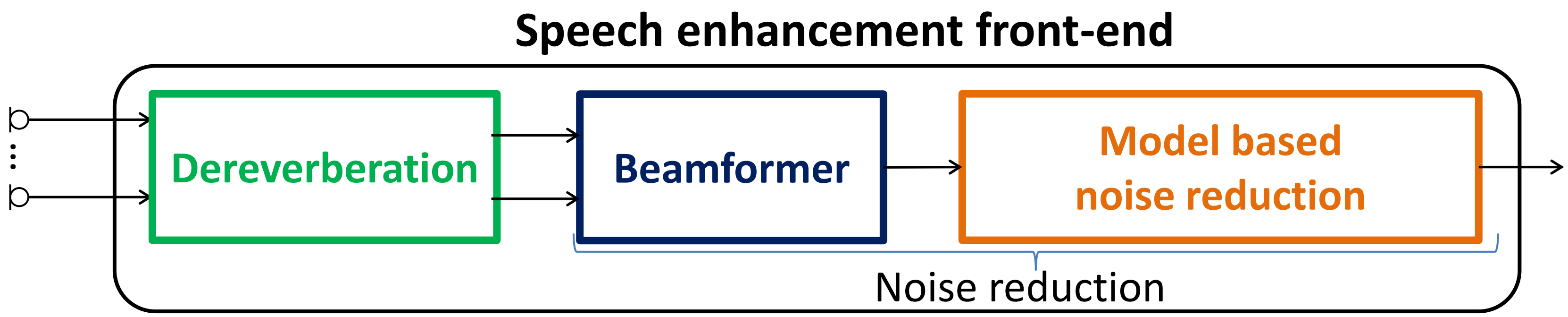
→ High performance w/o overfitting

Extended training data
+ unsupervised environmental adaptation

Proposed system

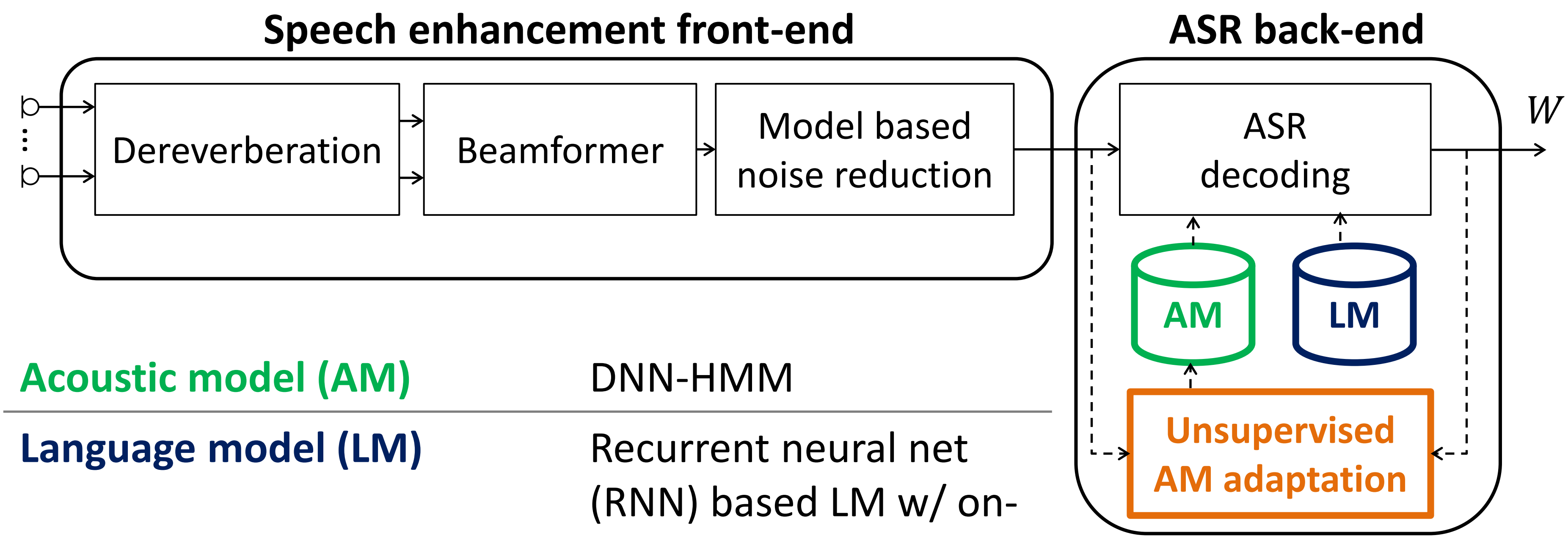


Characteristics of the SE front-end



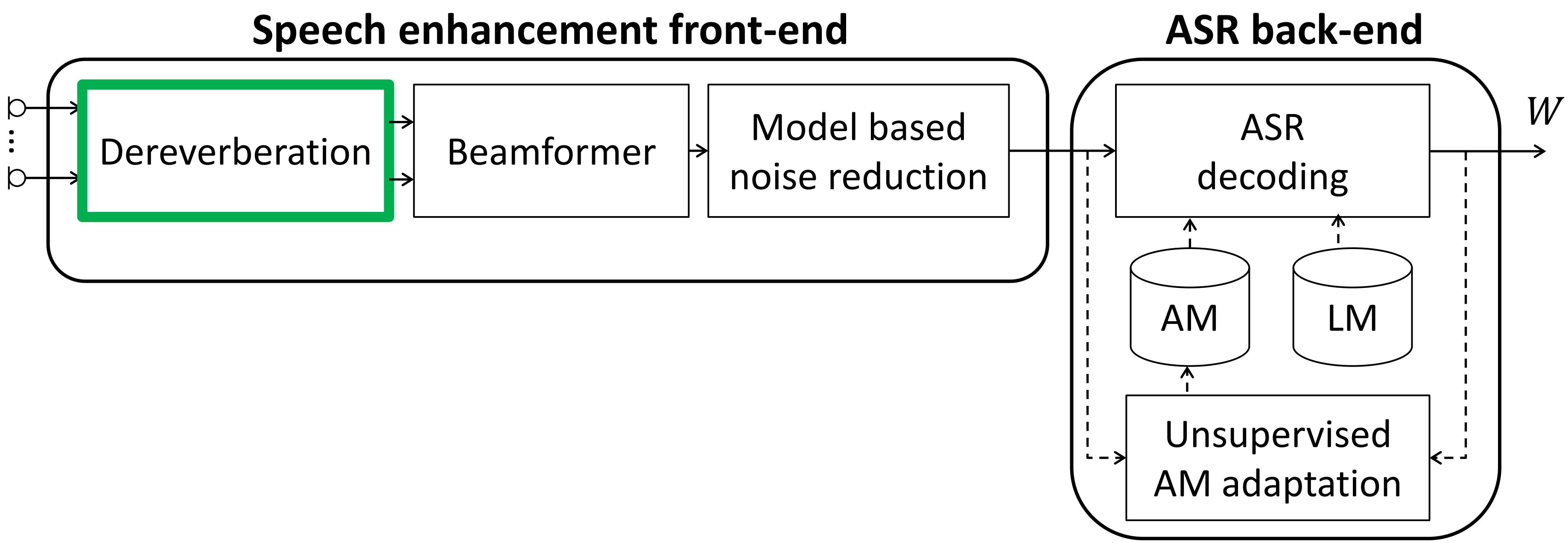
Approach	**Linear-prediction based derev. [Yoshioka, 2012]**	**MVDR beamformer [Souden, 2010]**	**Modified VTS [Fujimoto, 2012]**	**DOLPHIN [Nakatani, 2013]**
Processing	**Linear filtering**	**Linear filtering**	Model-based SE	Model-based SE
Scenario	1ch/2ch/8ch SE/ASR	2ch/8ch SE/ASR	**2ch/8ch** **SE**	**2ch/8ch** **ASR**
Output	**1ch/2ch/8ch**	1ch	1ch	1ch
Proc. mode	Utterance batch	Utterance batch	Utterance batch	Full batch
RTF	0.2-2.8	0.03	0.5	6-10

