Speaker Adapted Beamforming for Multi-Channel Automatic Speech Recognition

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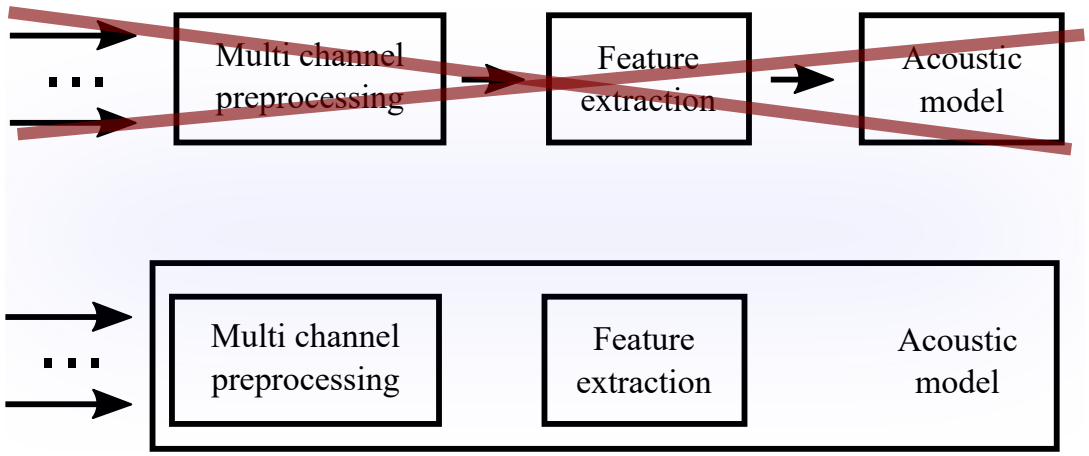
Content

- Introduction
- Mask based beamforming
- Integration into the acoustic model
- Speaker adaptation
- Results (on CHiME-4)

Motivation

- Integration of signal preprocessing into the acoustic model
- Joint optimization towards ASR objective
- Here:
  adjusting preprocessing to specific acoustic scenario (e.g. speaker of interest)



Previous Work

- Learning beamforming from the (raw) input signal
  [Sainath & Weiss$^+$ 15, Sainath & Weiss$^+$ 16, Li & Sainath$^+$ 16]

- Estimating the filter matrix of filter and sum beamforming
  [Xiao & Watanabe$^+$ 16, Meng & Watanabe$^+$ 17]

- Incorporation of statistically optimal beamforming into the acoustic model
  [Heymann & Durde$^+$ 17]

Mask based beamforming

Recorded noisy multi-channel signal:

$$\mathbf{Y}_{t,f} = \mathbf{X}_{t,f} + \mathbf{N}_{t,f} \tag{0.1}$$

$\mathbf{Y}_{t,f}, \mathbf{X}_{t,f}, \mathbf{N}_{t,f} \in \mathbb{C}^M$

t - time frame index

f - frequency bin index

M - nr of microphones

Mask based beamforming

Recorded noisy multi-channel signal:

$$\mathbf{Y}_{t,f} = \mathbf{X}_{t,f} + \mathbf{N}_{t,f} \tag{0.2}$$

$\mathbf{Y}_{t,f}, \mathbf{X}_{t,f}, \mathbf{N}_{t,f} \in \mathbb{C}^M$

t - time frame index

f - frequency bin index

M - nr of microphones

Filter and sum beamforming:

$$\hat{S}_{t,f} = \mathbf{w}_f^H \cdot \mathbf{Y}_{t,f} \tag{0.3}$$

$\hat{S}_{t,f} \in \mathbb{C}$ - estimate of the speech component

$\mathbf{w}_f \in \mathbb{C}^M$ - beamforming vector

Mask based beamforming

Beamforming vector by speech and noise mask:

$$\mathbf{w}_f^H = g(\lambda_{t,f}^{(X)}, \lambda_{t,f}^{(N)}, \mathbf{Y}_{\cdot,f}) \tag{0.4}$$

$\lambda^{(\nu)} = f_\Theta^{(\nu)}(\mathbf{Y})$ - Mask estimated by neural network

