Binaural Extension and Performance of Single-Channel Spectral Subtraction Dereverberation Algorithms

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WHY?

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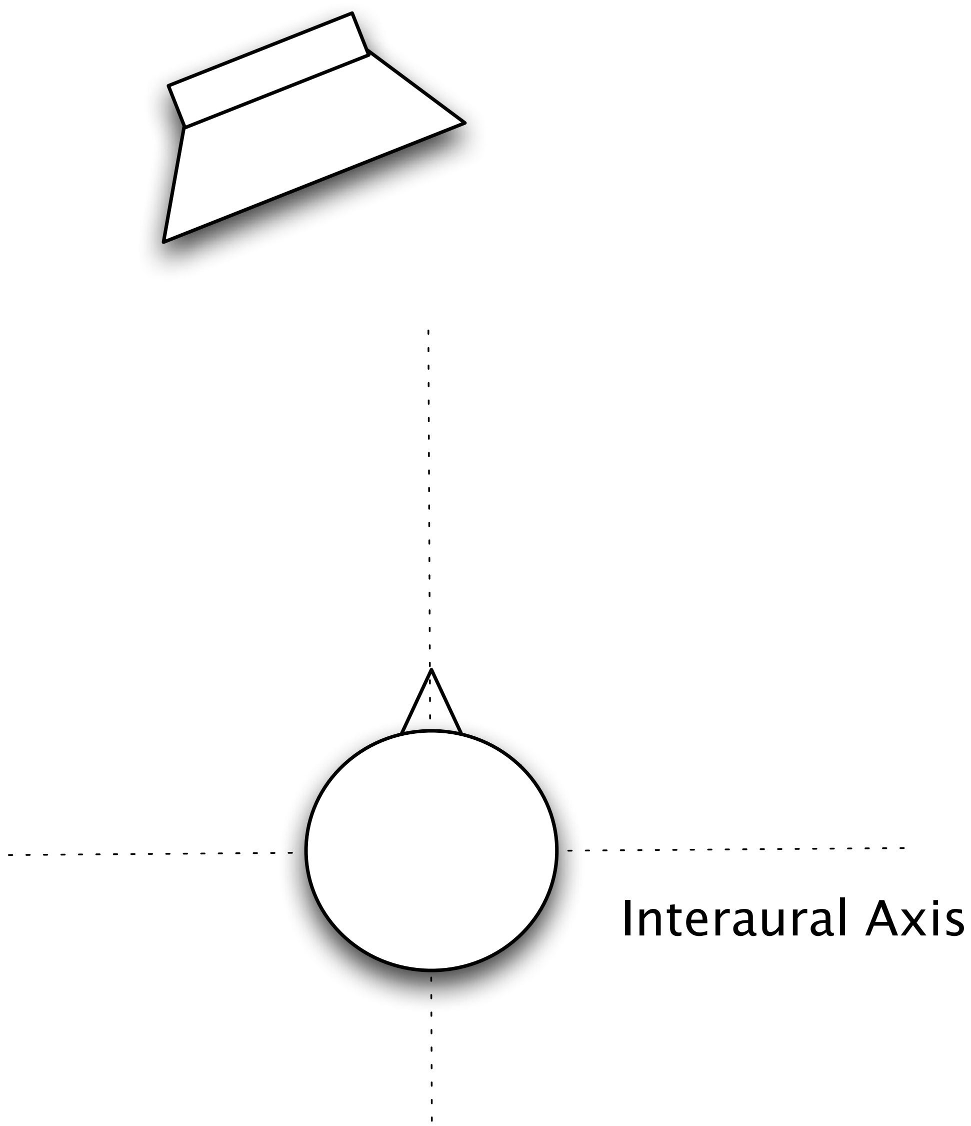
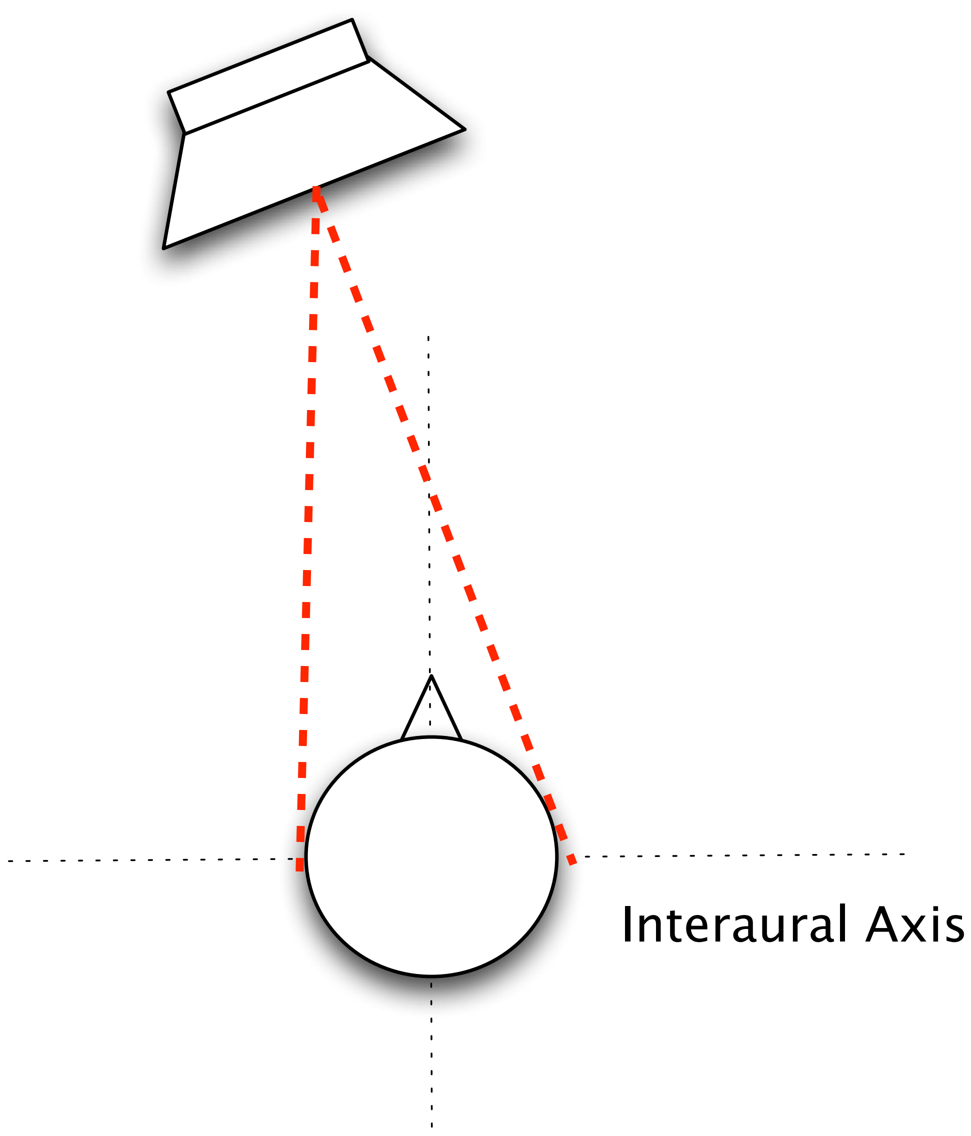
WHY?



WHY?



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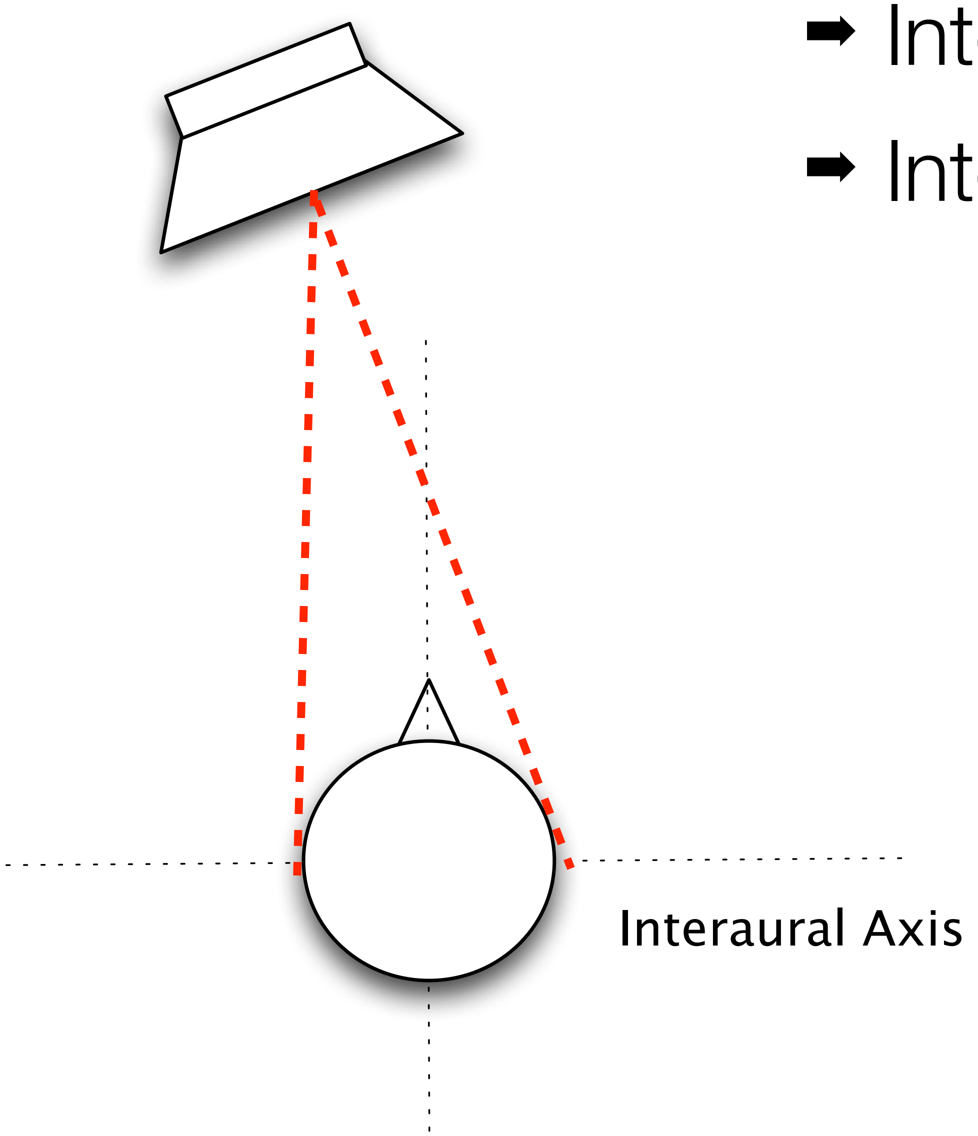
WHY?

Binaural Cues



- ➡ Interaural Time Difference (ILD)
- ➡ Interaural Level Difference (ITD)

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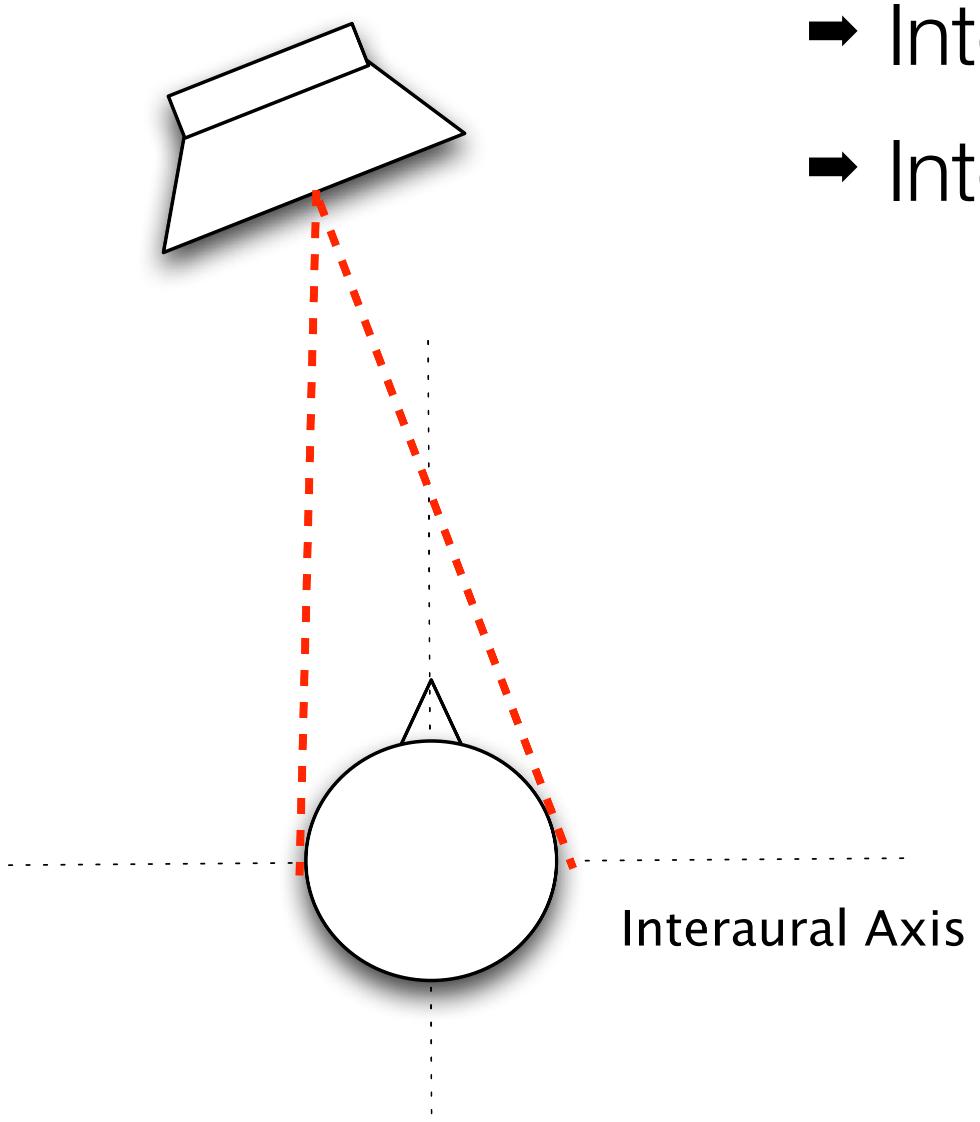
WHY?



Binaural Cues

- ➡ Interaural Time Difference (ILD)
- ➡ Interaural Level Difference (ITD)

Applied in:

- Hearing Aids
- Binaural Telephony
- Hands-Free Devices
- Immersive Audio Applications

HOW?

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Improved single-channel spectral subtraction dereverberation

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Dereverberation based on perceptual reverberation modeling

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Semi Blind Dereverberation based on a handclap recording

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Extend single-channel dereverberation techniques

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- ✓ Implement an efficient way to prevent overestimation errors

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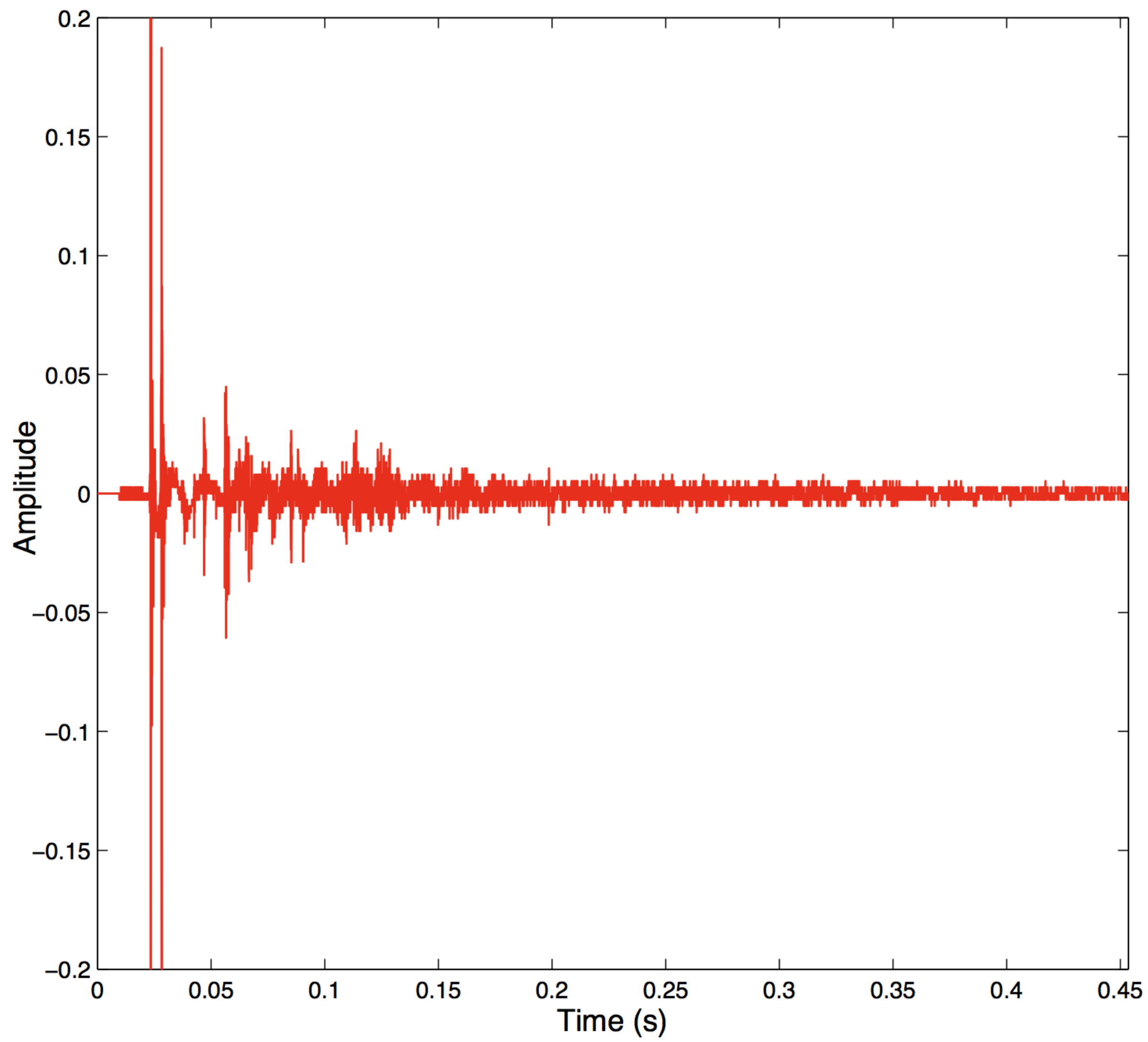
- ✓ Propose a simple framework for the extension of single channel spectral subtraction dereverberation algorithms
- ✓ Implement an efficient way to prevent overestimation errors
- ✓ Evaluate the proposed framework in state-of-the-art spectral subtraction dereverberation techniques