Characteristics of the ASR back-end



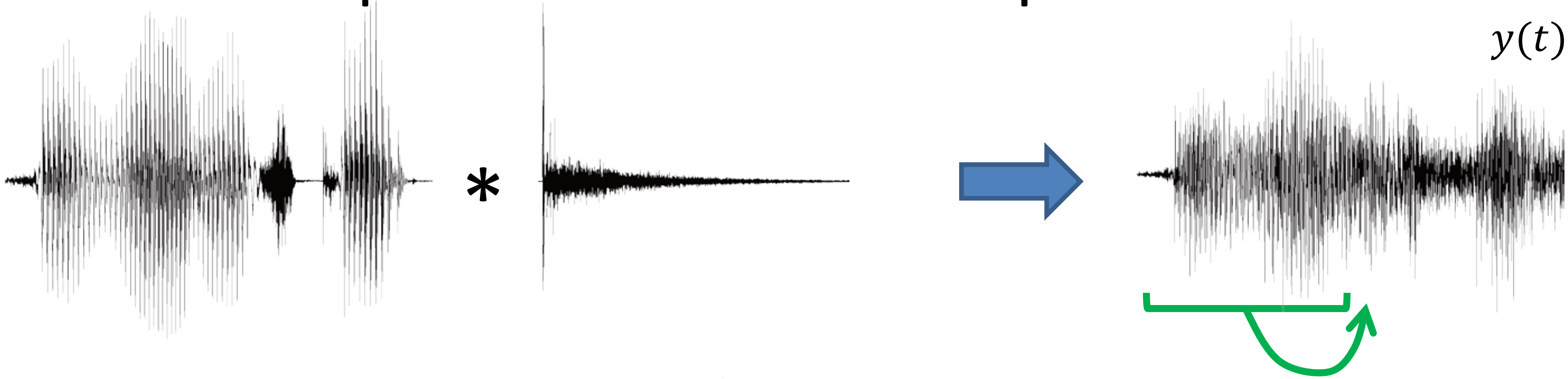
Acoustic model (AM)	DNN-HMM
Language model (LM)	Recurrent neural net (RNN) based LM w/ on-the-fly rescoring [Hori, 2014]
Unsupervised environmental adaptation	Retraining of the input layer of DNN-HMM

Dereverberation



Dereverberation based on linear prediction (1/2)

- Linear prediction for blind equalization



Predict reverberation in current observation from past obs.

- Prediction residual:

$$e(t) = y(t) - \sum_{n=1} g_n \, y(t-n)$$

g_n: prediction filter

- Assuming $e(t)$ is Gaussian, g_n can be obtained by minimizing:

$$F = \sum_{t} \left| y(t) - \sum_{n=1}^{N} g_n \, y(t-n) \right|^2$$

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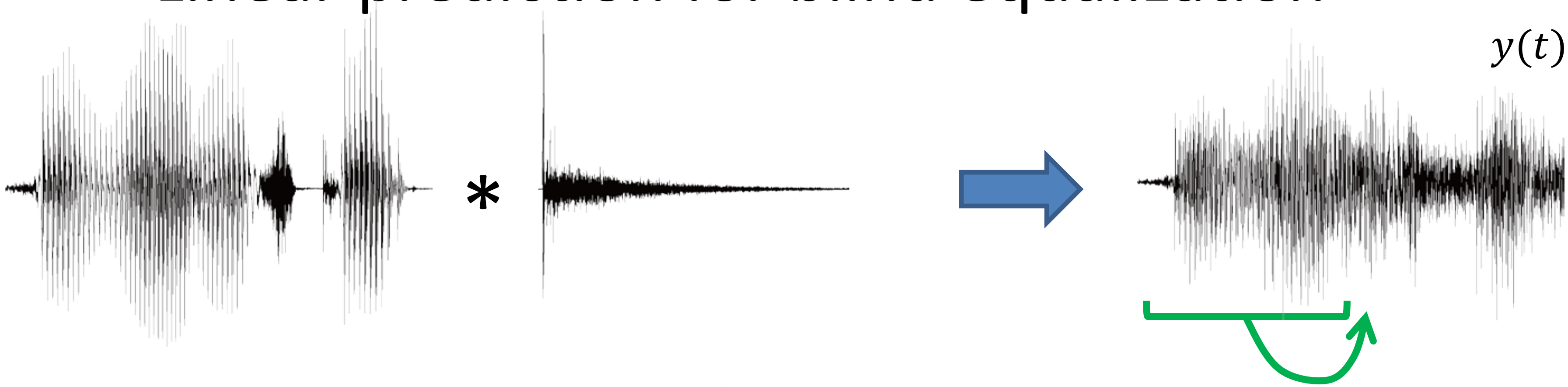