Mask based beamforming

Beamforming vector by speech and noise mask:

$$\mathbf{w}_f^H = g(\lambda_{t,f}^{(X)}, \lambda_{t,f}^{(N)}, \mathbf{Y}_{\cdot,f}) \tag{0.5}$$

$\lambda^{(\nu)} = f_\Theta^{(\nu)}(\mathbf{Y})$ - Mask estimated by neural network

GEV Beamformer

$\mathbf{w}_f^{(\mathrm{GEV})} = \mathcal{P}(\mathbf{\Phi}_{NN,f}^{-1}\mathbf{\Phi}_{XX,f})$

[Warsitz & Haeb-Umach 07]

MVDR Beamformer

$\mathbf{w}_f^{(\mathrm{MVDR})} = \mathcal{P}(\mathbf{\Phi}_{XX,f})$

[Higuchi & Ito$^+$ 16]

Mask based beamforming

Beamforming vector by speech and noise mask:

$$\mathbf{w}_f^H = g(\lambda_{t,f}^{(X)}, \lambda_{t,f}^{(N)}, \mathbf{Y}_{\cdot,f}) \tag{0.6}$$

$\lambda^{(\nu)} = f_\Theta^{(\nu)}(\mathbf{Y})$ - Mask estimated by neural network

GEV Beamformer

$\mathbf{w}_f^{(\mathrm{GEV})} = \mathcal{P}(\mathbf{\Phi}_{NN,f}^{-1}\mathbf{\Phi}_{XX,f})$

[Warsitz & Haeb-Umach 07]

MVDR Beamformer

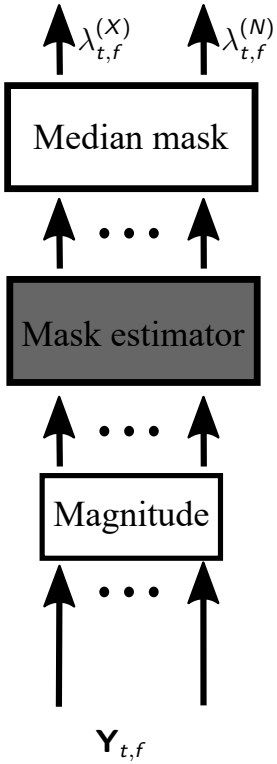
$\mathbf{w}_f^{(\mathrm{MVDR})} = \mathcal{P}(\mathbf{\Phi}_{XX,f})$

[Higuchi & Ito$^+$ 16]

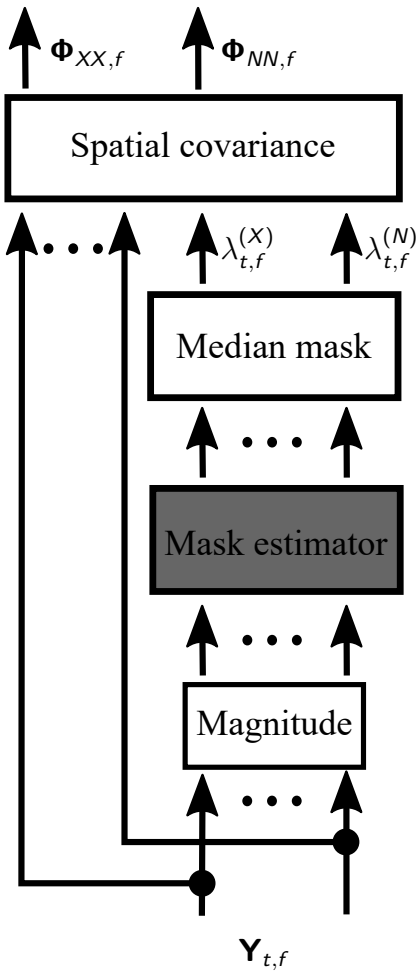
$\mathcal{P}(\cdot)$ - Principal eigenvector

$$\mathbf{\Phi}_{\nu\nu,f} = \frac{1}{\sum_{t=1}^{T} \lambda_{t,f}^{(\nu)}} \sum_{t=1}^{T} \lambda_{t,f}^{(\nu)} \mathbf{Y}_{t,f}\mathbf{Y}_{t,f}^H \tag{0.7}$$