Spectral Subtraction

Spectral Subtraction

✓ originally proposed for denoising applications

Spectral Subtraction



for denoising applications

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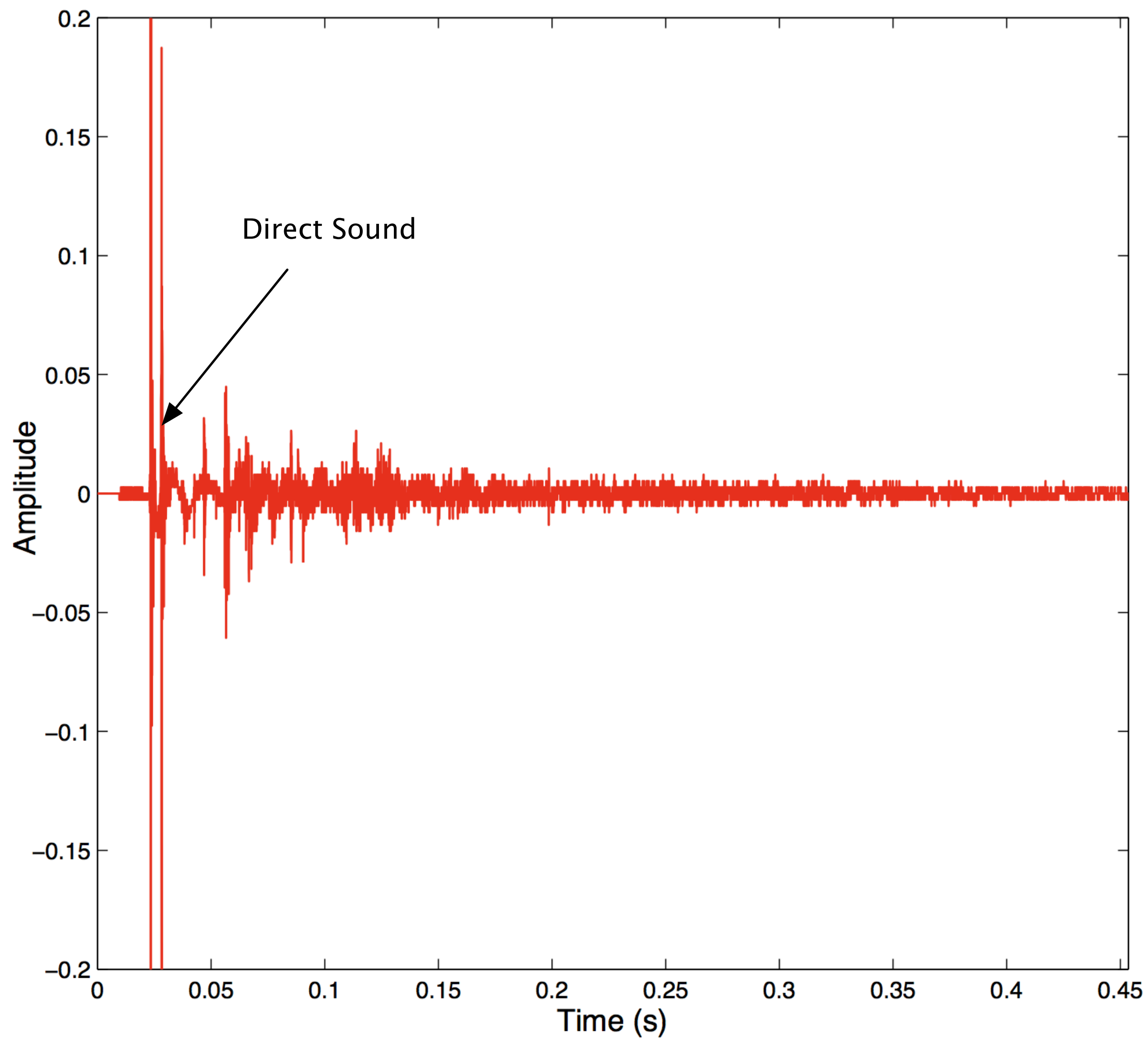

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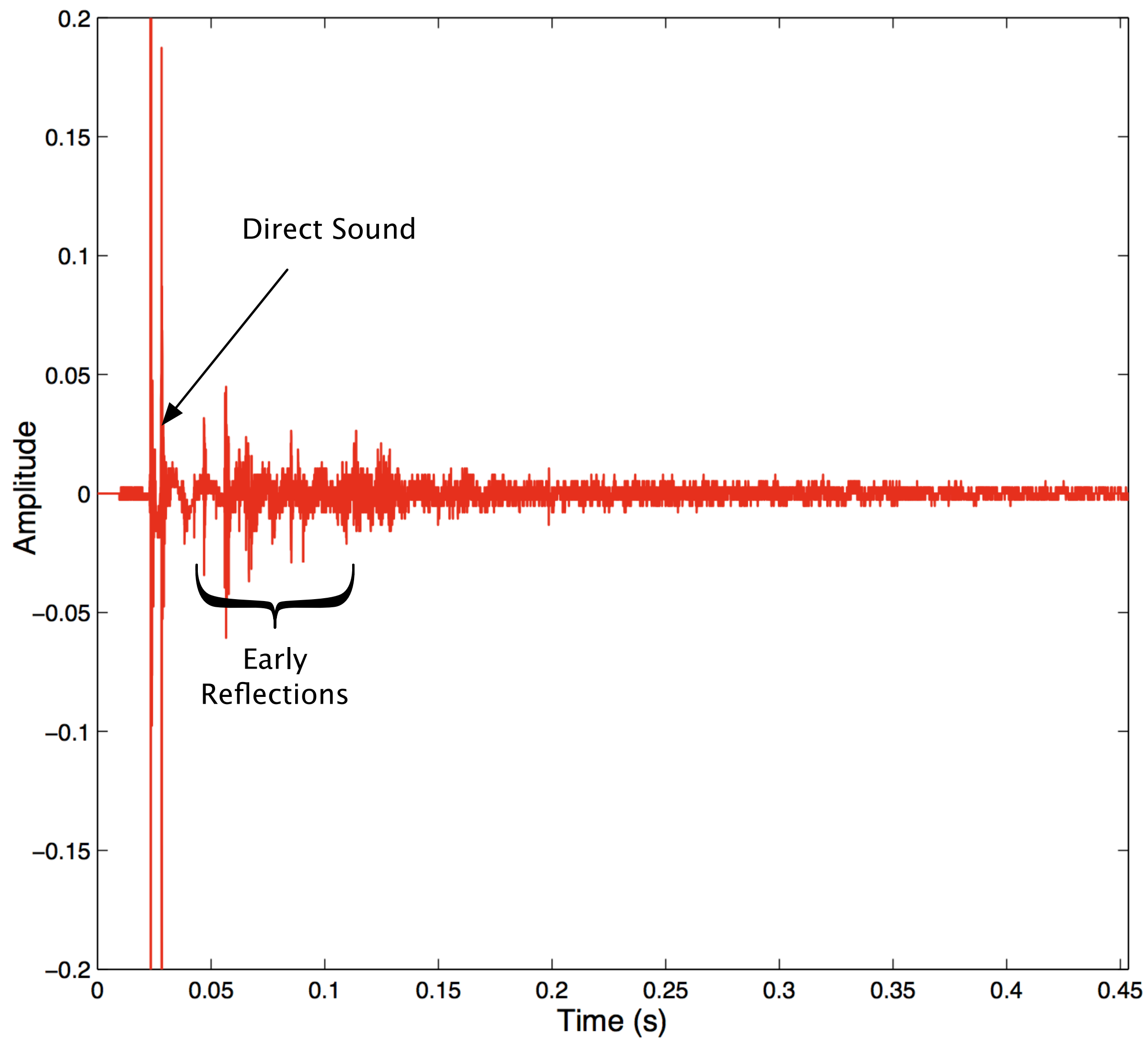

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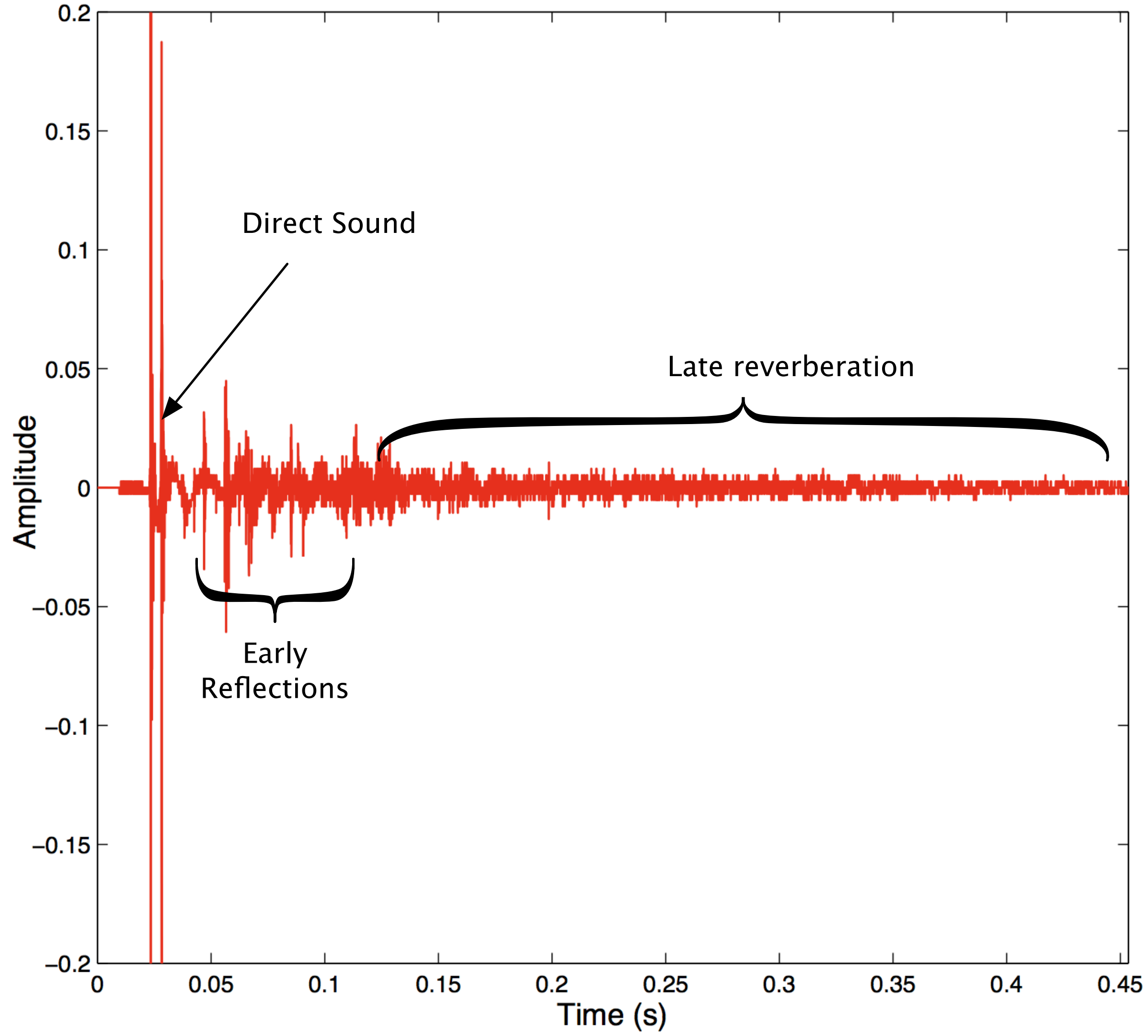

for denoising applications

Spectral Subtraction

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Spectral Subtraction

$$\underbrace{S_e(\omega, j)}_{} = Y(\omega, j) - R(\omega, j)$$

Frequency bin (ω) Time frame (j)

✓ originally proposed for denoising applications

Spectral Subtraction

Anechoic
Estimation

$$\boxed{S_e(\omega, j)} = Y(\omega, j) - R(\omega, j)$$

Frequency bin Time frame

✓ originally proposed for denoising applications

Spectral Subtraction

Anechoic Estimation

Reverberant Signal

$$\underbrace{S_e(\omega, j)}_{} = \boxed{Y(\omega, j)} - R(\omega, j)$$

Frequency bin

Time frame

✓ originally proposed for denoising applications

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Spectral Subtraction

Anechoic Estimation — Reverberant Signal — Late Reverberation Estimation

$$\underbrace{S_e(\omega, j)}_{\text{Anechoic Estimation}} = \underbrace{Y(\omega, j)}_{\text{Reverberant Signal}} - \underbrace{\boxed{R(\omega, j)}}_{\text{Late Reverberation Estimation}}$$

ω: Frequency bin

j: Time frame

✓ originally proposed for denoising applications

Spectral Subtraction

Late Reverberation
Estimation

$$R(\omega, j)$$

Spectral Subtraction

Late Reverberation Estimation

$$R(\omega, j) \rightarrow \text{Signal Statistics}$$

- M Wu and D Wang. A two-stage algorithm for one-microphone reverberant speech enhancement. IEEE Transactions on Audio, Speech and Language Processing, 14:774–784, 2006. **(WW)**
- K Furuya and A Kataoka. Robust speech dereverberation using multichannel blind deconvolution with spectral subtraction. IEEE Transactions on Audio, Speech and Language Processing, 15:1571–1579, 2007. **(FK)**

Spectral Subtraction

Late Reverberation Estimation

$$R(\omega, j)$$

Signal Statistics

Reverberation Characteristics

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$$S_e(\omega, j) = Y(\omega, j) - R_{late}(\omega, j)$$

$$S_e(\omega, j) = G(\omega, j)Y(\omega, j)$$

Gain Function: $$G(\omega, j) = \frac{Y(\omega, j) - R(\omega, j)}{Y(\omega, j)}$$