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☹ Not well suited for speech dereverberation

Dereverberation based on linear prediction (2/2)

- For speech dereverberation [Yoshioka, 2012]
  - **Introduce time delay τ**

    Do not equalize speech generative process

    → Focus on late reverberation
  - **Better modeling of speech**

    Short time Gaussianity of speech w/ time varying variance $\sigma_t{}^2$

    → Weighted prediction error (WPE)
- g_n , $\sigma_t{}^2$ can be obtained by minimizing:

$$F = \sum_t \frac{|y(t) - \sum_{n=\tau}^{N} g_n \, y(t-n)|^2}{\sigma_t{}^2} + \sum_t \log(\sigma_t{}^2)$$

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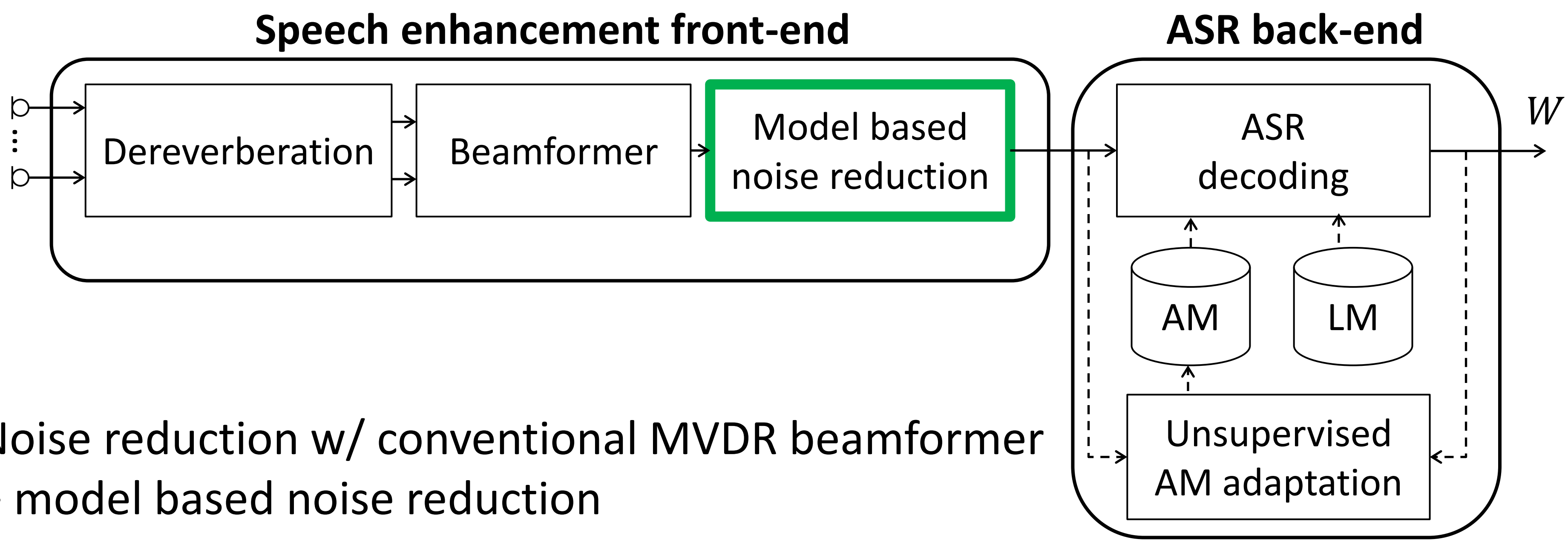
☺ Precise speech dereverberation

☺ Relatively robust to noise

☺ Implemented in STFT domain → efficient

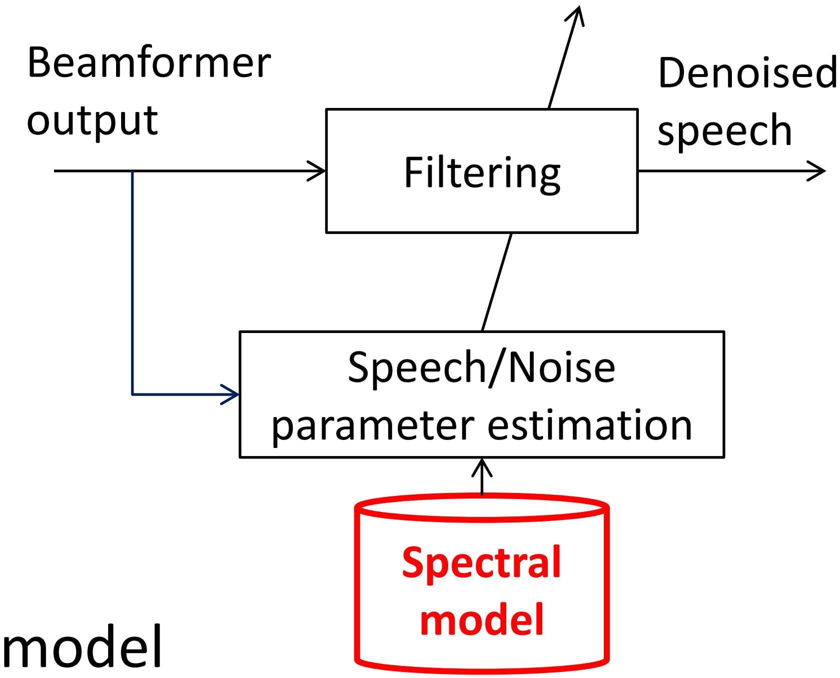
Model based Noise reduction



Noise reduction w/ conventional MVDR beamformer
+ model based noise reduction

Modified VTS (M-VTS)

VTS-like model-based noise reduction [Fujimoto, 2012]



- Spectral model
  - Speech model: pre-trained using clean training data + adaptation (per utterance)
  - Noise model: estimated per utterance