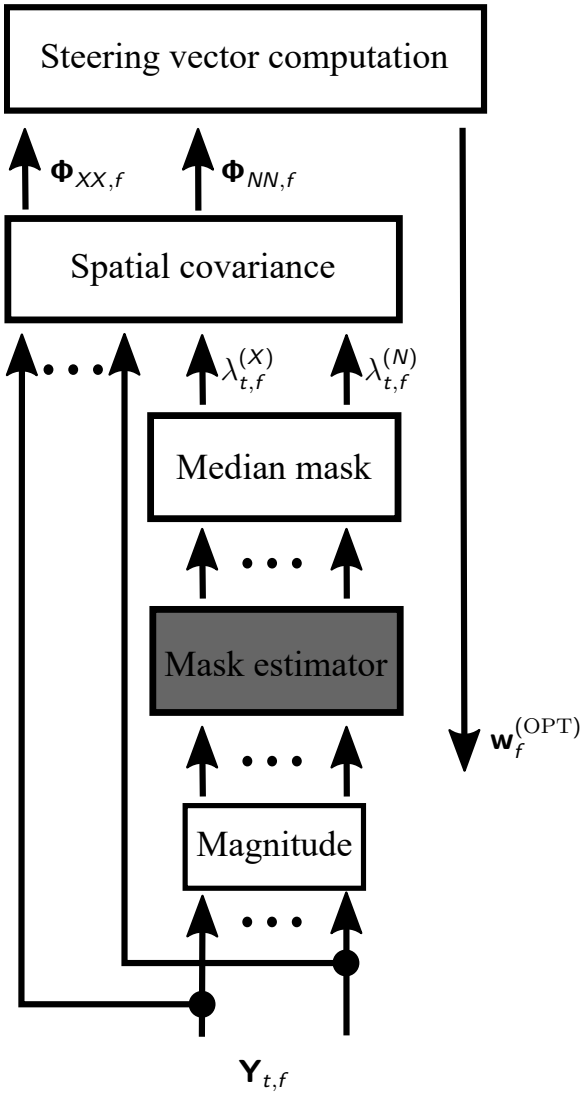
Integration



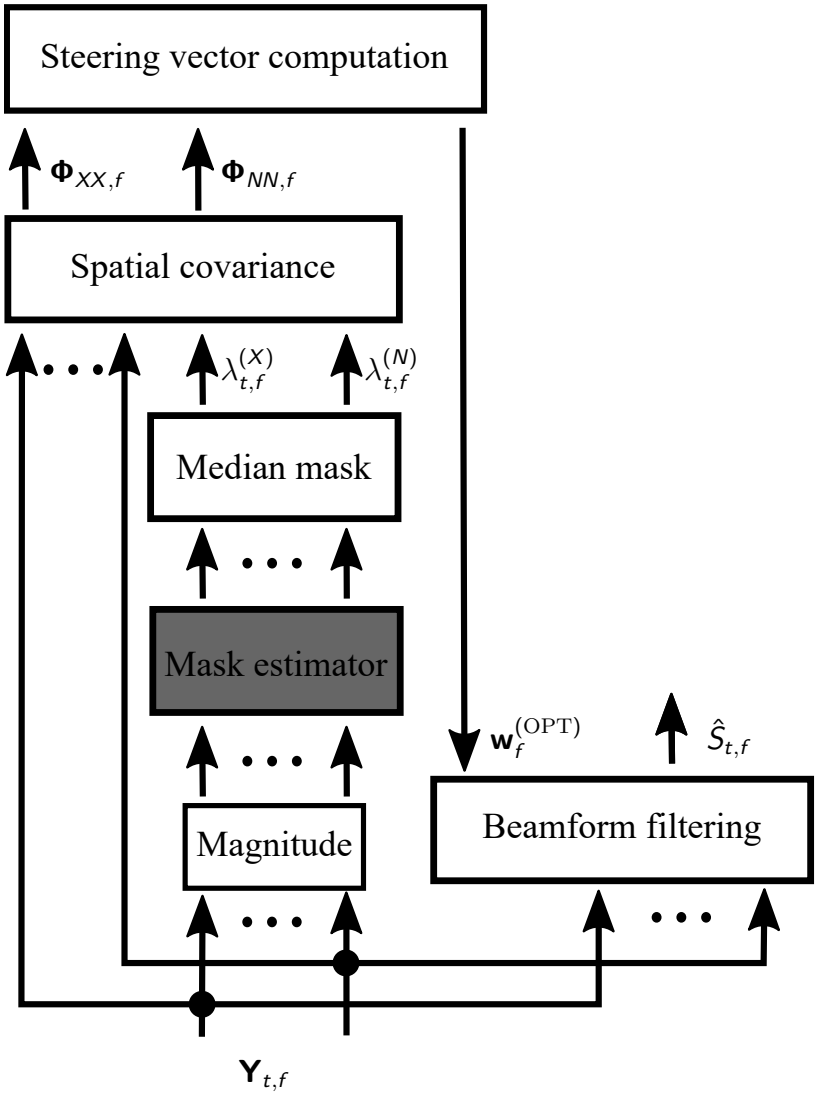
Integration