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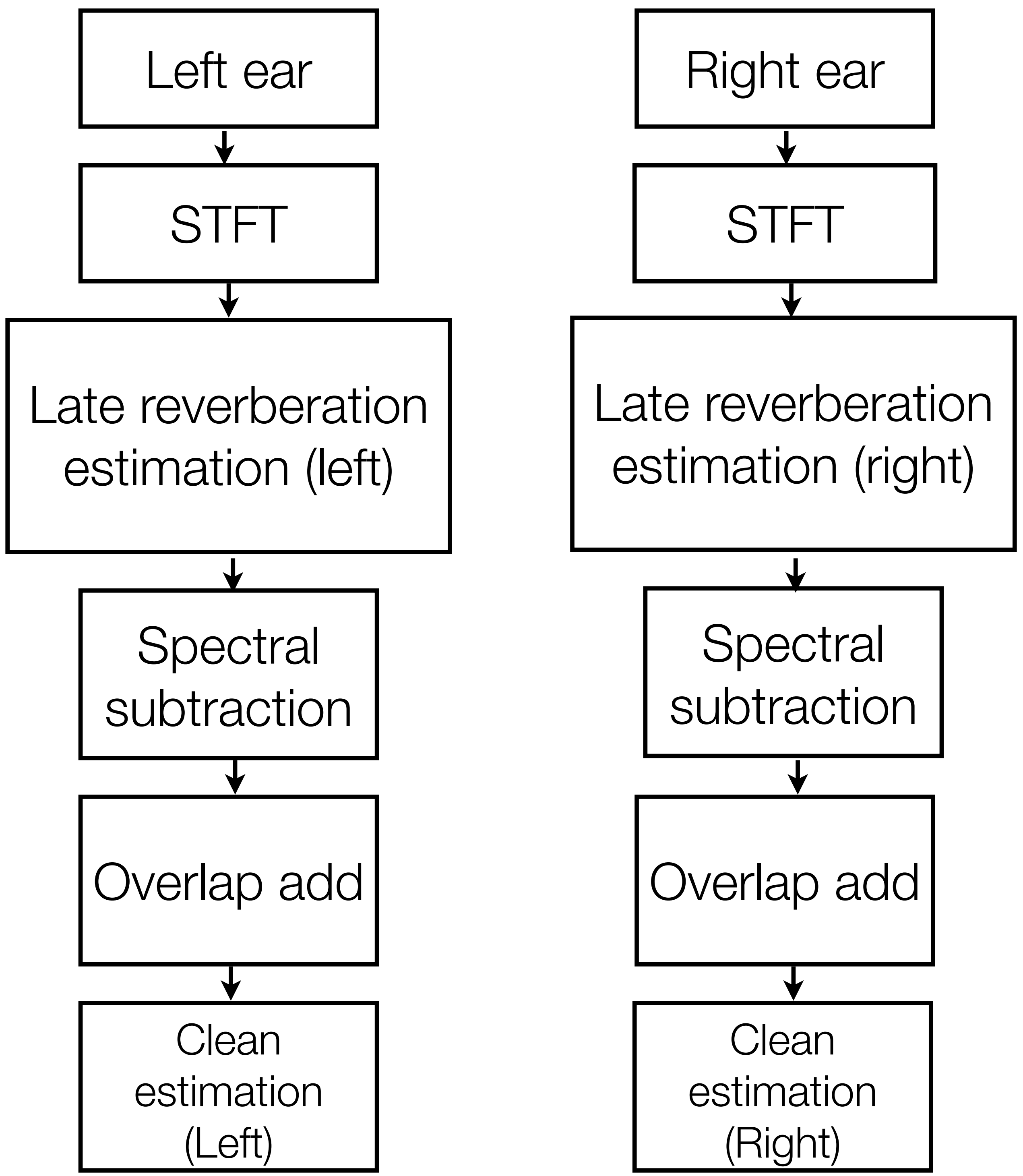
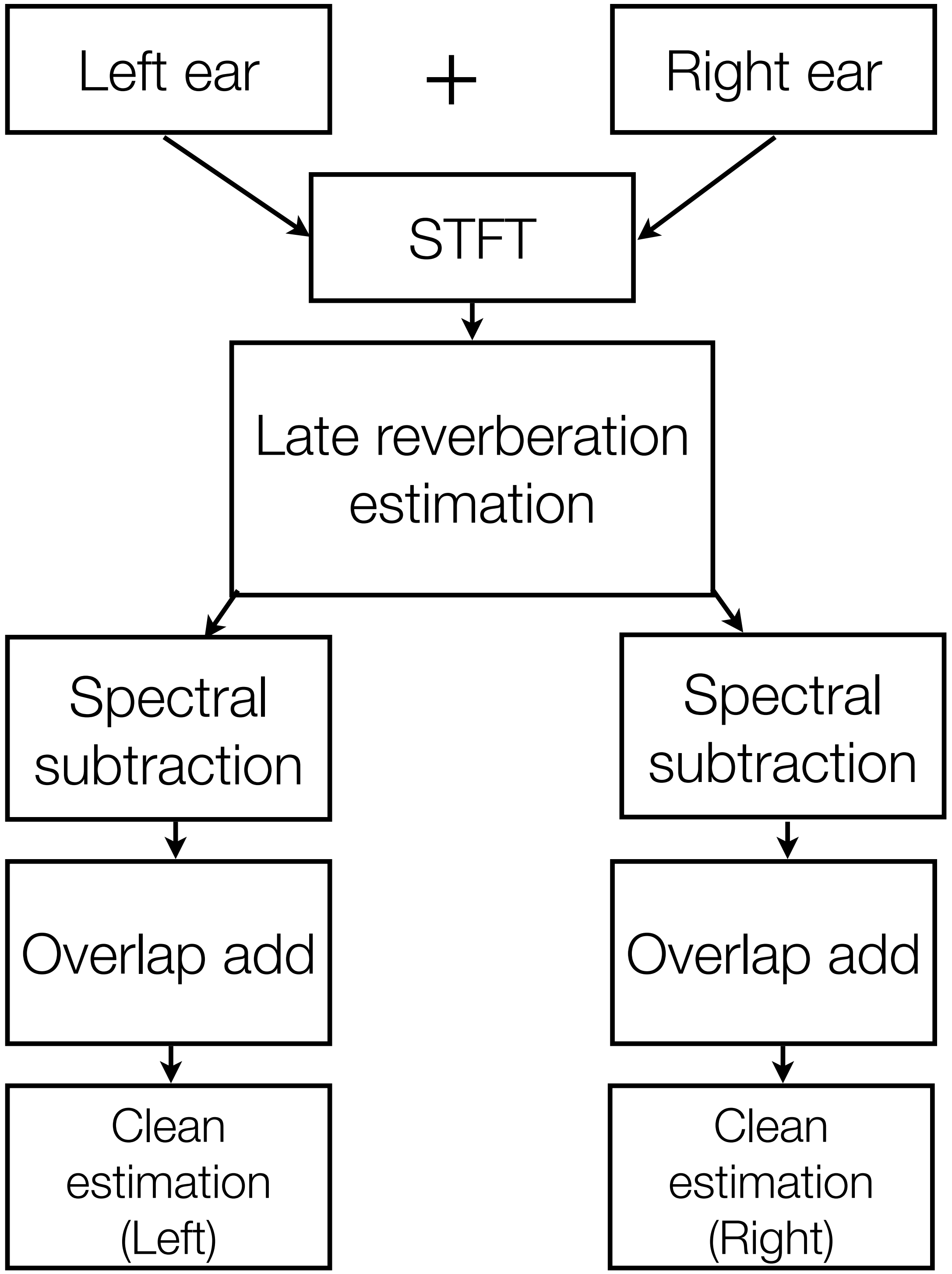


Spectral Subtraction

Bilateral signal processing <u>destroys</u> binaural cues !



Spectral Subtraction

Bilateral signal processing destroys binaural cues !

↓

Spectral Subtraction extension based on a Delay and Sum Beamformer (DSB)

M Jeub, M Schafer, T Esch, and P Vary. *Model-Based Dereverberation Preserving Binaural Cues.* IEEE Transactions on Audio, Speech, and Language Processing, 18:1732–1745, 2010

Here:

- ✓ Relative delay **<** typical analysis windows (depends on the width of the human head)
- ✓ Binaural extension of single-channel spectral subtraction dereverberation based on Bilateral Gain Adaptation

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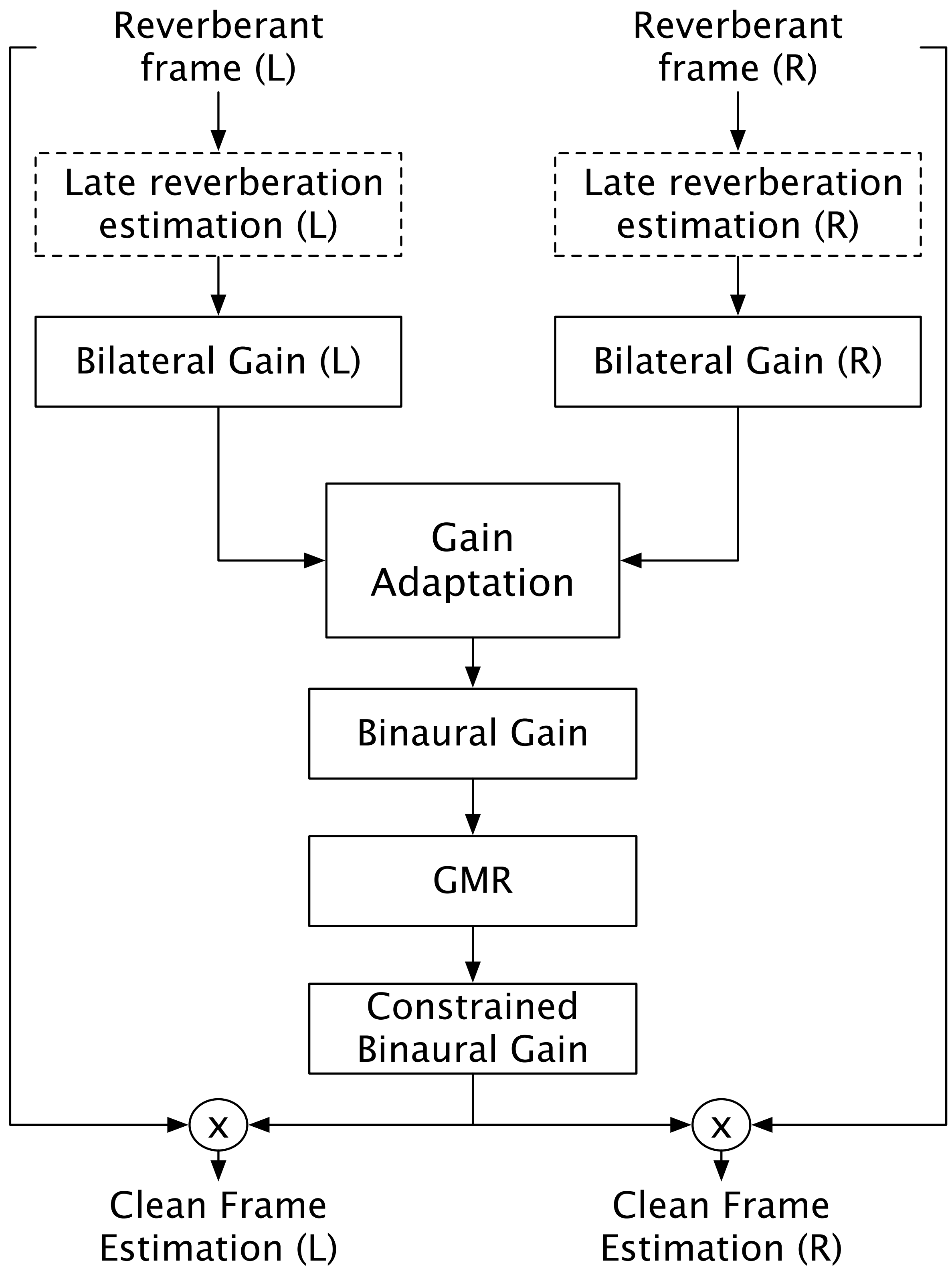
Signal Flow



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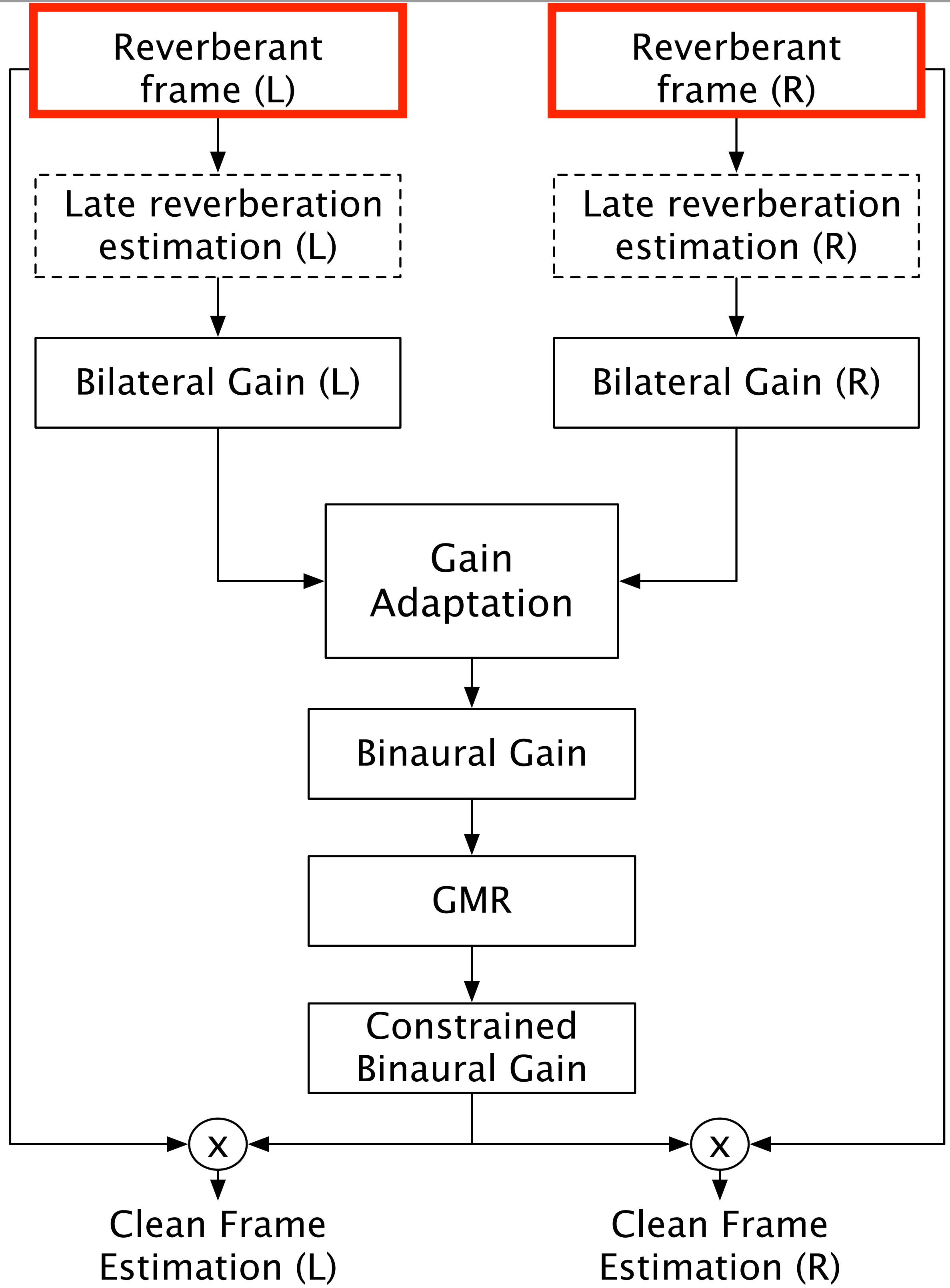

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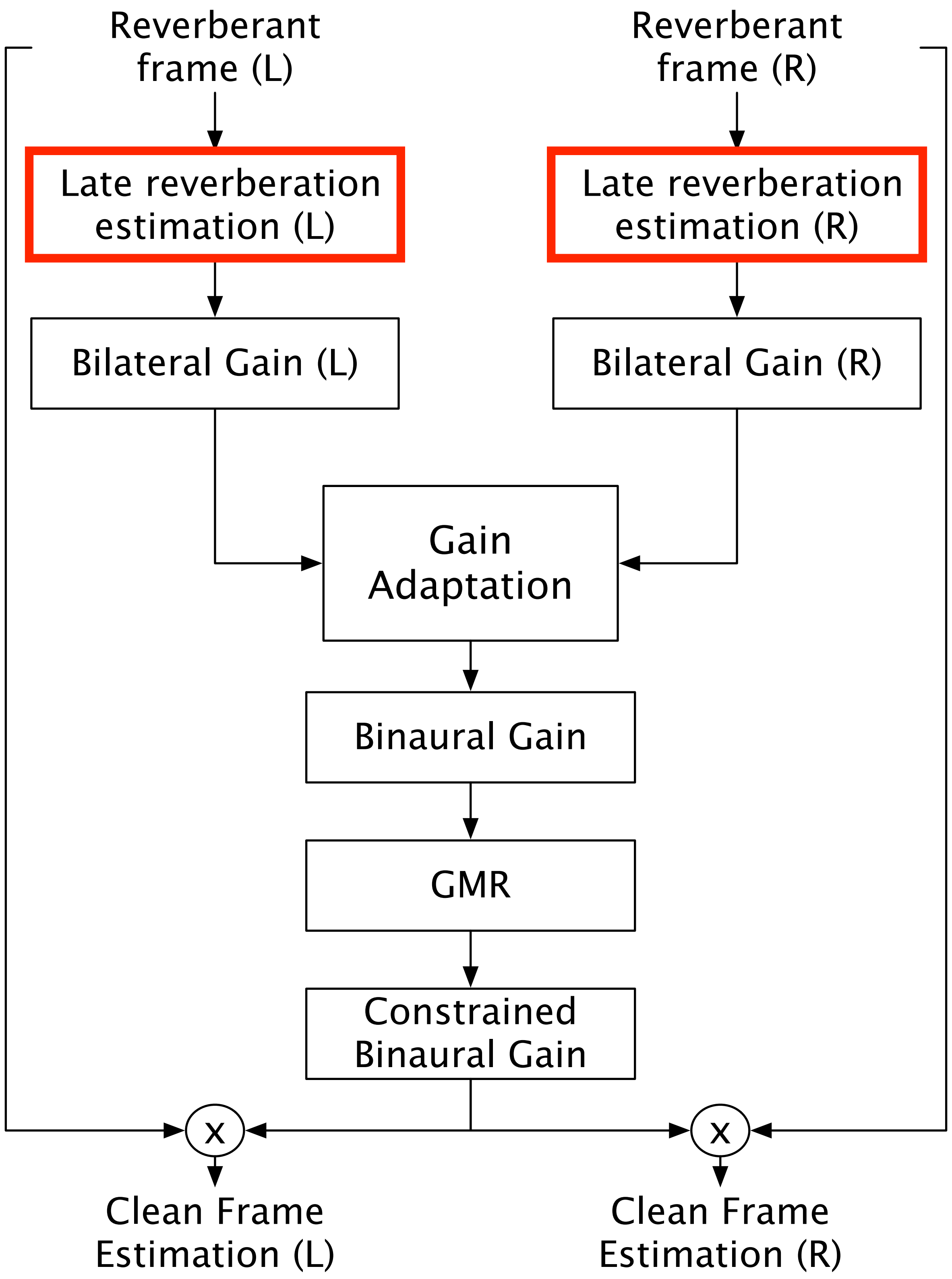