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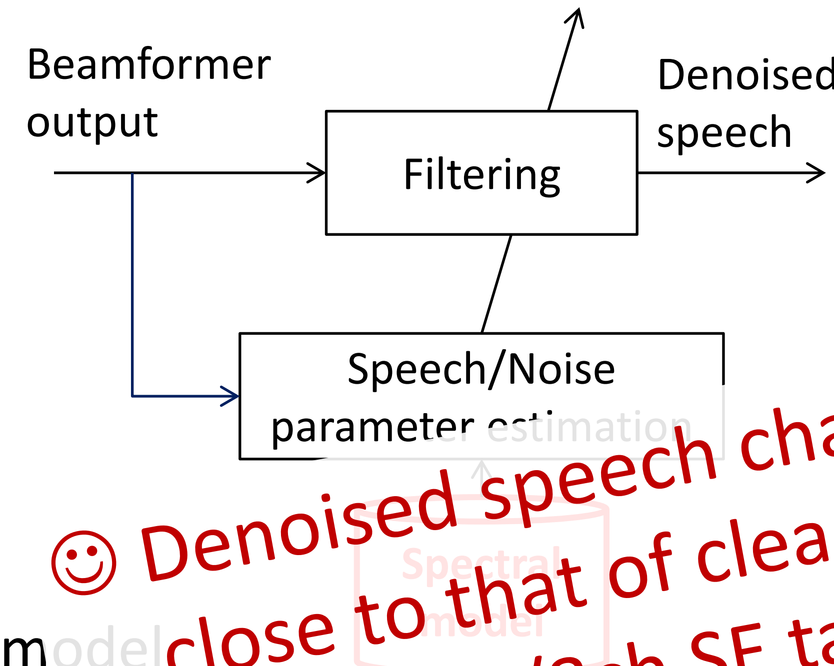


☺ Denoised speech characteristics close to that of clean speech

Used for 2ch/8ch SE tasks

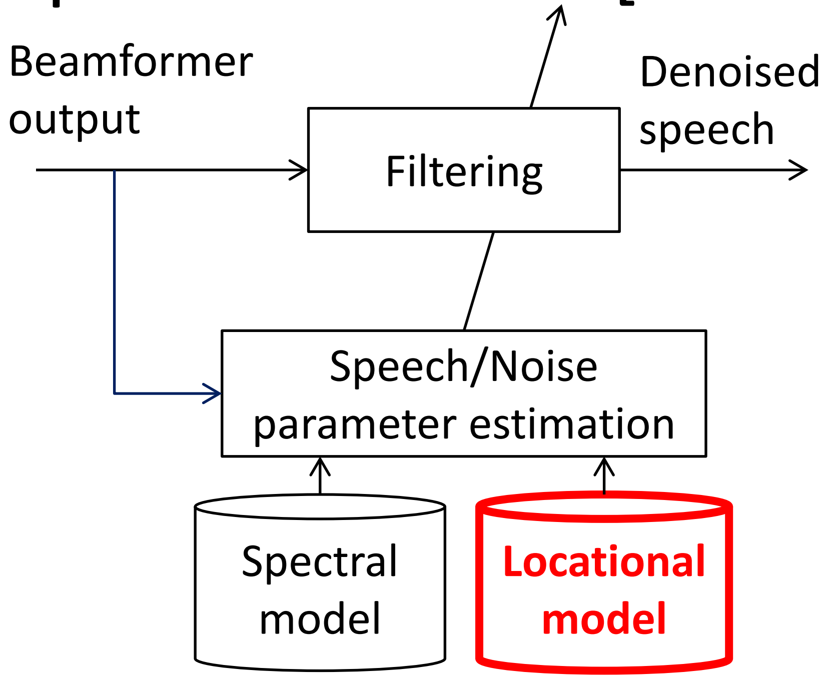
Utterance batch

- Spectral model
  - Speech model: pre-trained using clean training data + adaptation (per utterance)
  - Noise model: estimated per utterance

DOLPHIN*

* Dominance based locational and power-spectral characteristics integration

Combines spectral and locational (DOA feature) models of speech and noise[Nakatani, 2013]



- Locational model estimated from multi-channel dereverberation output

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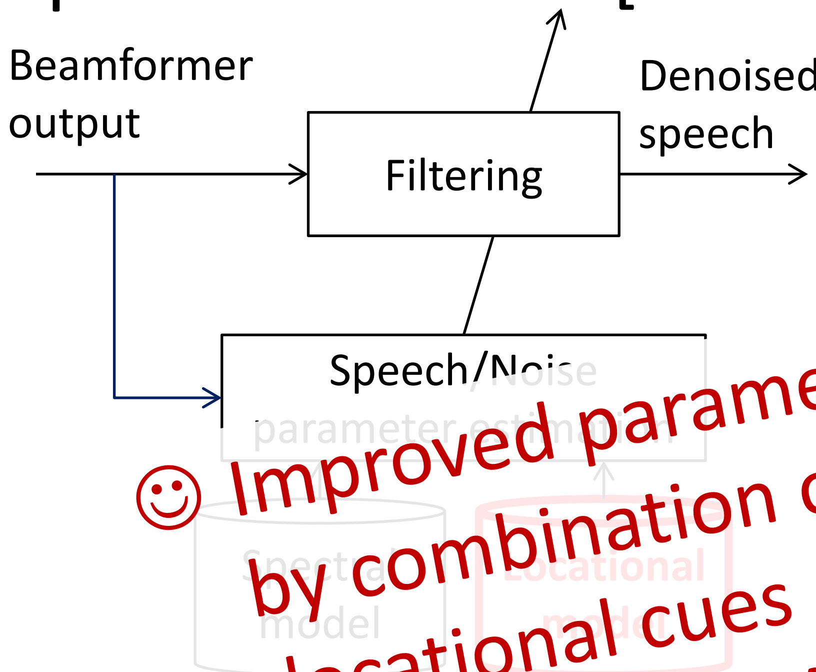


☺ Improved parameter estimation by combination of spectral and locational cues

Used for 2ch/8ch ASR tasks

Full batch

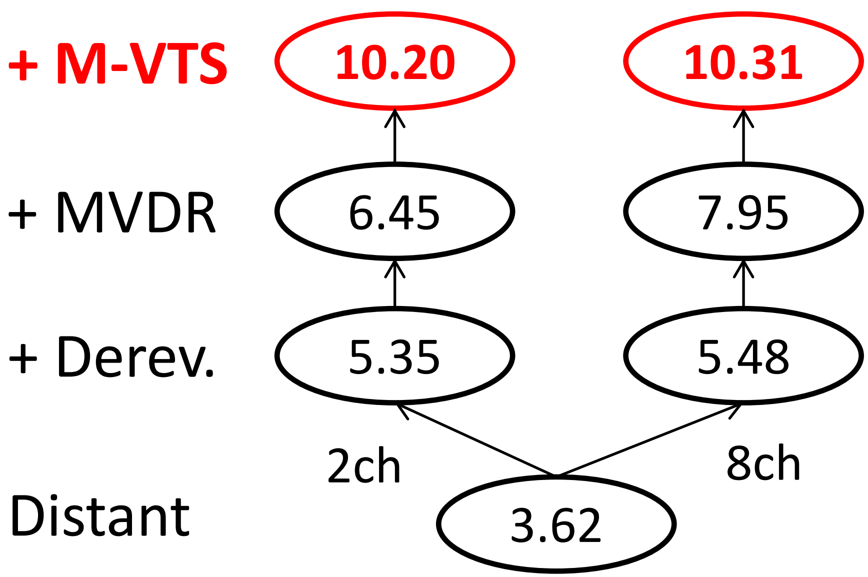
- Locational model estimated from multi-channel dereverberation output