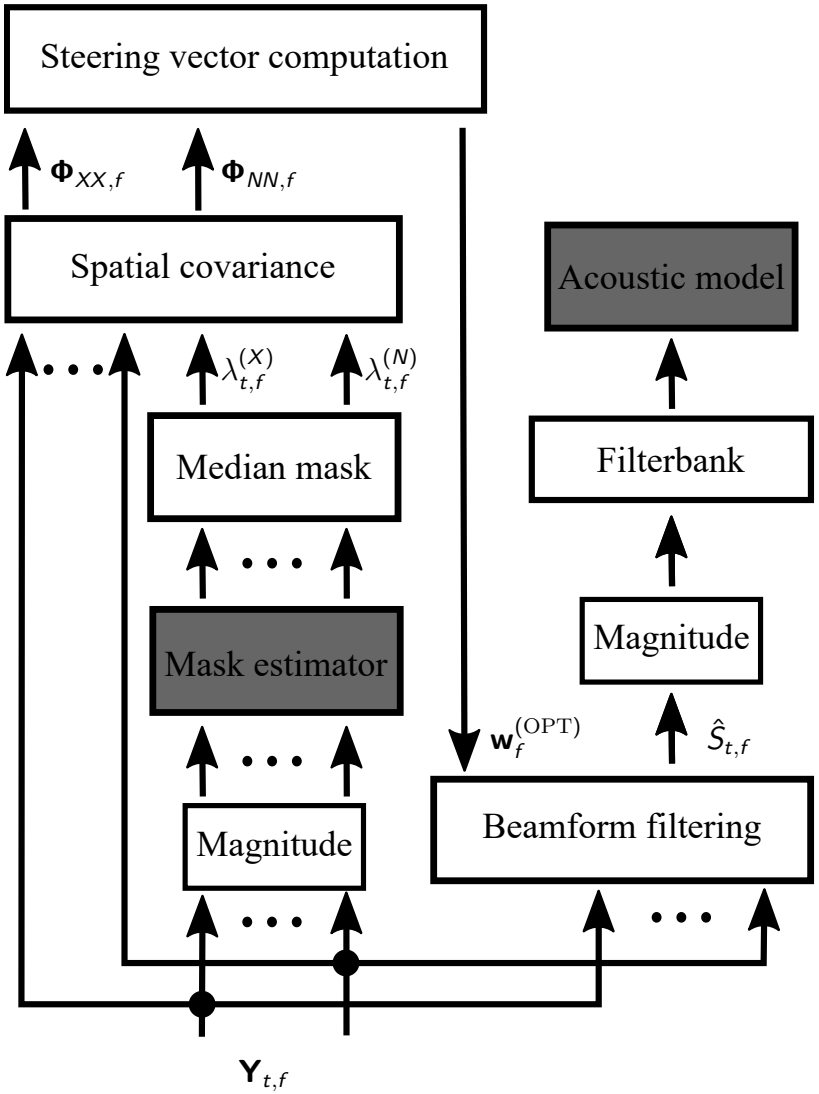
Integration



Integration



Integration



QR algorithm

[Francis 61]