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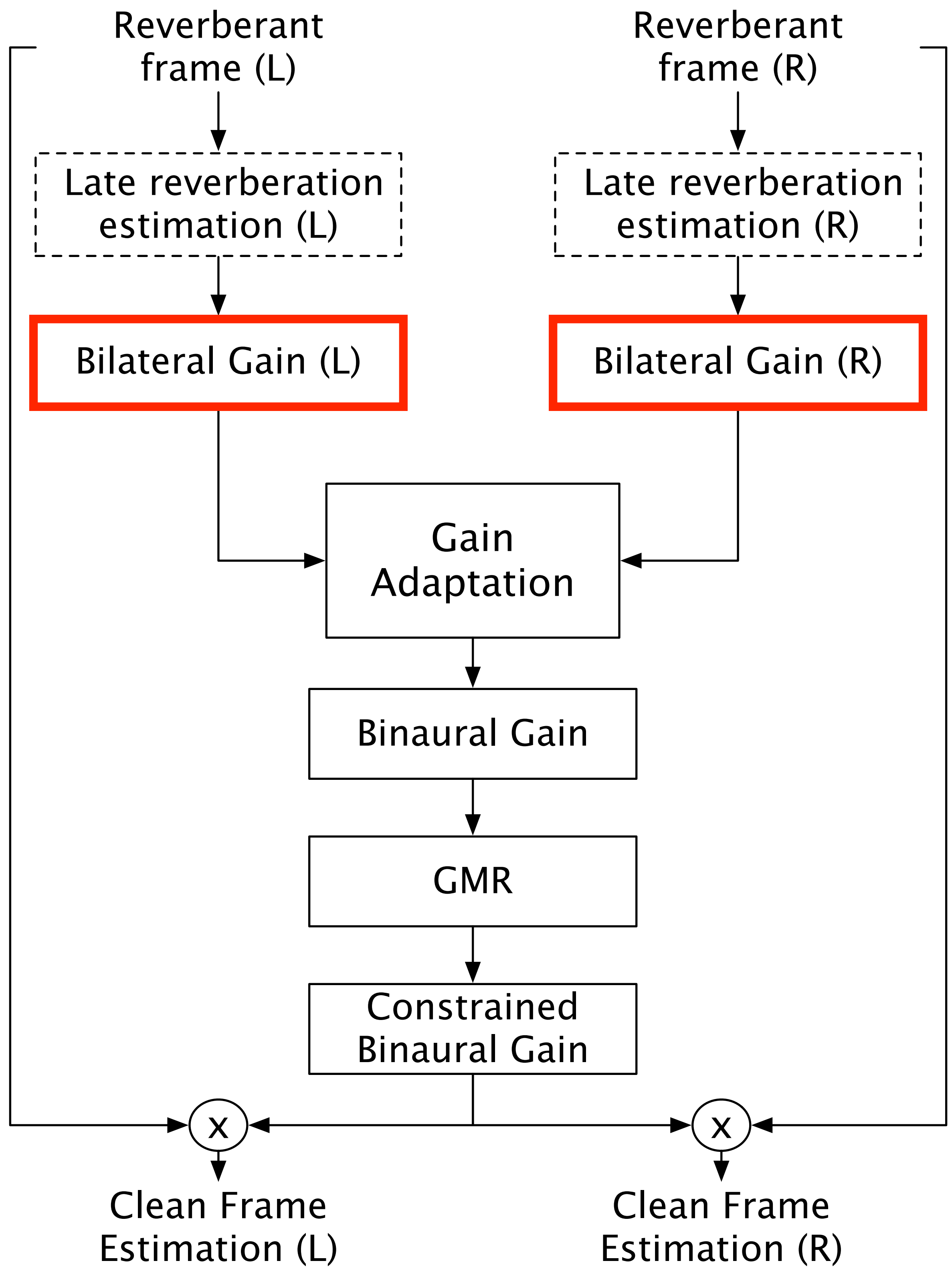

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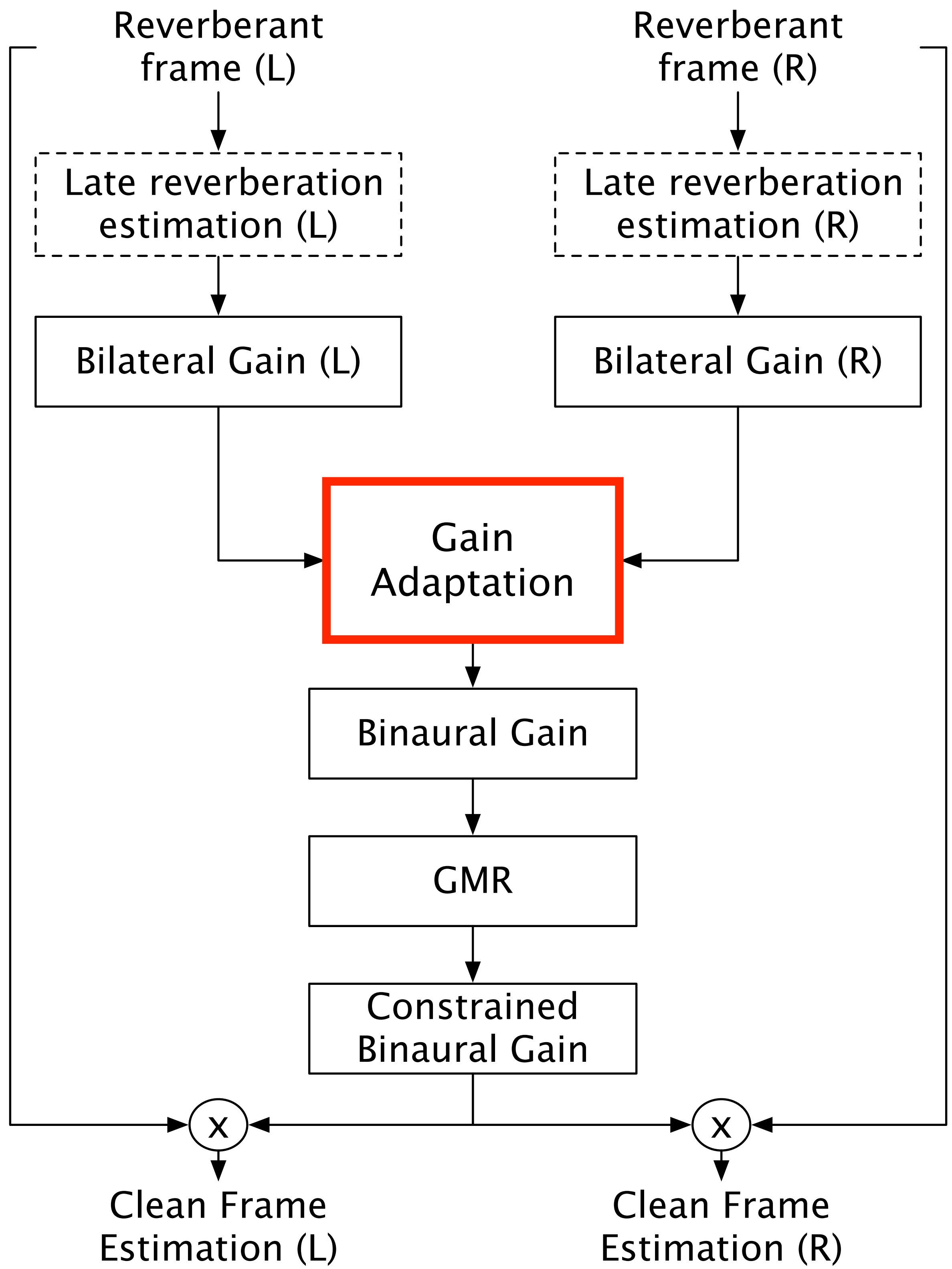

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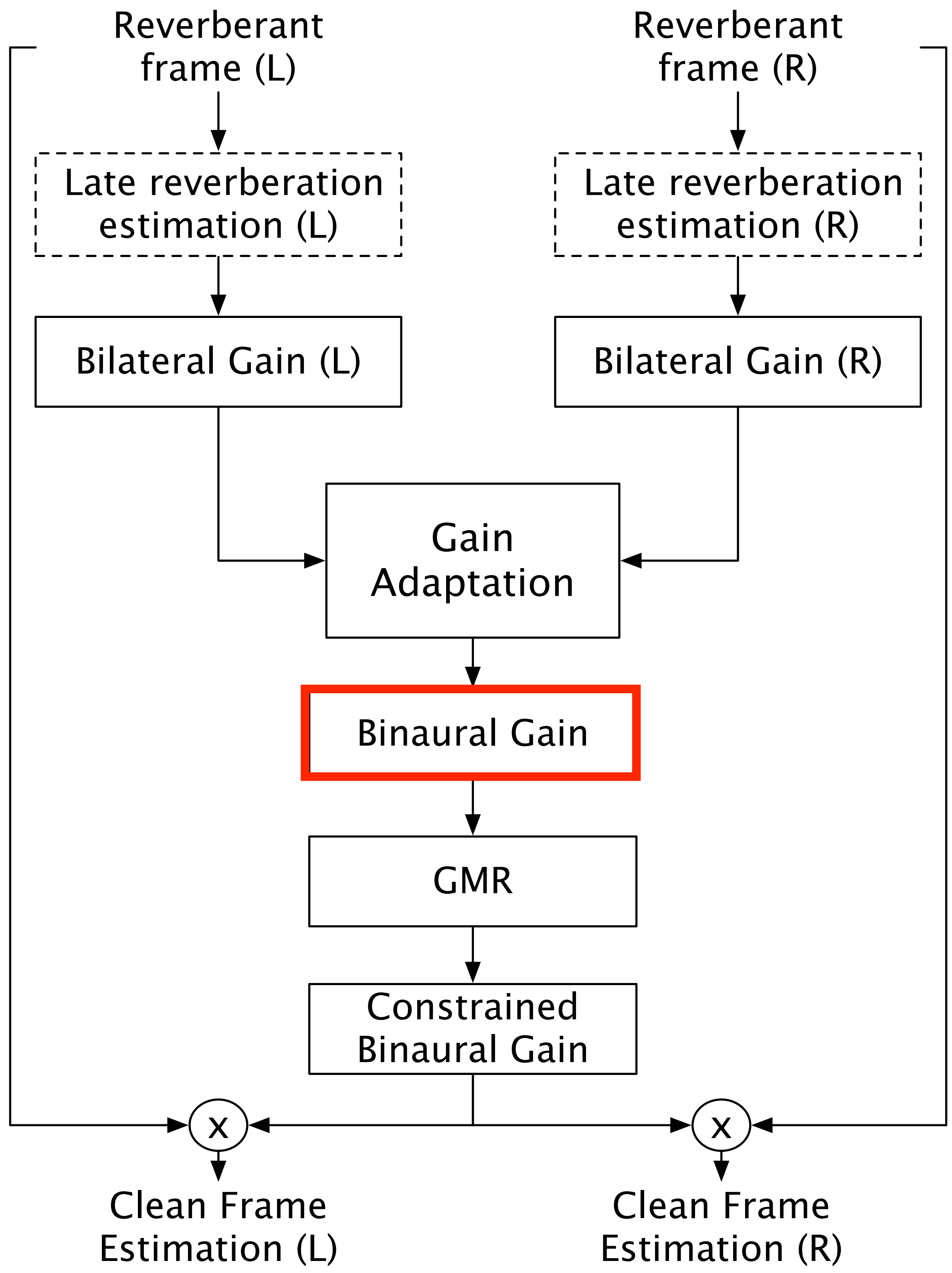

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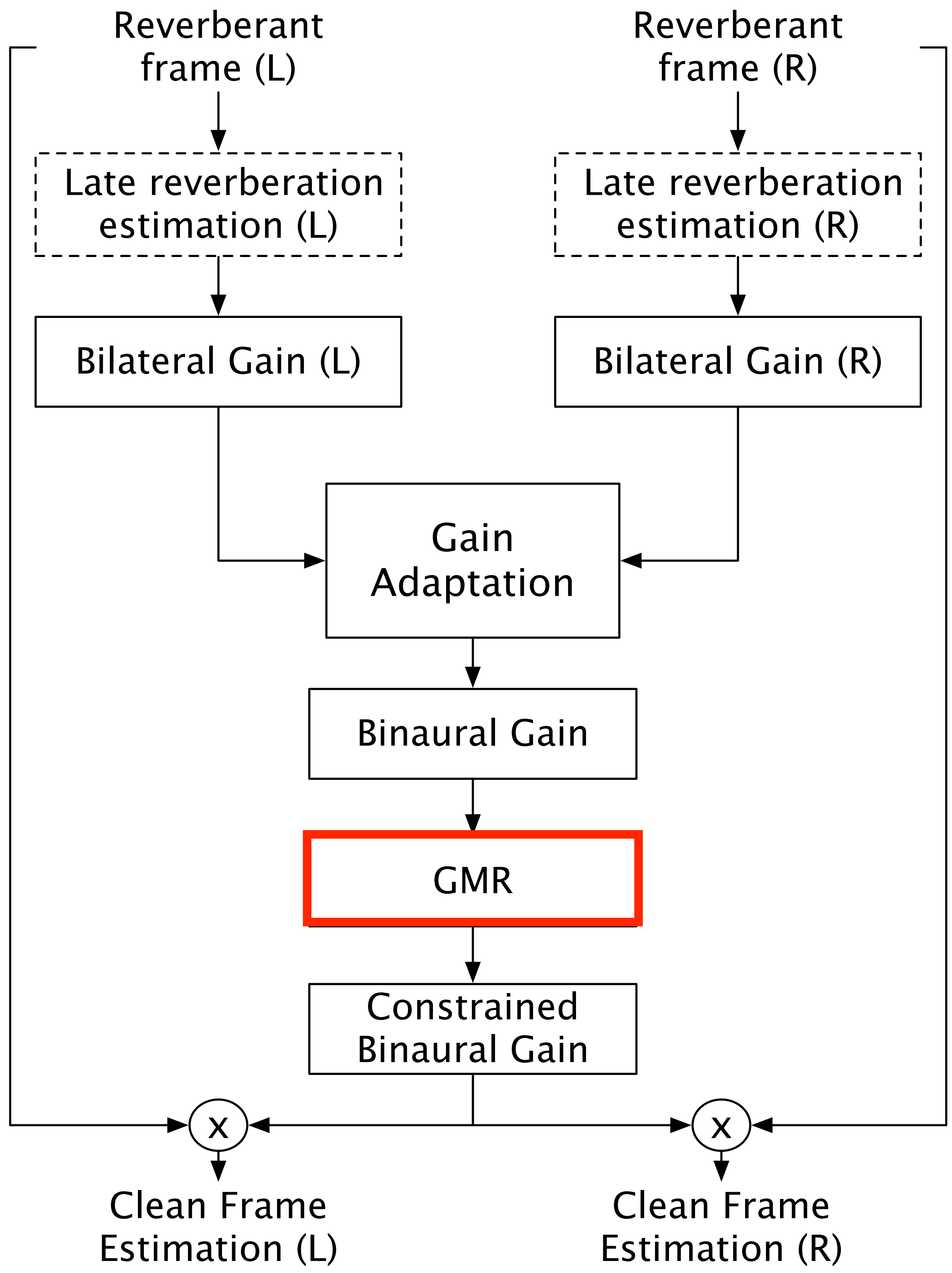

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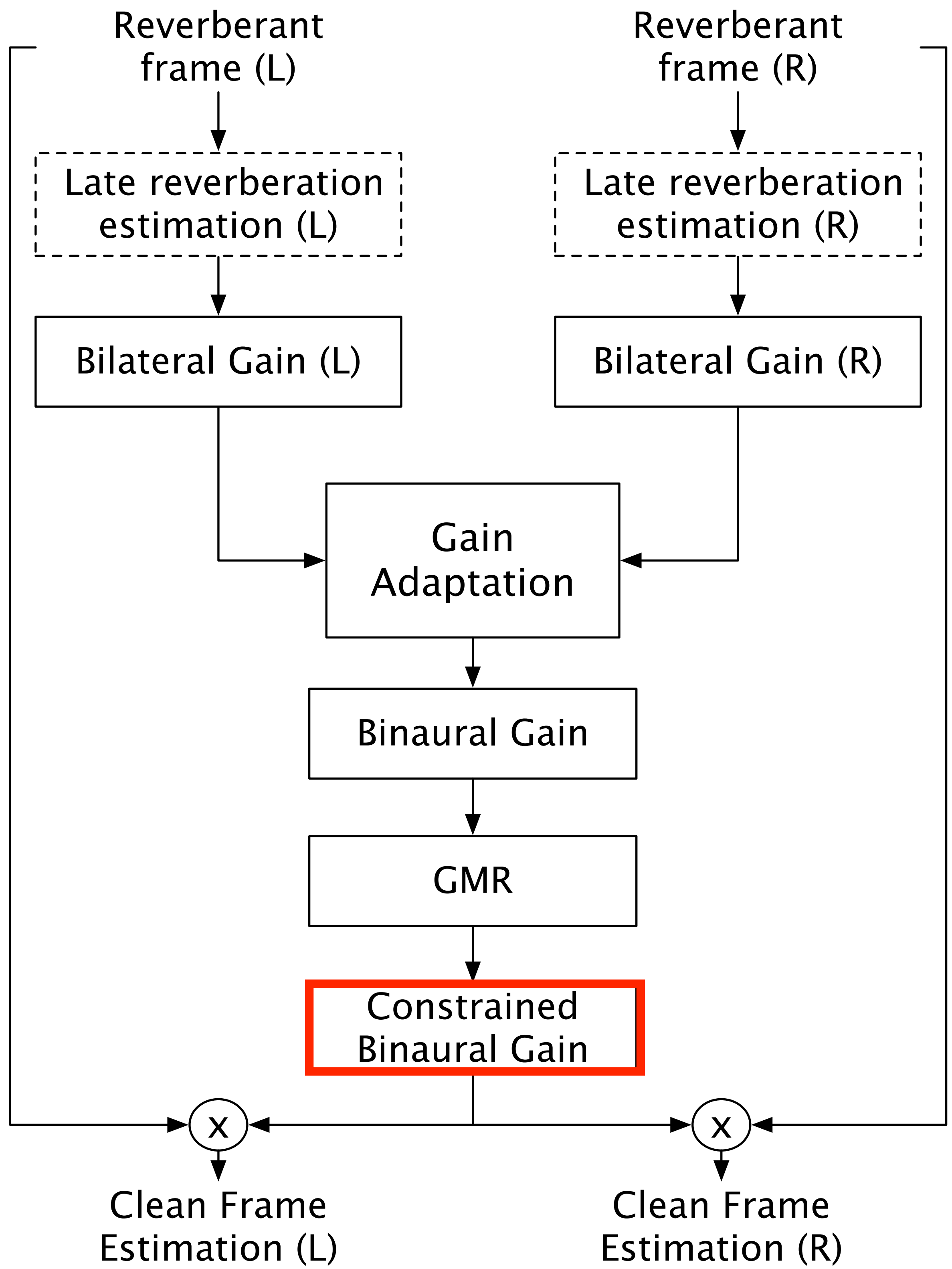