SE results: Objective evaluation (Eval set)

	CD	SRMR	LLR	FWSegSNR	PESQ
w/o front-end	3.97	3.68	0.58	3.62	1.48
Proposed (2ch)	2.34	5.06	0.41	10.20	2.43
Proposed (8ch)	2.25	5.39	0.43	10.31	2.82

Improvement for all measures

Avg. FWSegSNR (dB) *for SimData*



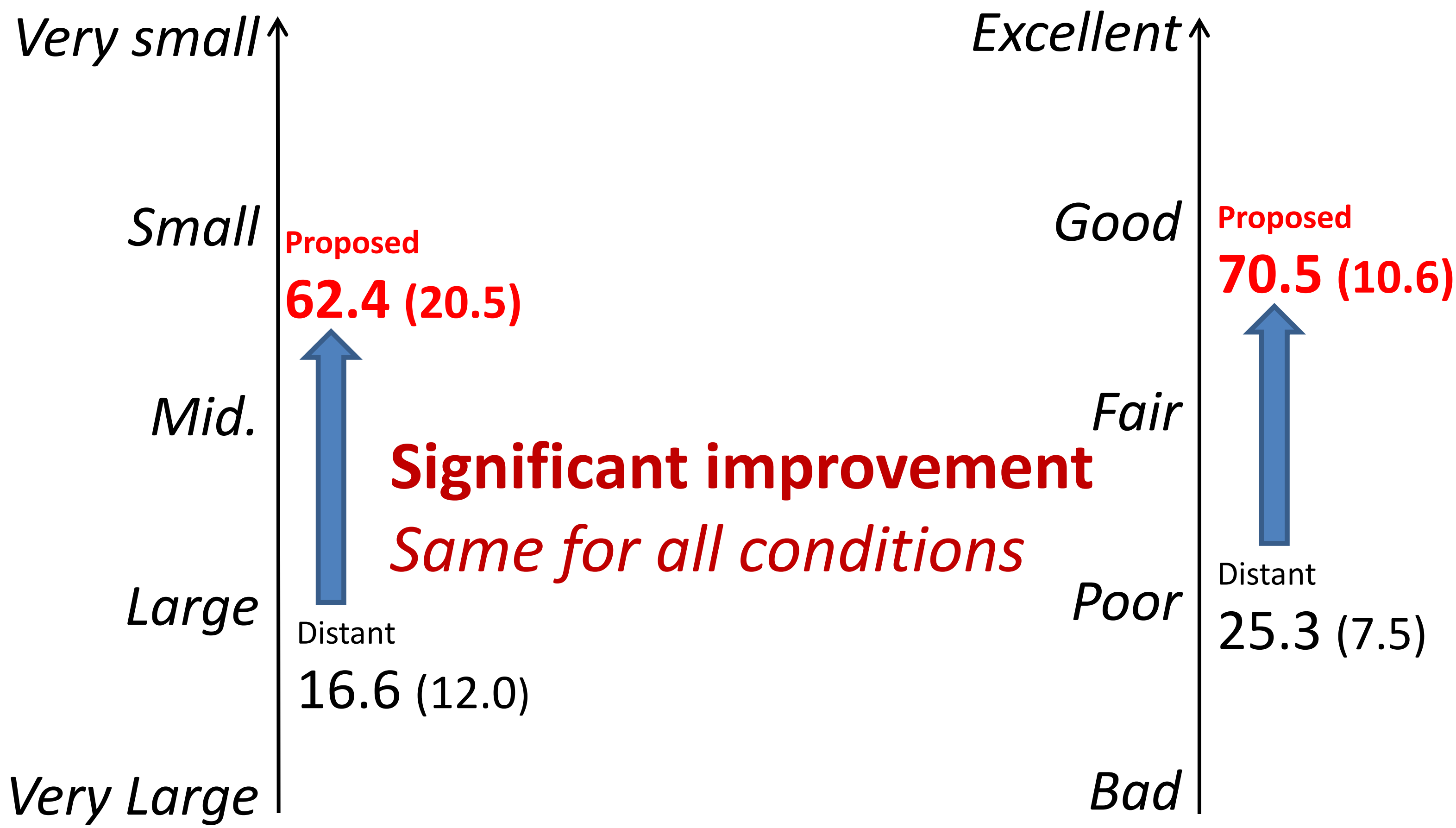
Consistent improvement

SE results: Subjective evaluation (Eval set)

For RealData (far) 8ch

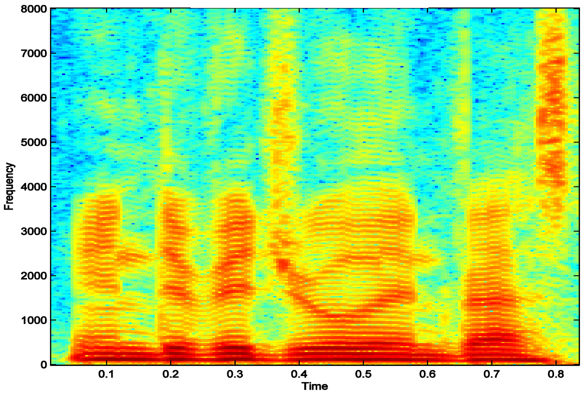
Perceived reverb.