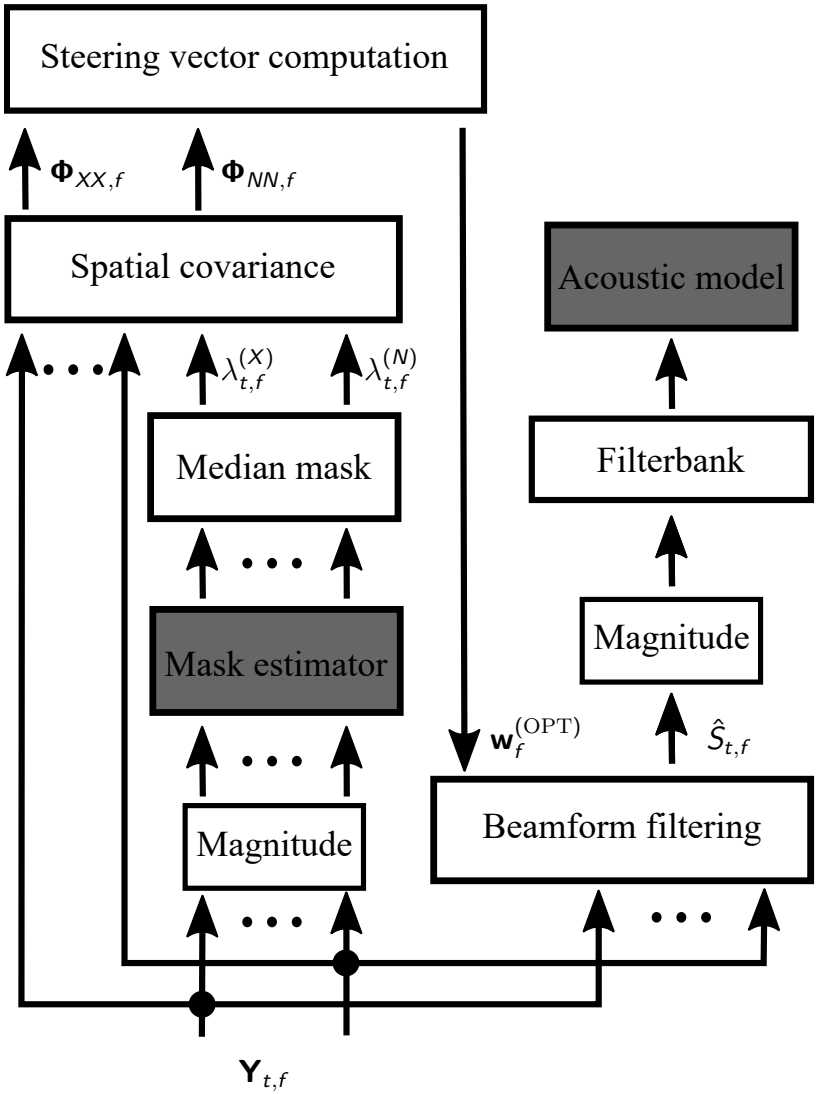
Objective: compute $\mathcal{P}(A_0)$

1. QR-decomposition of $A_k = Q_k R_k$
2. set $A_{k+1} = R_k Q_k$

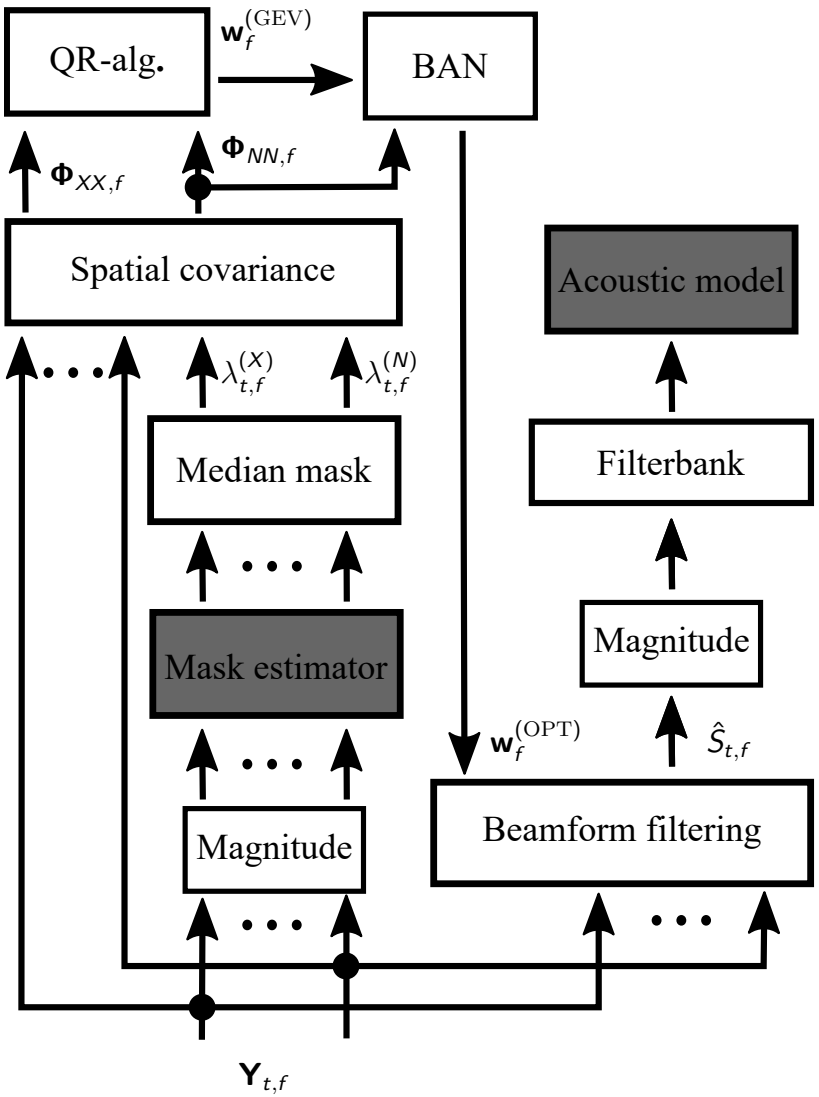
For $K \to \infty$ the diagonal of A_K contains eigenvalues of A_0
With $\prod_{k=0}^{K} Q_k$ containing the respective eigenvectors

QR-decomposition is differentiable as shown in [Walter & Lehmann$^+$ 12].