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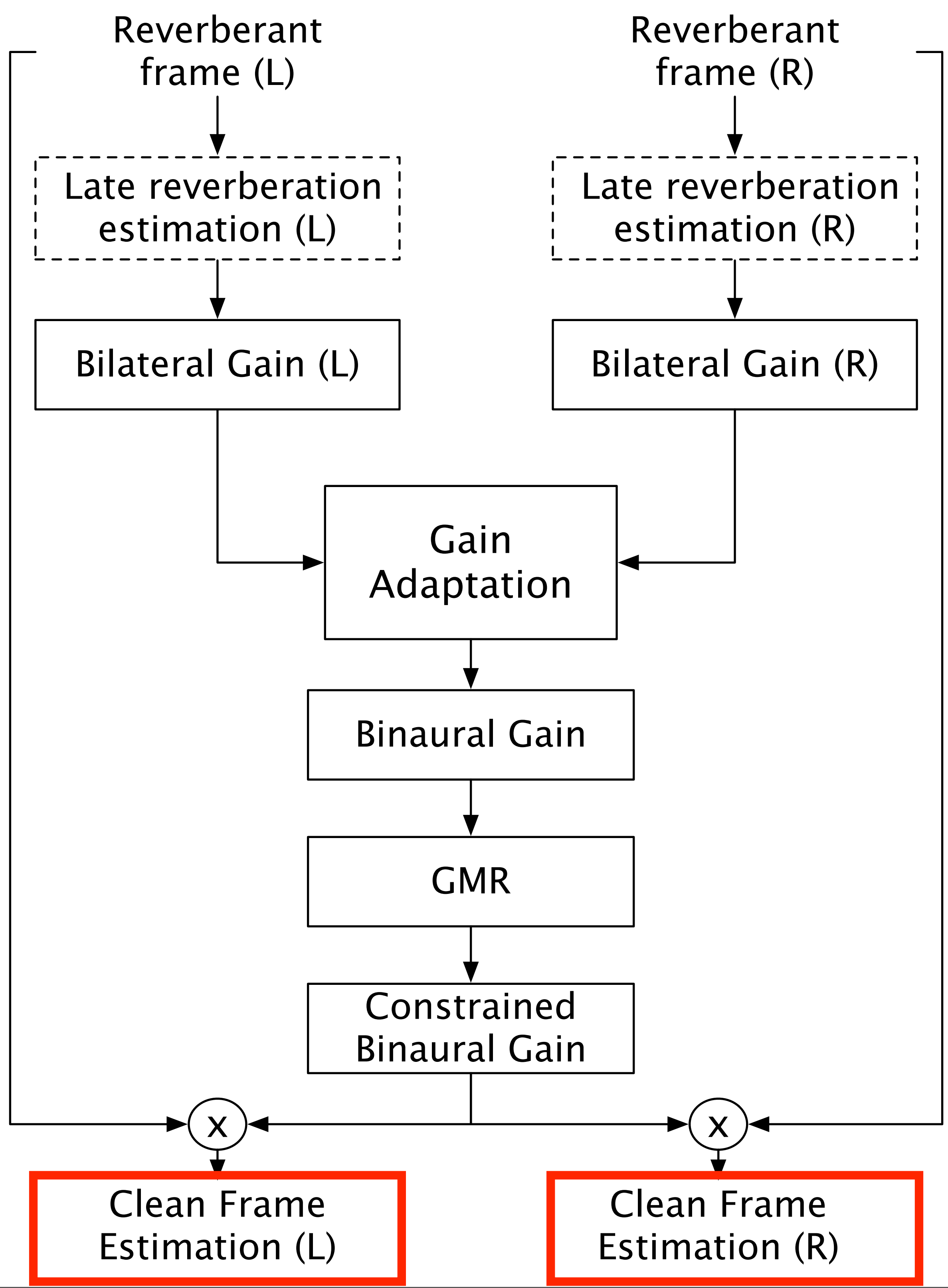

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Gain Adaptation

maxGain:		
avgGain:		
minGain:		

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Gain Adaptation

maxGain:	$G(\omega, j) = max(G_l(\omega, j), G_r(\omega, j))$	moderate suppression, fewer processing artifacts
avgGain:		
minGain:		

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minGain:		

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selection of the gain adaptation scheme according to the application scenario

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Gain Magnitude Regularization
(GMR)

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$$G'(\omega, j) = \begin{cases} \dfrac{G(\omega, j) - \theta}{r} + \theta & \text{when } \zeta < \zeta_{th} \\ & \text{and } G(\omega, j) < \theta \\ G(\omega, j) & \text{otherwise} \end{cases}$$

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Low SRR detector

$$\boxed{\zeta = \frac{\sum_{\omega=1}^{\Omega} G(\omega, j)|Y(\omega, j)|^2}{\sum_{\omega=1}^{\Omega} |Y(\omega, j)|^2}}$$

M Jeub, M Schafer, T Esch, and P Vary. *Model-Based Dereverberation Preserving Binaural Cues.* IEEE Transactions on Audio, Speech, and Language Processing, 18:1732–1745, 2010

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Regularization application threshold

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Regularization ratio

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Regularization ratio

Regularization application threshold

Low SRR detector

$$\zeta = \frac{\sum_{\omega=1}^{\Omega} G(\omega, j) |Y(\omega, j)|^2}{\sum_{\omega=1}^{\Omega} |Y(\omega, j)|^2}$$

- Compensate for overestimation.
- Prevents musical noise.

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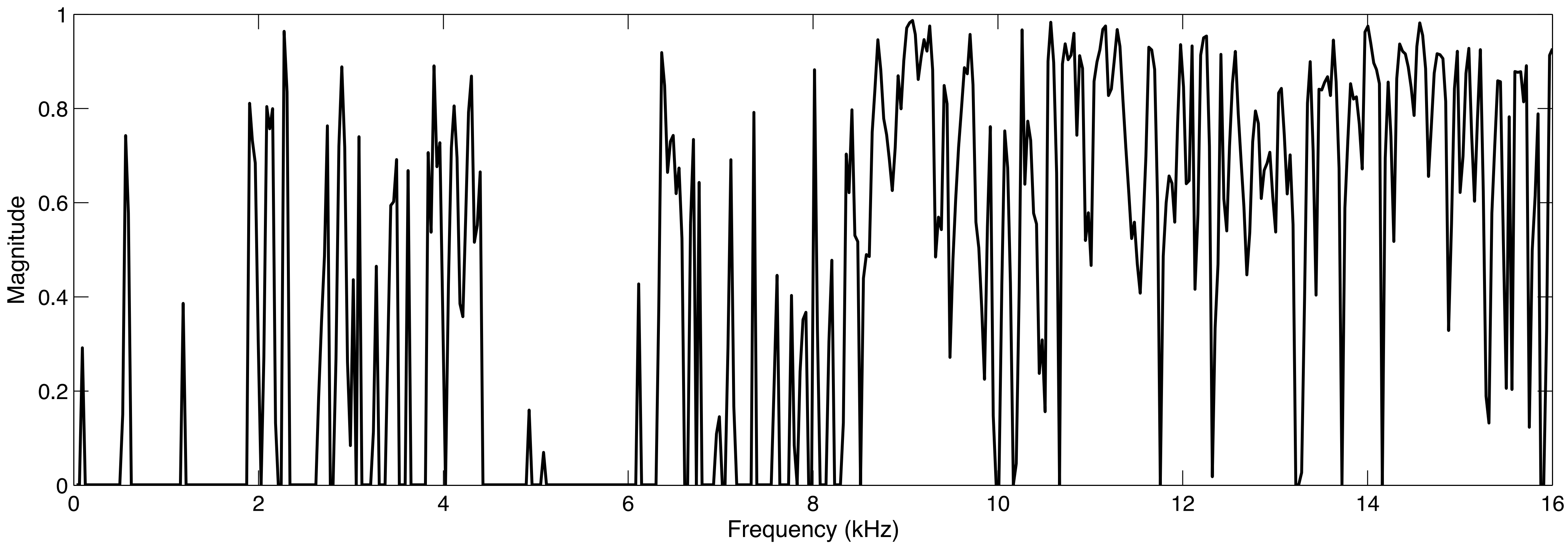
Binaural Dereverberation



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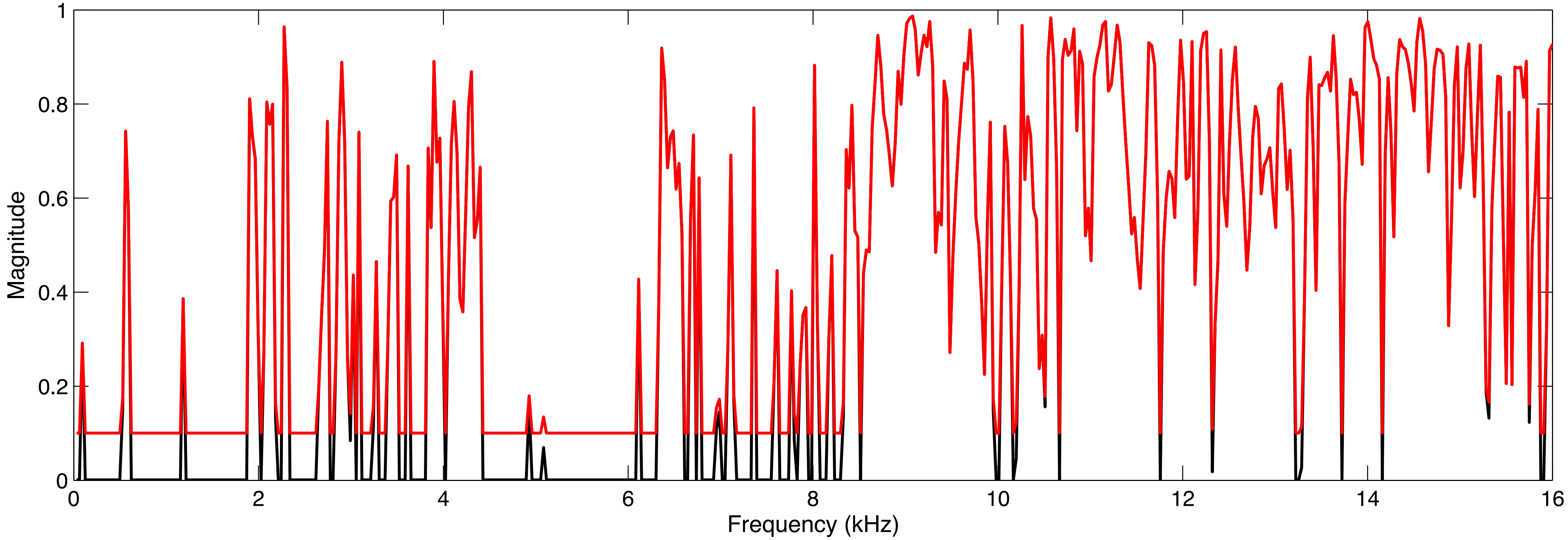
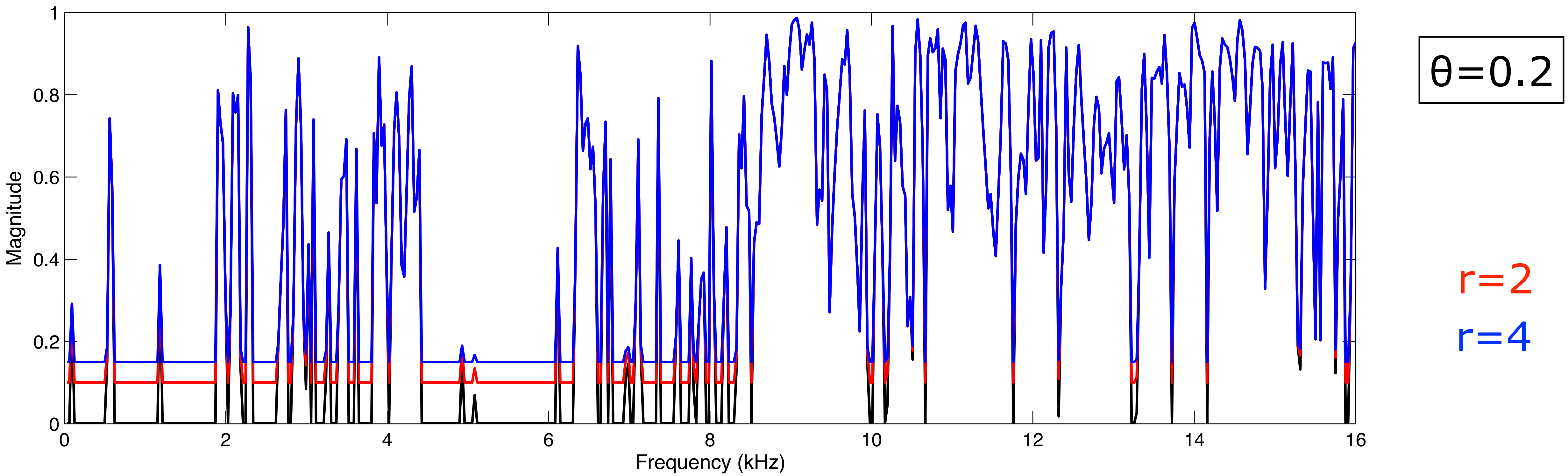


θ=0.2

r=2

Binaural Dereverberation



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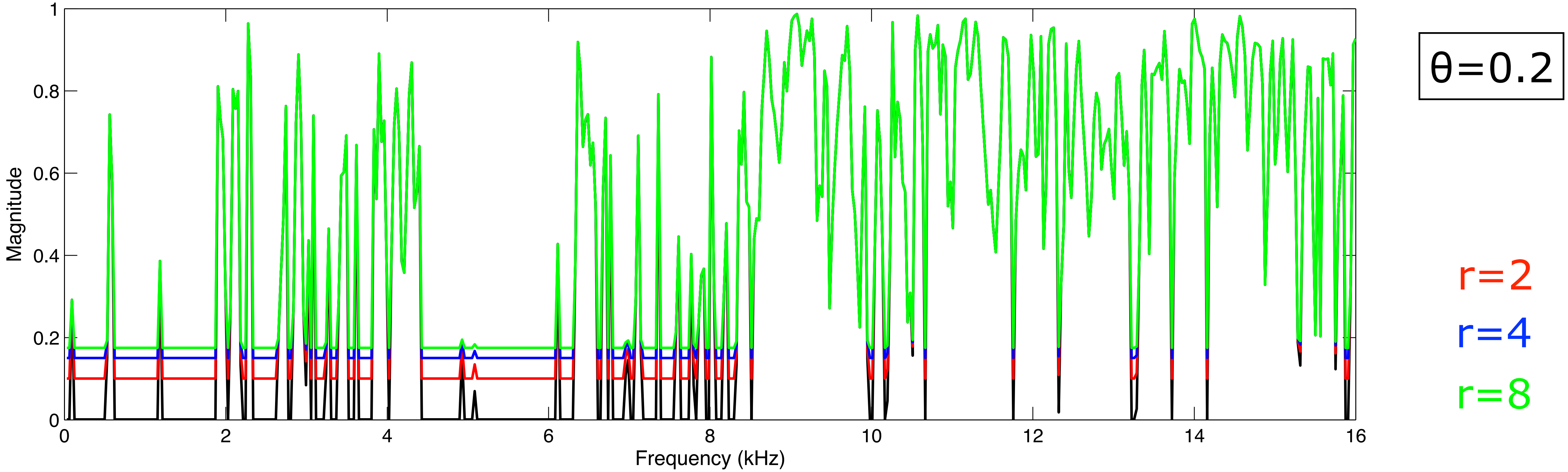