Overall Quality

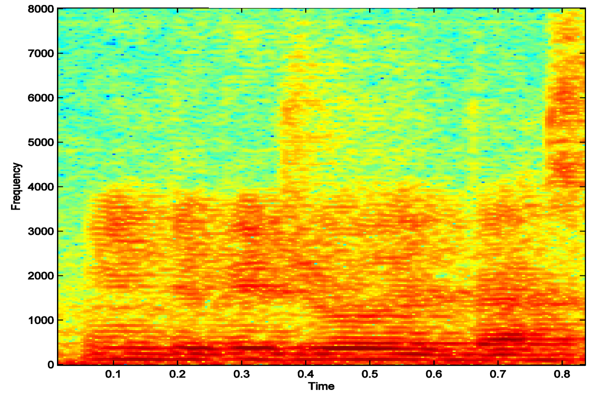


SE results: Spectrograms RealData (Eval)

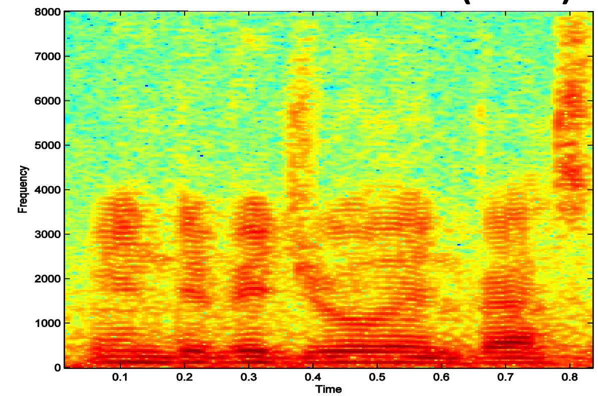
Headset



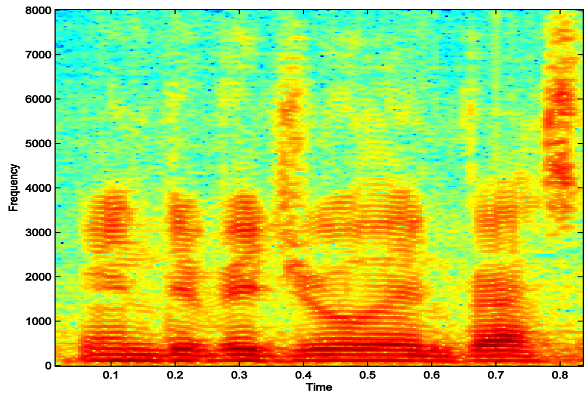
Distant



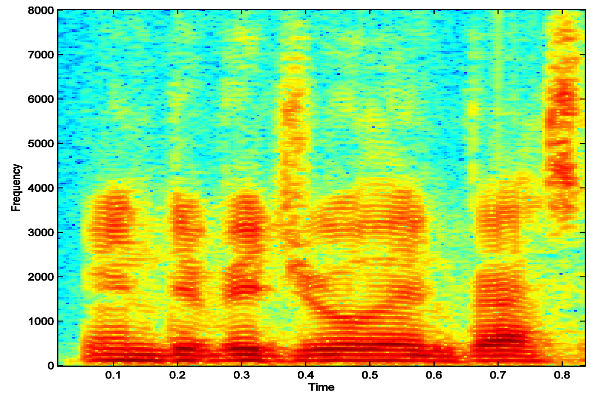
Dereverb. (8ch)