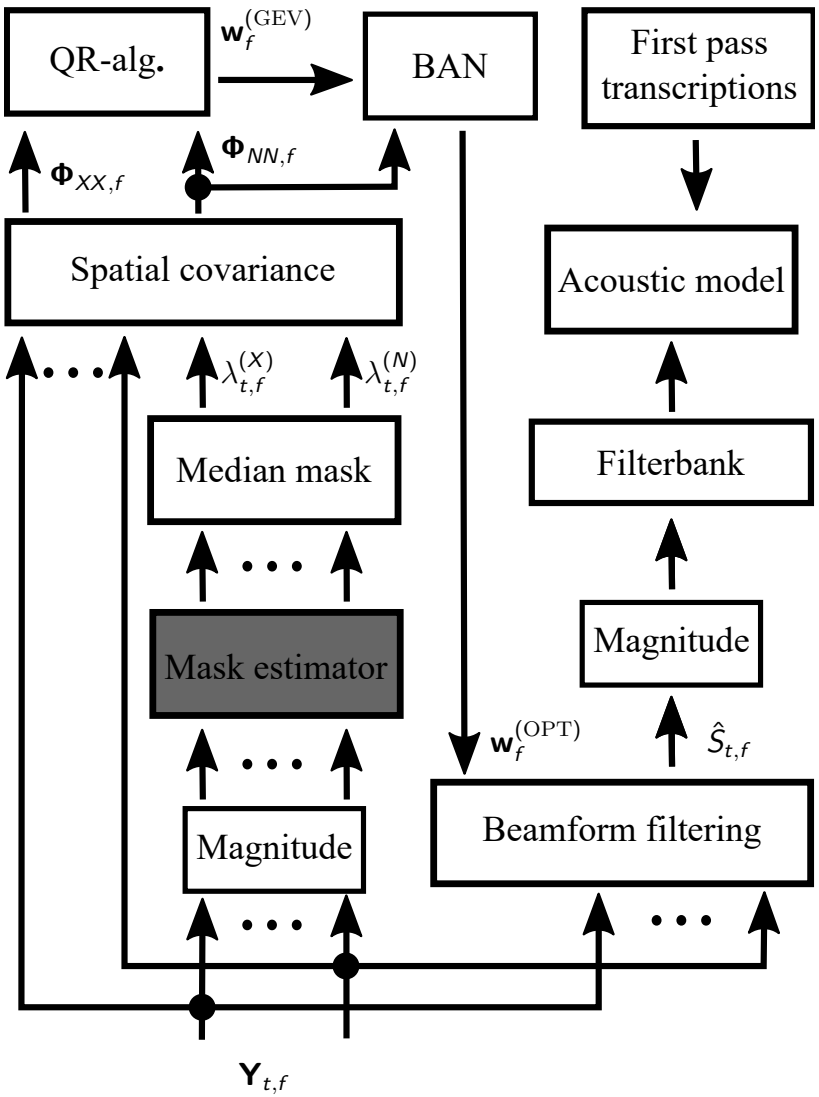
Integration



Integration



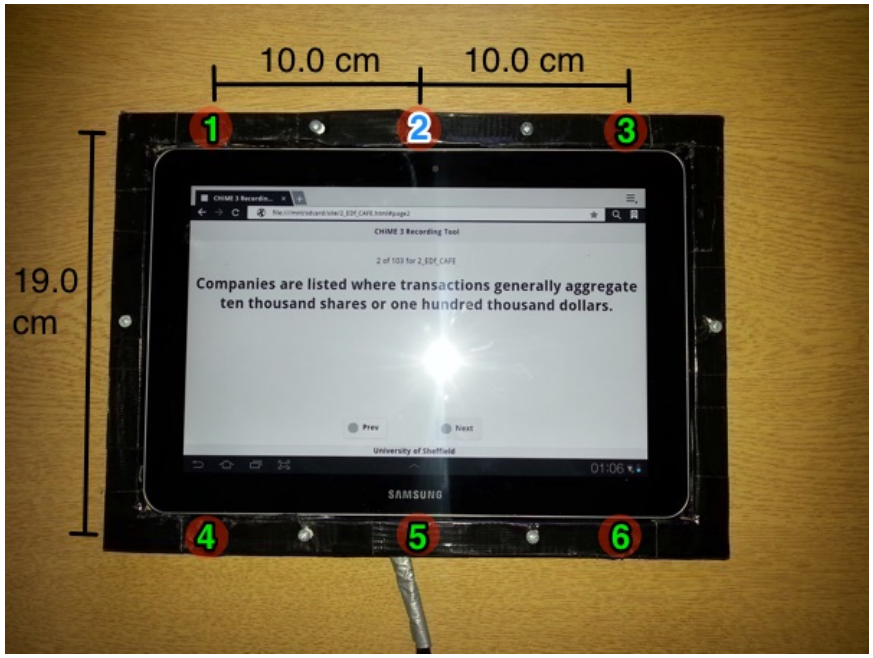
Speaker adaptation



CHiME-4 dataset

- 18 h of simulated and real 6-channel data (87 speakers)
- recorded with handheld device
- noise scenarios: caffee, bus, pedestrian area, street junction

Set	female	male	time (h) per speaker
Dev	2	2	0.7
Eval	2	2	0.5



System

Mask estimator

- 1 BLSTM (256 units)A
- 2 fully connected ReLU (512 units)
- 5 iterations of QR-algorithm
- hyper parameters of speaker adaptation tuned on dev set

Acoustic model

- unnormalized 80 dimensional log mel filterbank features
- linear layer (80 units) with batch normalization
- 5 BLSTM layers (600 units each)

System performance at different training stages

Average WER (%) for the described systems for different stages of the integrated training.