Binaural Dereverberation

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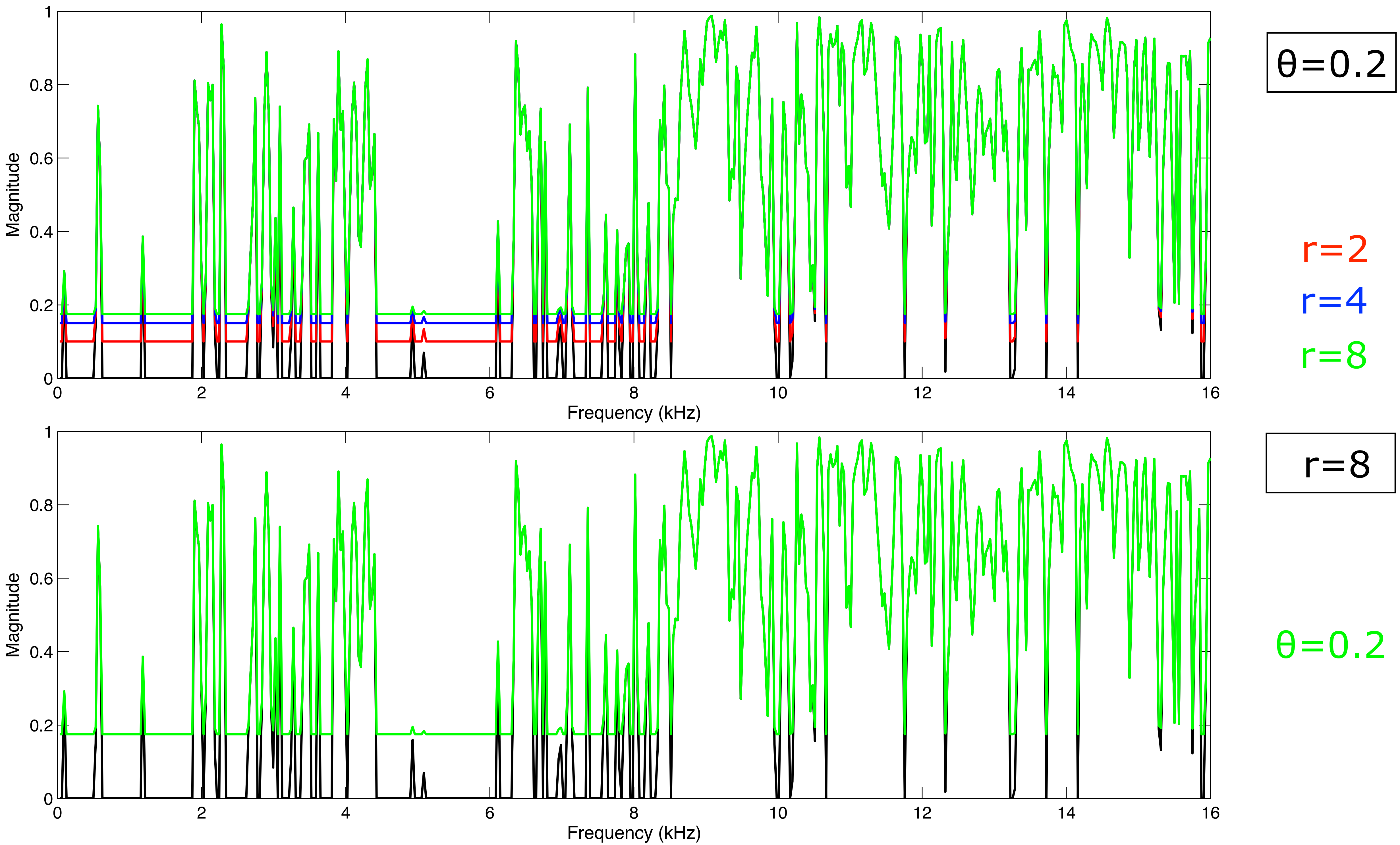

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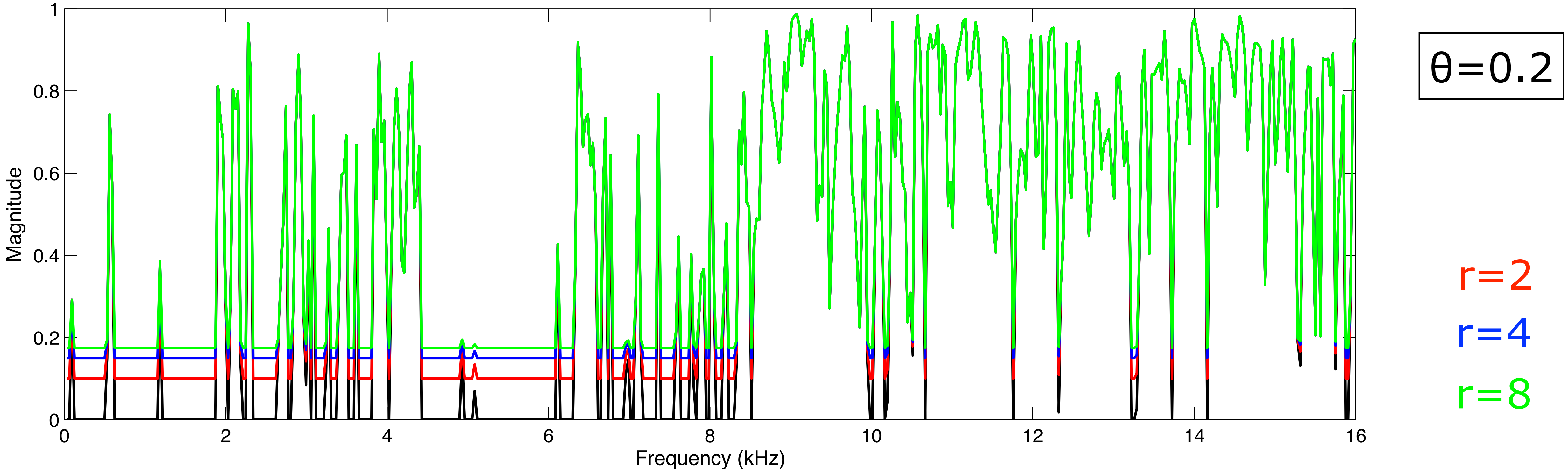

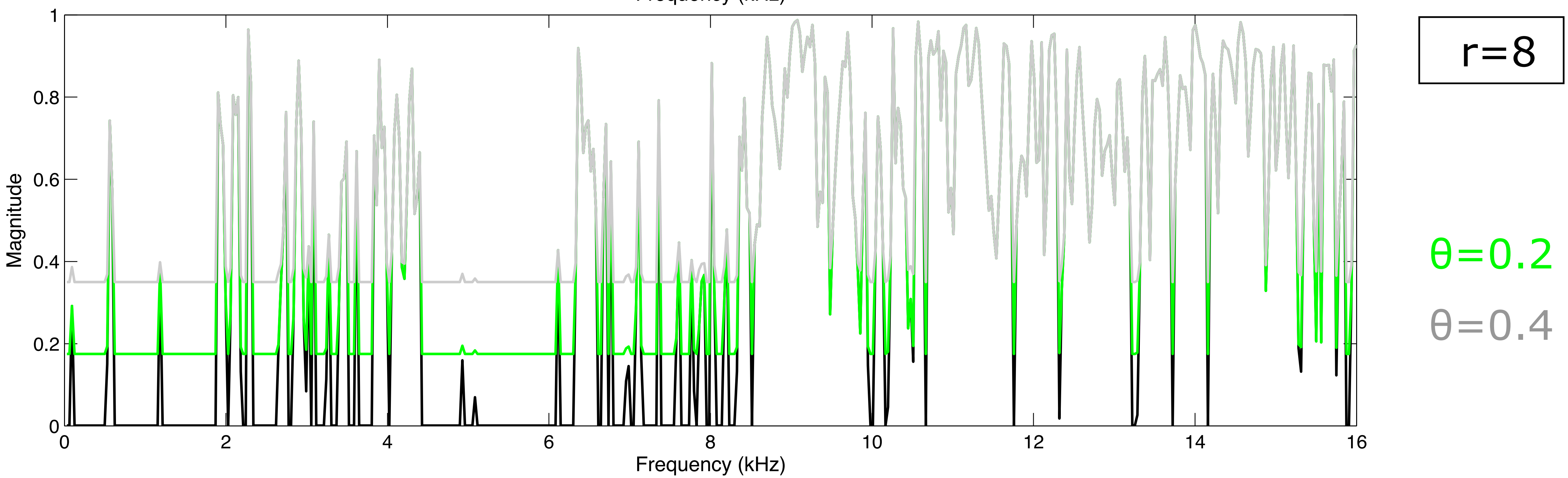

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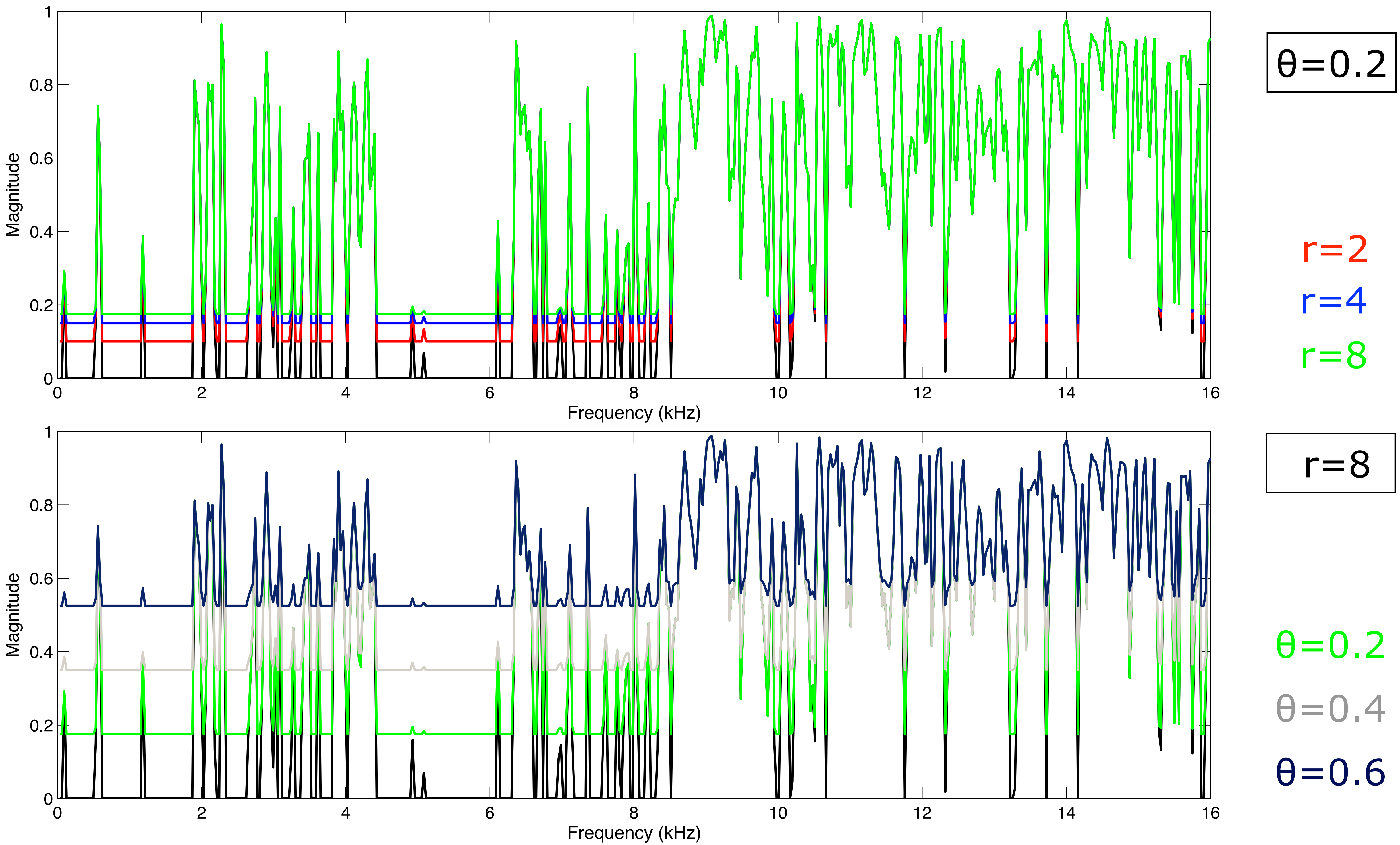

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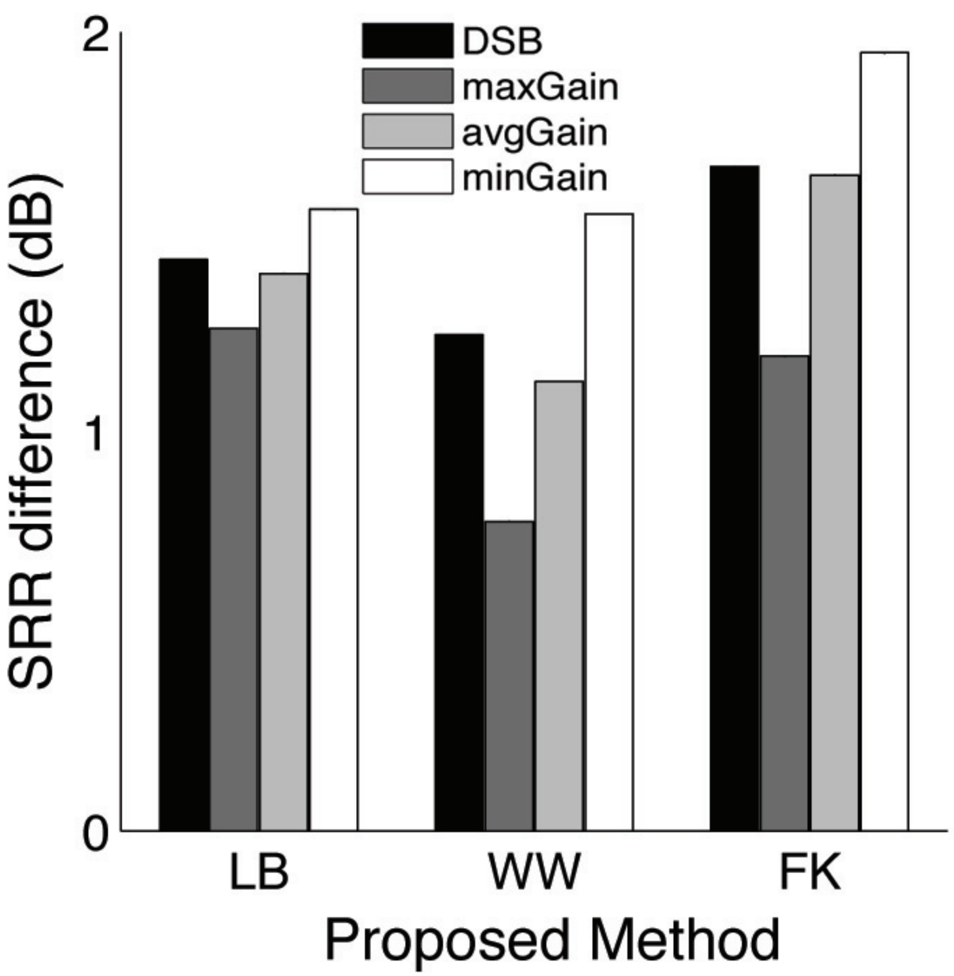
Results

- Stairway Hall

RT = 0.69 s, Distance= 3m, Angles = 0, 30, 60, 90° (Aachen Database)

Sampling Frequency: 16 kHz



	Stairway Hall			
Method	**DSB**	**maxGain**	**avgGain**	**minGain**
LB	0.153	0.142	0.147	**0.158**
WW	0.206	0.160	0.208	**0.258**
FK	0.160	0.180	**0.186**	-0.029

PESQ difference

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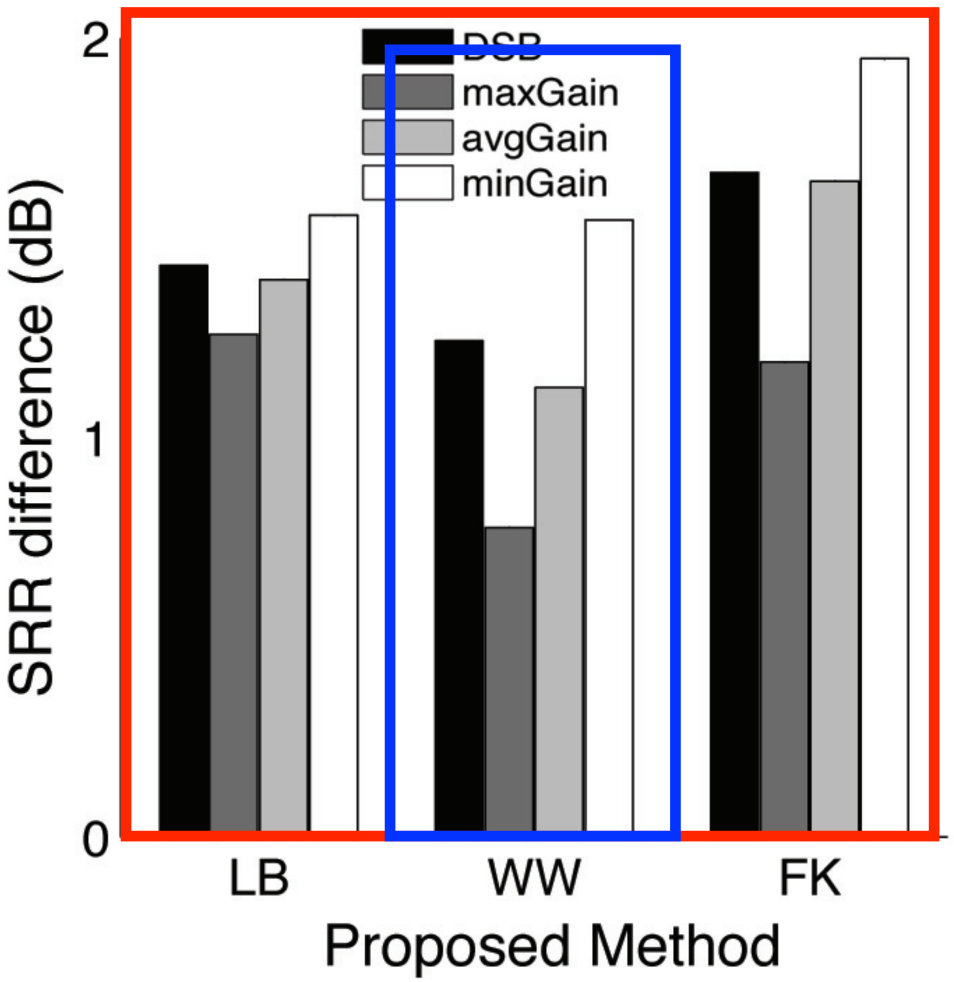