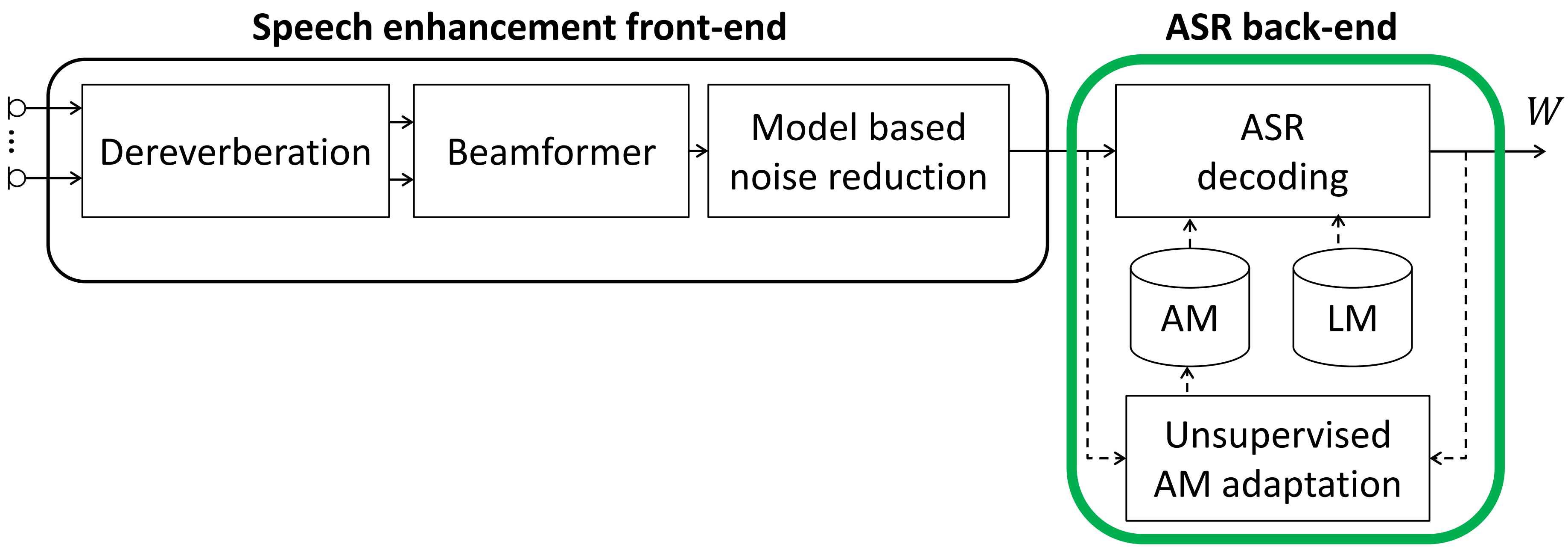
Dereverb.(8ch) + MVDR



Dereverb.(8ch) + MVDR + M-VTS



System overview



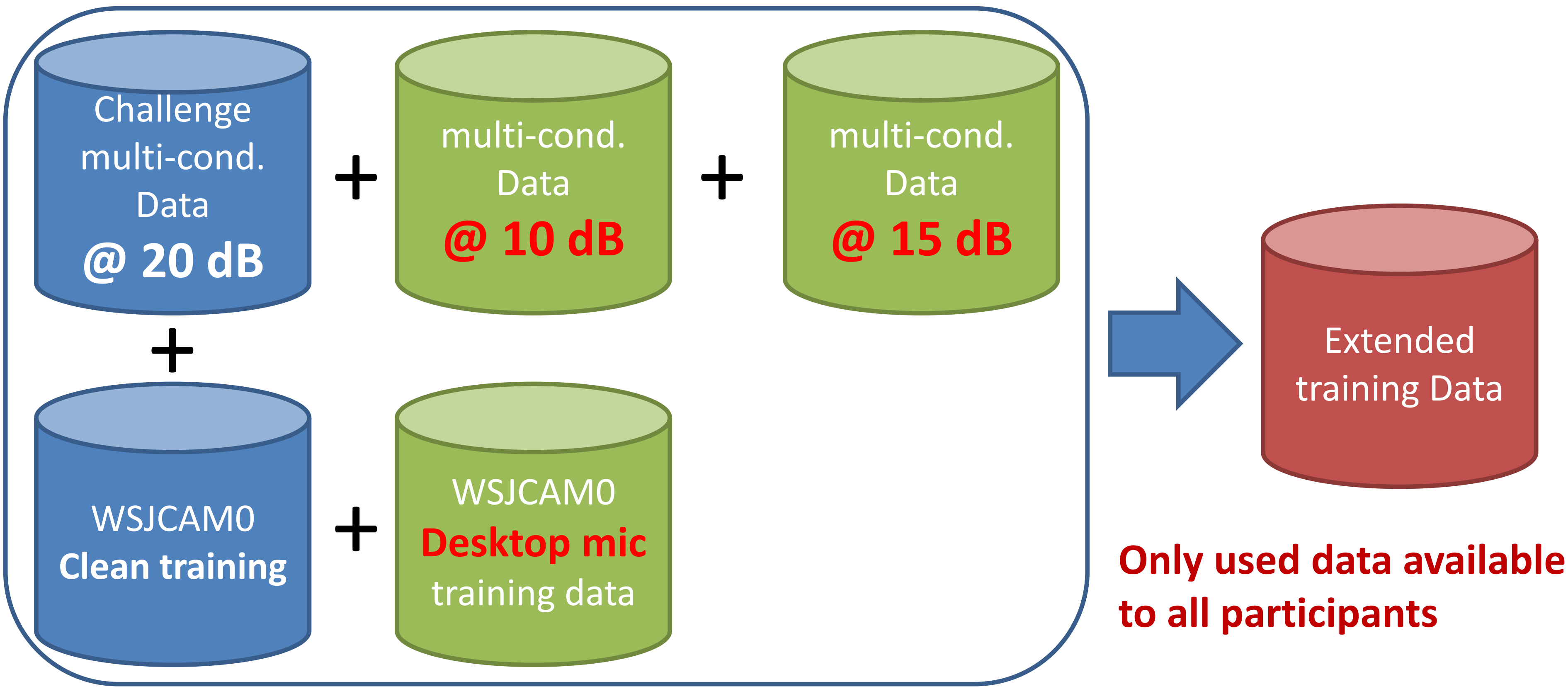
ASR back-end

- DNN-HMM based acoustic model
  - *layer-wise RBM pre-training + fine tuning w/ stochastic gradient descent*
  - *3129 HMM states/ State alignment from clean training data*
  - *7 hidden layers (2048 units)*
- Features
  - *40 Log mel filter-bank coefficients + Δ + $\Delta\Delta$ (120)*
  - *5 left+5 right context (11 frames)*
- Language model LM
  - *Trigram*
  - *RNN with fast decoding using on-the-fly rescoring [Hori, 2014]*
- Unsupervised environmental adaptation
  - *Retrain 1st layer of DNN-HMM w/ small learning rate using labels obtained from a 1st recognition pass*

Extended training data

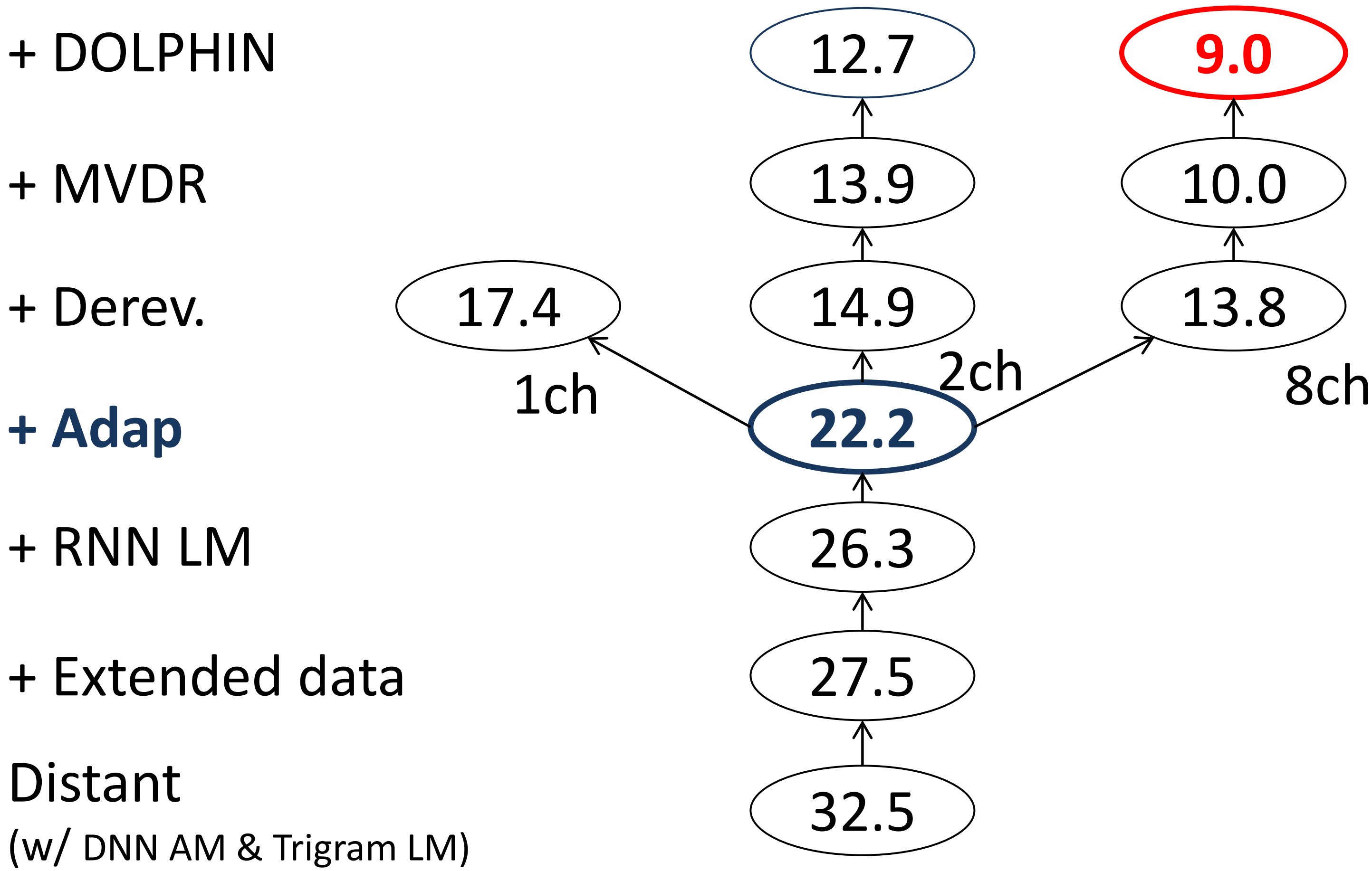
- Combat mismatch between training/SimData and RealData