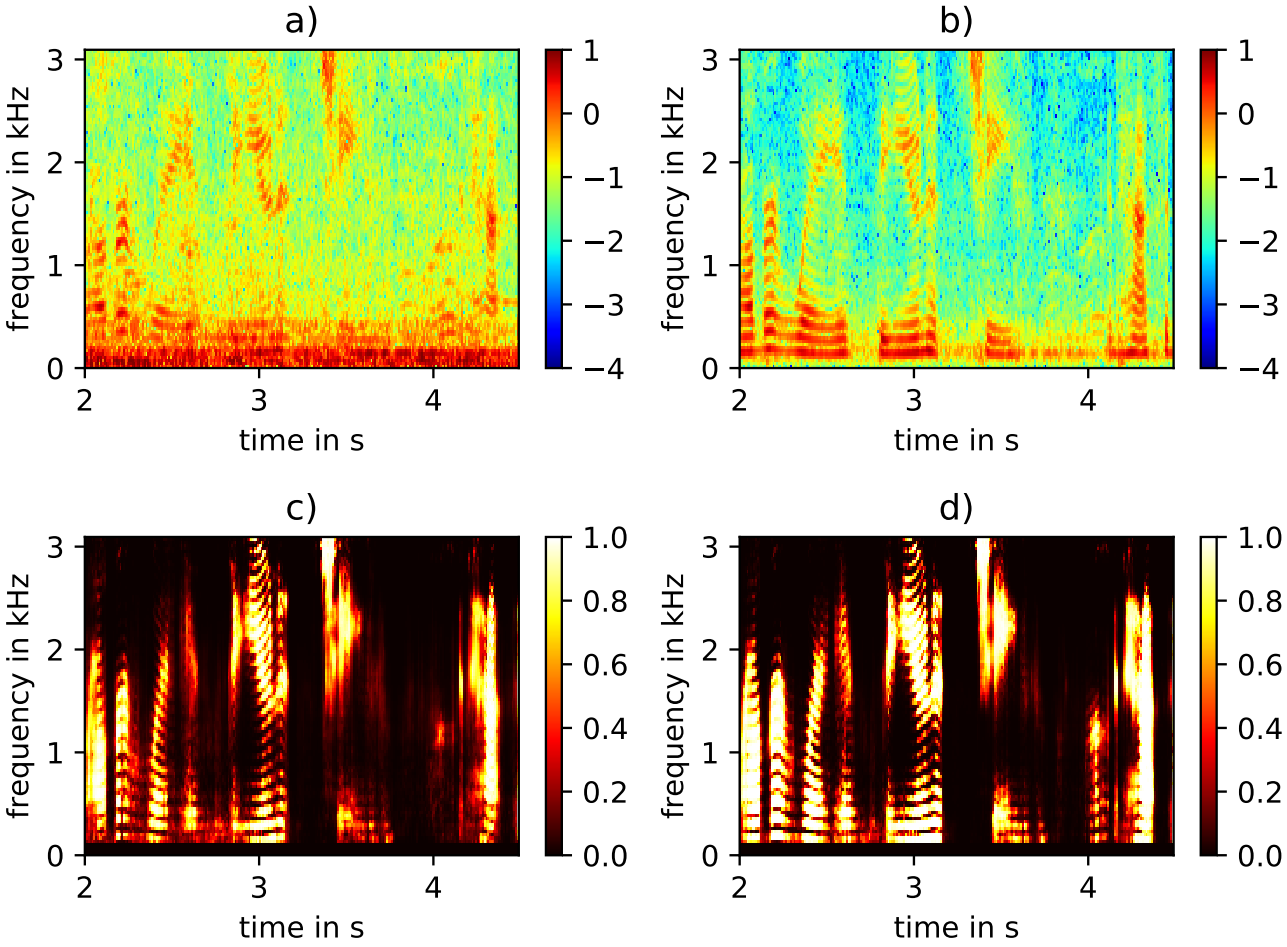
System				Dev	Eval
System id	Front-end	Joint training	Speaker adapted		
0	BFIT	-	-	4.36	7.17
1	GEV			3.46	5.18
2		+		3.32	4.84
3			+	**3.09**	**4.58**

Speaker specific performance

WER (%) of separate speakers for the jointly trained system and the speaker adapted system

System id	Dev				Eval			
	F01	F04	M03	M04	F05	F06	M05	M06
2	4.19	3.23	2.77	**3.07**	6.88	**4.09**	3.83	4.58
3	**3.55**	**3.20**	**2.48**	3.14	**6.35**	**4.09**	**3.38**	**4.48**

Mask estimations



Conclusion

- Joint optimization of preprocessing and acoustic modeling is beneficial
- Speaker adaptation of mask estimator for beamforming can be beneficial depending on target speaker
- Adaptation does not decrease performance otherwise
- Masks after adaptation show stronger emphasis of speakers fundamental frequency and harmonics

Thank you for your attention

Any questions?

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