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PESQ difference

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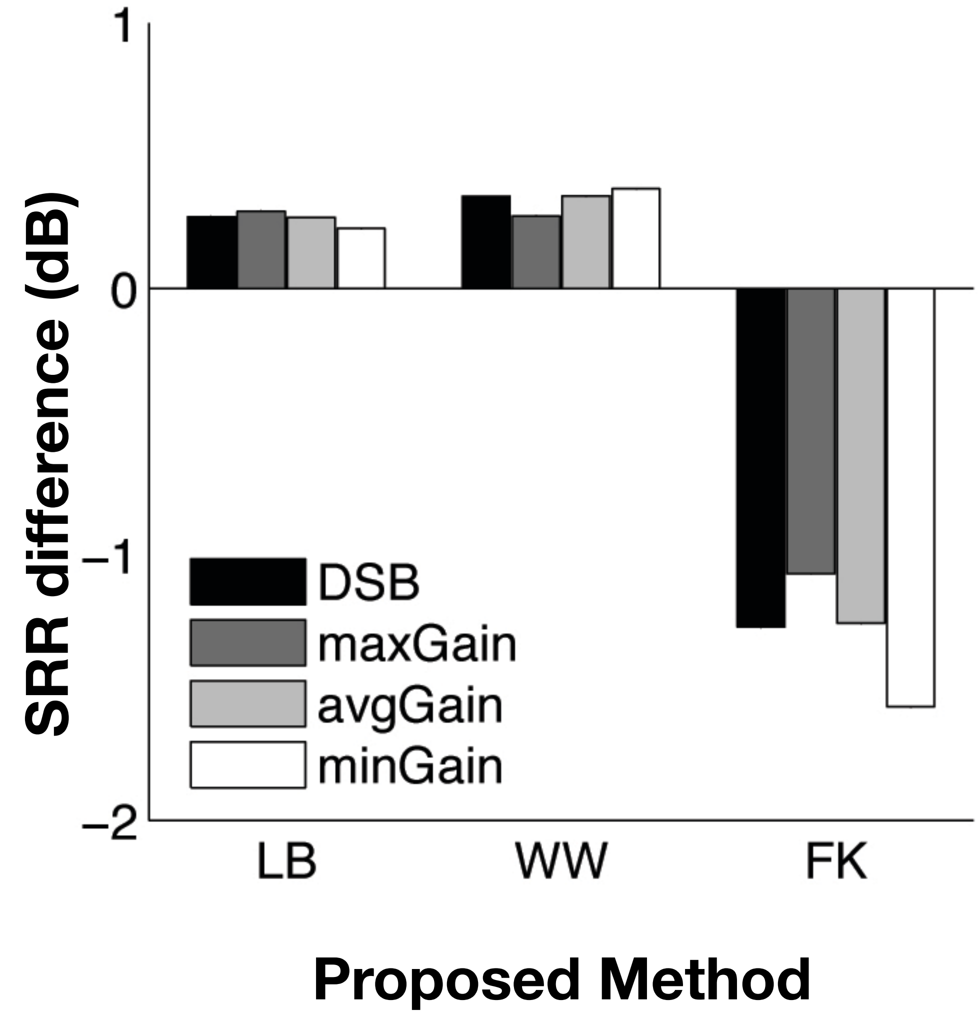
Results

- Cafeteria
  RT = 1.29 s, Distance= 1.18-1.62m, Angles = -30, 0, 90° (Oldenburg Database)

Sampling Frequency: 16 kHz



	Cafeteria			
Method	**DSB**	**maxGain**	**avgGain**	**minGain**
LB	0.133	**0.136**	0.135	0.133
WW	0.205	0.208	**0.216**	0.198
FK	-0.235	**-0.141**	-0.228	-0.428

PESQ difference

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Results

- **Cafeteria**

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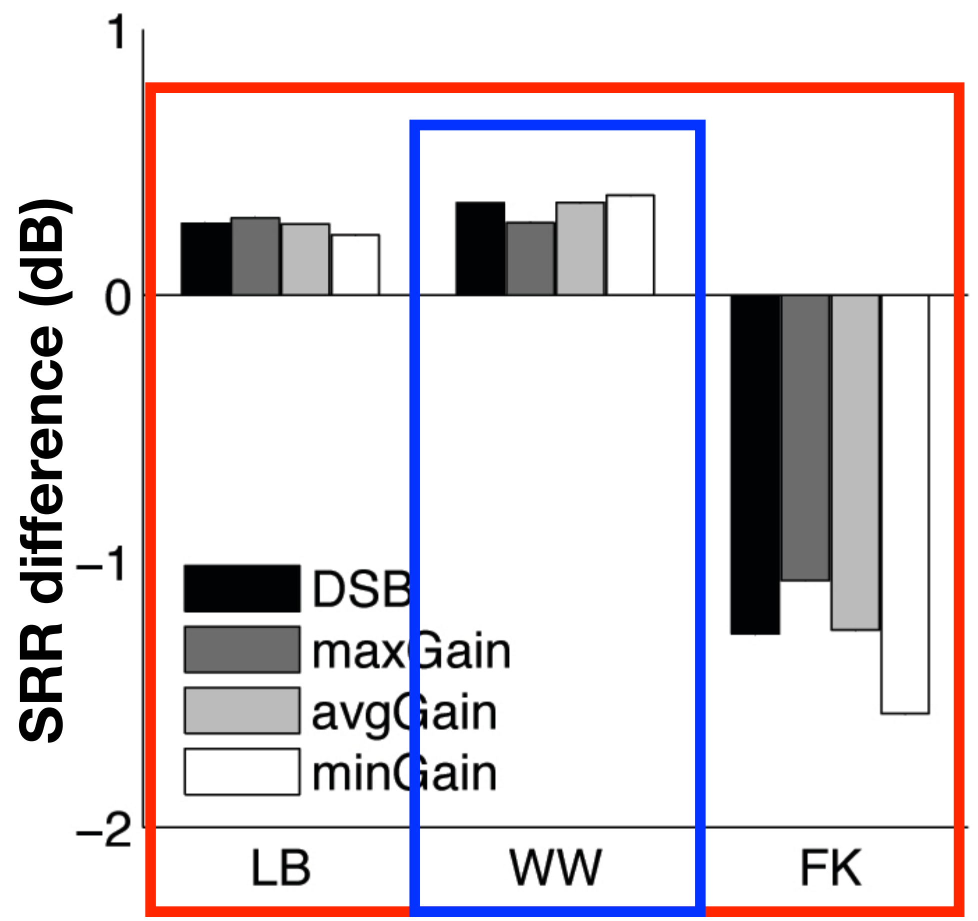

Proposed Method

	Cafeteria			
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PESQ difference

Results

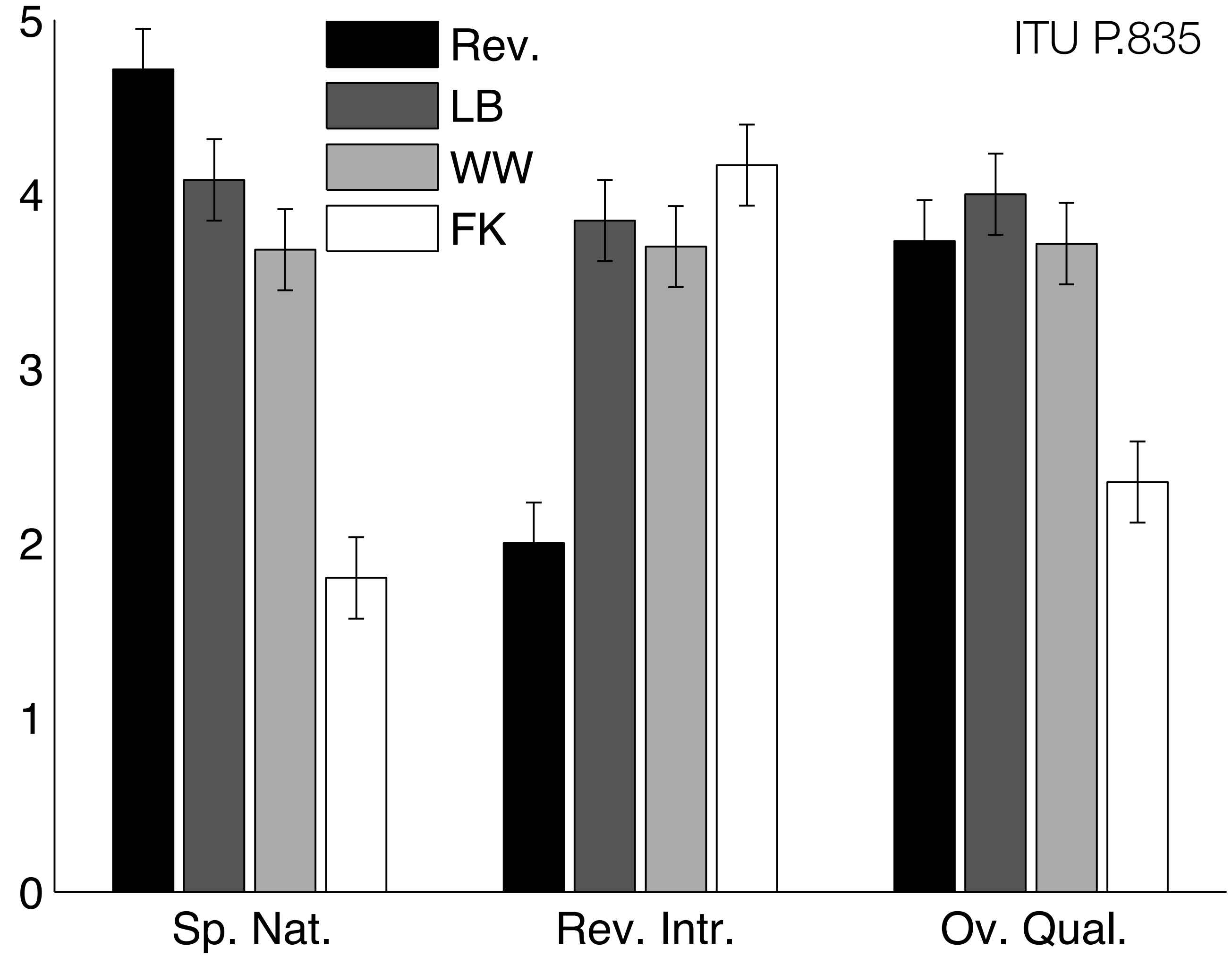
- Stairway Hall
  RT = 0.69 s, Distance= 3m,
  Angles= 0, 45, 90°

Sampling Frequency: 44.1 kHz

- 17 test subjects

LB, WW → avgGain

FK → minGain



A. Tsilfidis, E. Georganti, and J. Mourjopoulos. "A binaural framework for spectral subtraction dereverberation". In Forum Acusticum, Aalborg, Denmark, 2011

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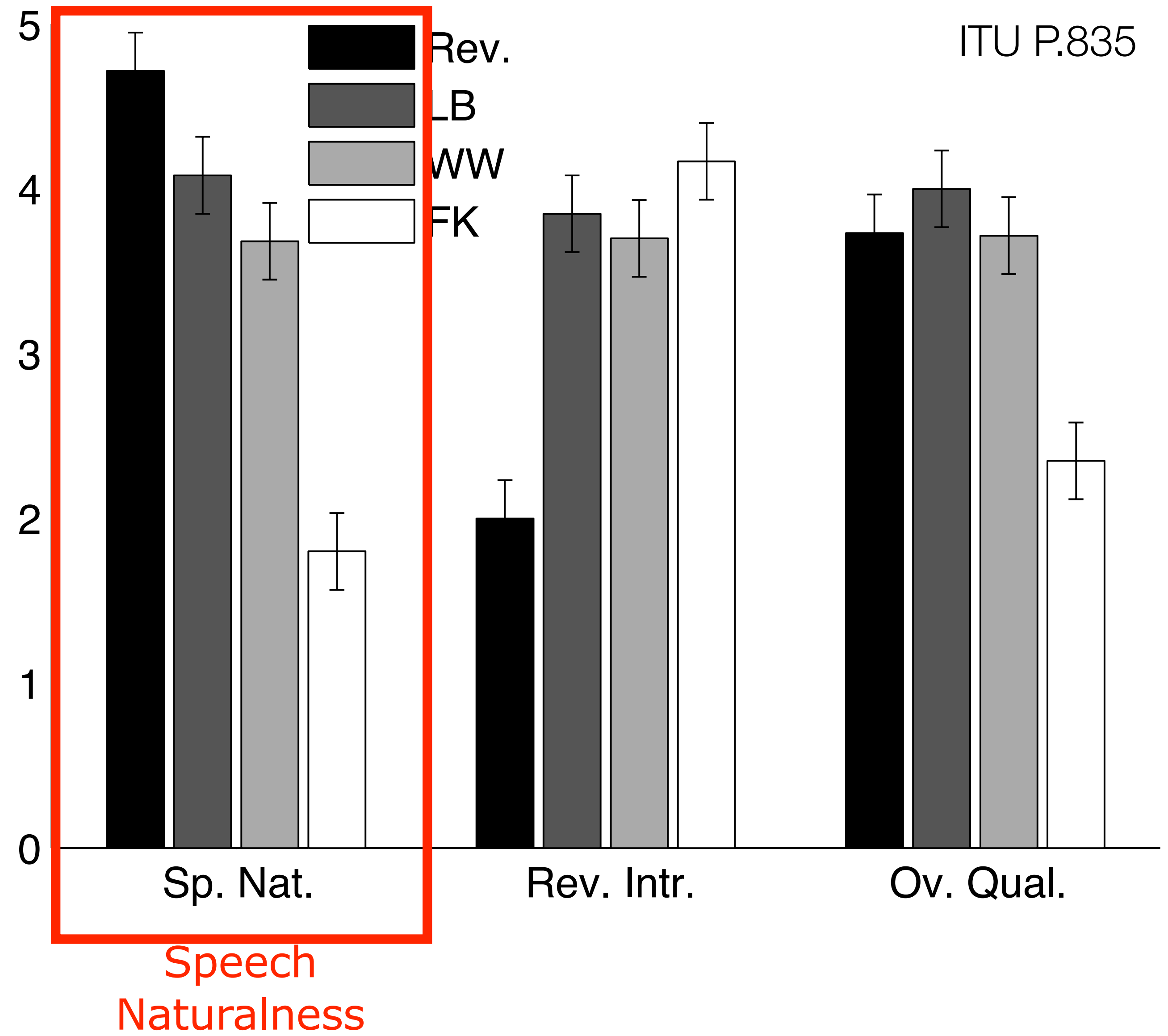

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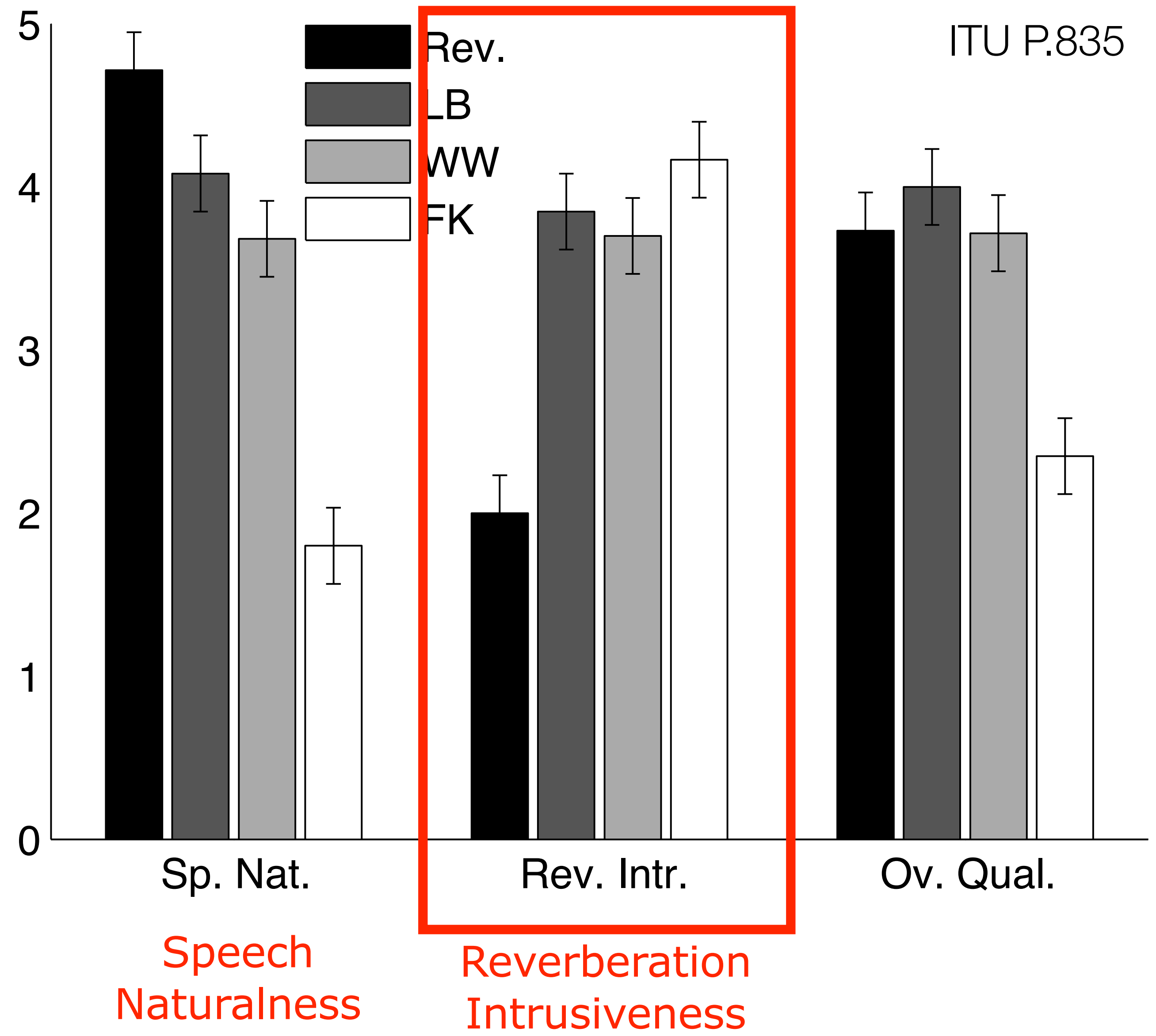