→ Add acoustic variety during DNN training



Summary of ASR results (Eval)

	SimData							RealData		
	Room 1		Room 2		Room 3		**Ave.**	Room1		**Ave.**
	Near	Far	Near	Far	Near	Far		Near	Far	
w/o front-end	3.8	4.4	5.3	8.5	5.8	9.5	**6.2**	21.1	23.3	**22.2**
Best system (8ch)	3.7	4.0	4.0	4.5	4.4	4.8	**4.2**	8.8	9.3	**9.0**



For RealData

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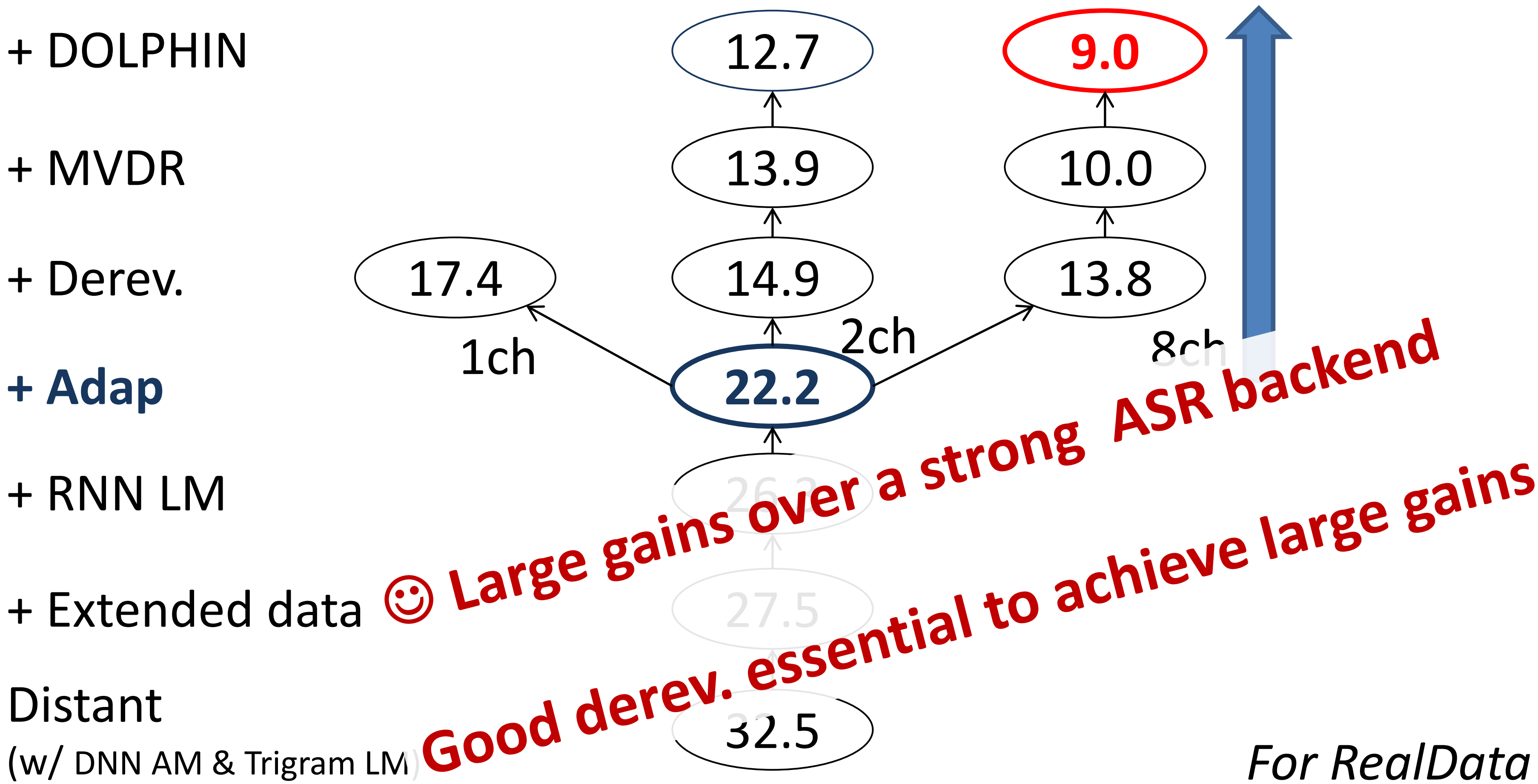

Conclusion

- Combined advanced SE and ASR techniques for reverberant speech
- Large performance improvement for both SE and ASR tasks

Where are we?

Proposed (1ch)	Proposed (2ch)	Proposed (8ch)	Lapel	Headset (MC-WSJ)	Clean (WSJCAM0)
17.4 %	**12.7 %**	**9.0 %**	8.3 %	**5.9 %**	3.6 %

Room for improvement for robust ASR

Non-environmental mismatch between SimData and RealData

Innovative R&D by NTT

Thank you!