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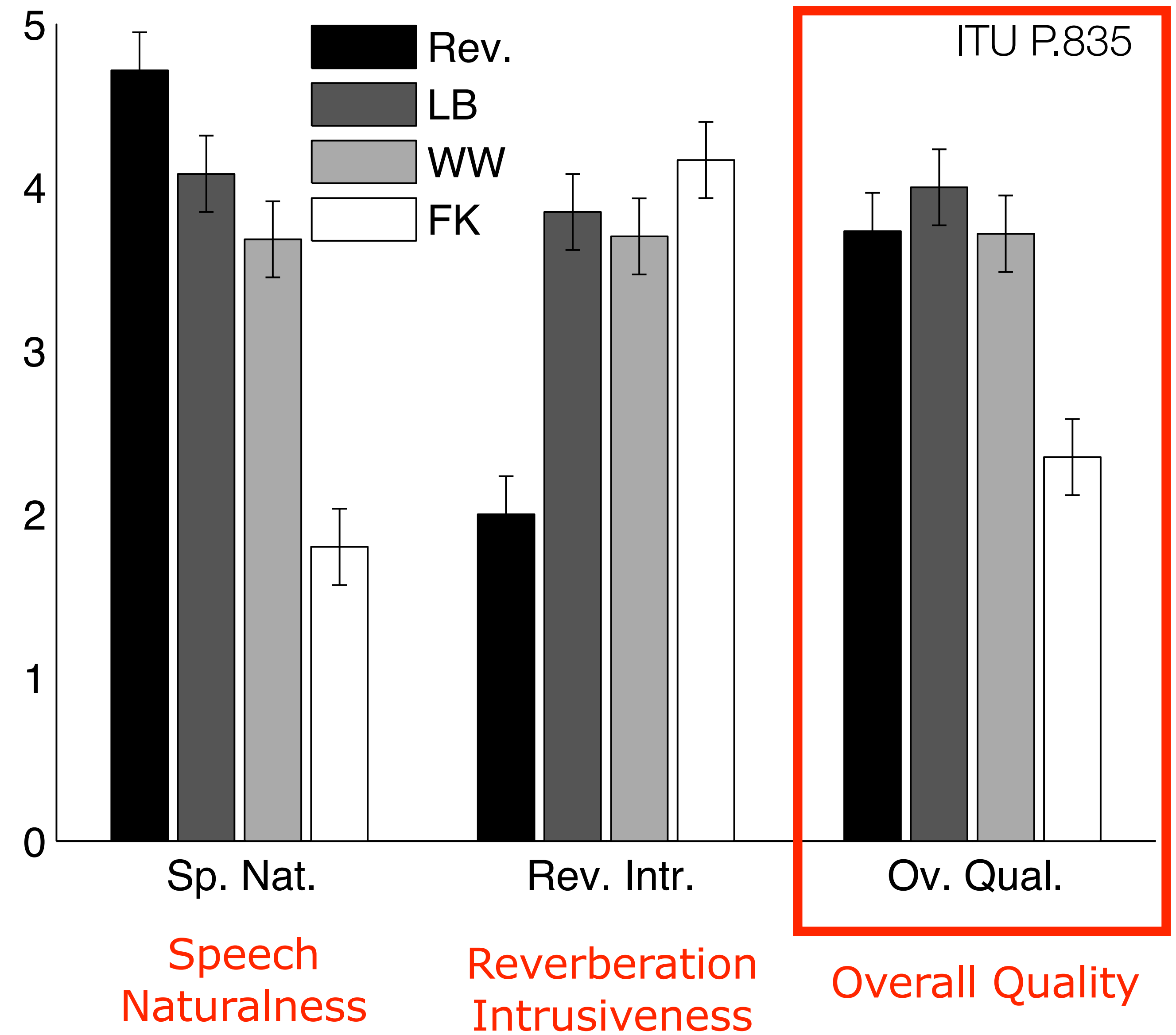

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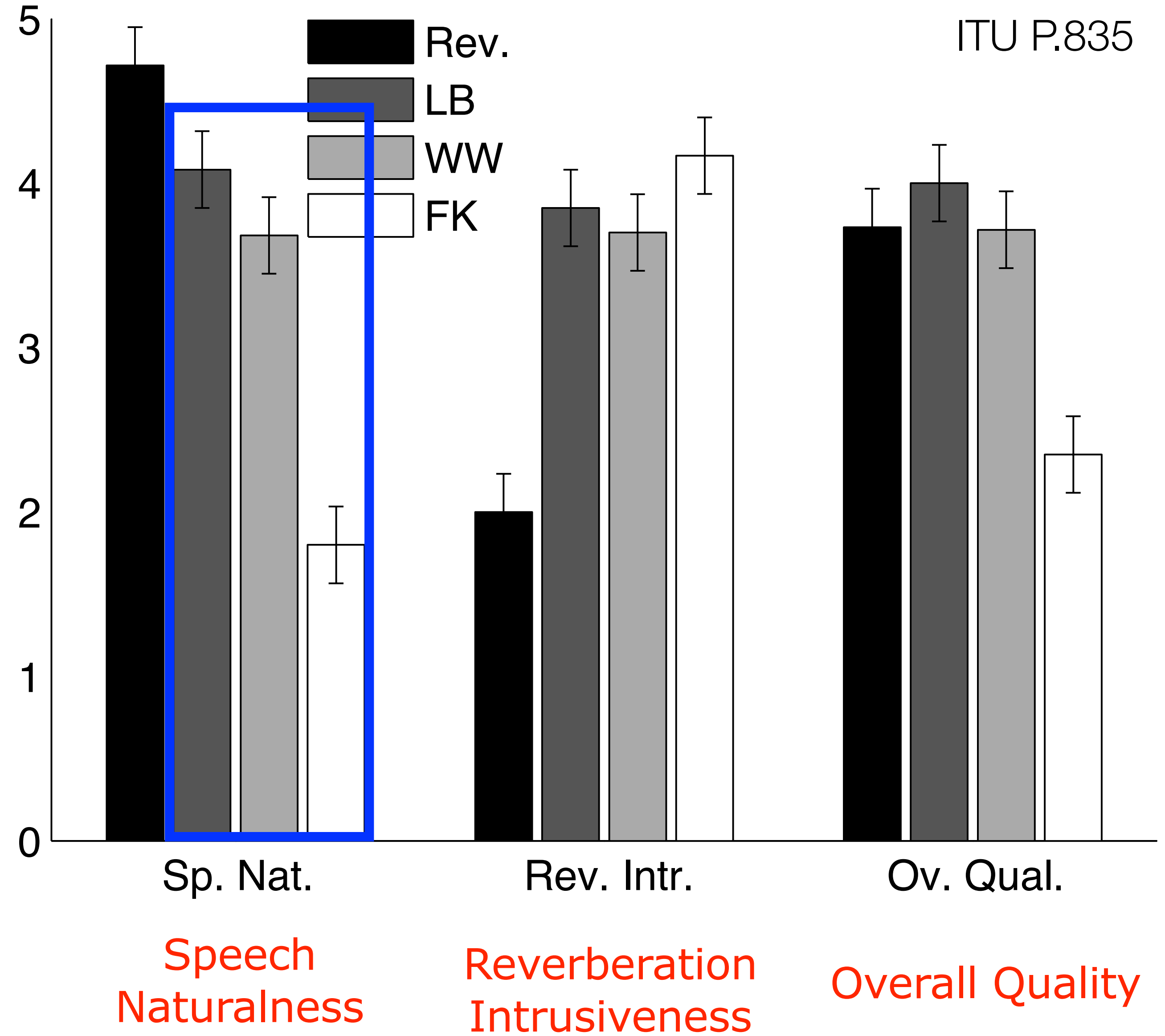
- Less natural speech



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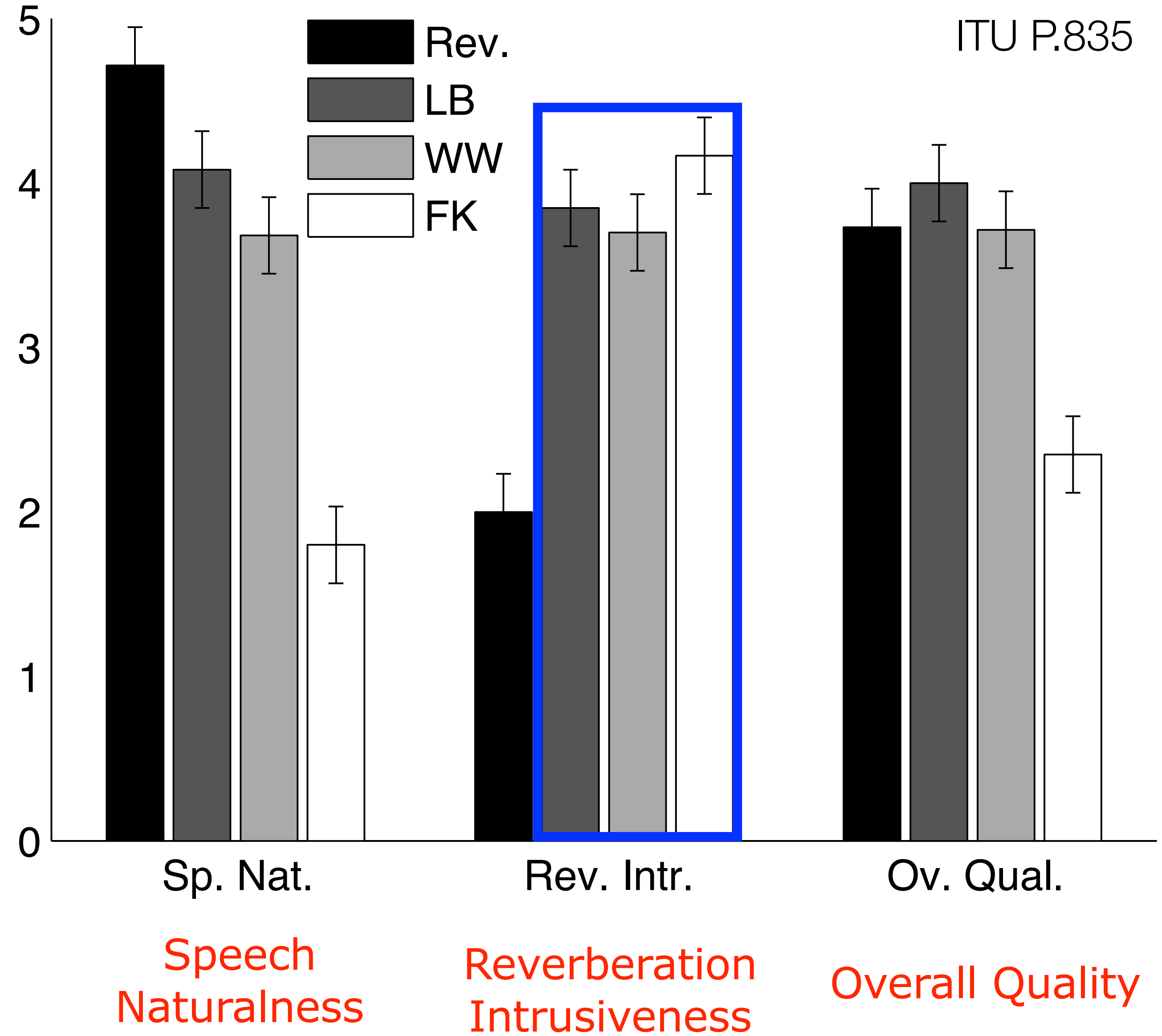

- Less natural speech
- Significant Reverberation reduction

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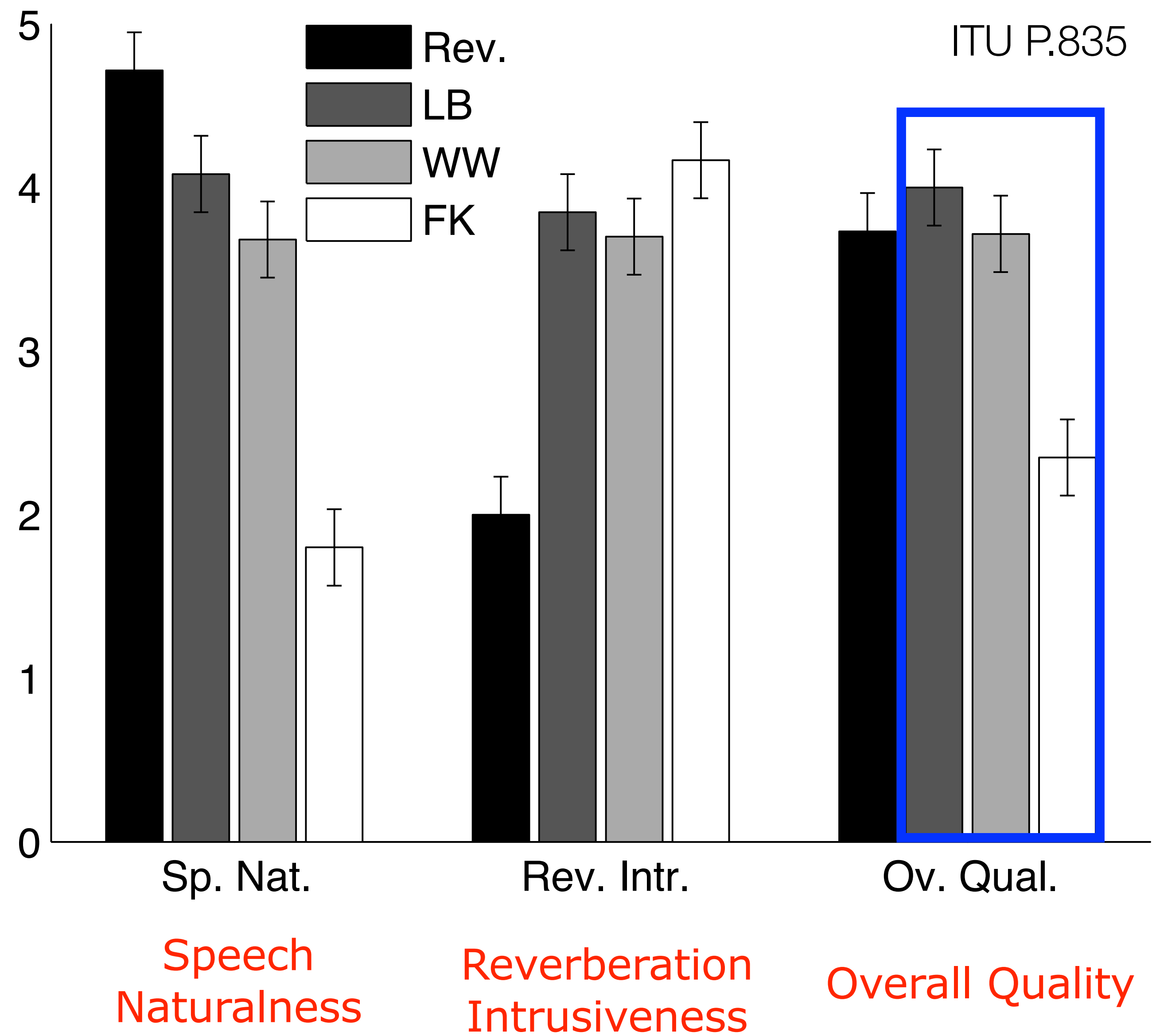
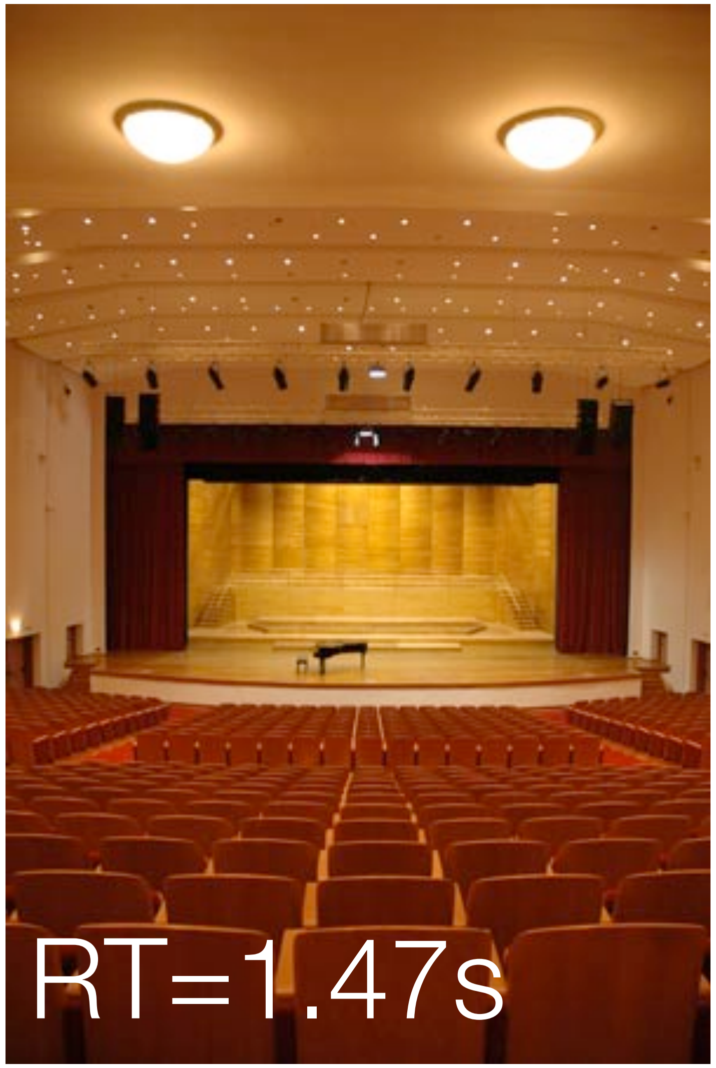


- Less natural speech
- Significant Reverberation reduction
- LB & WW preserve signal quality

A. Tsilfidis, E. Georganti, and J. Mourjopoulos. “A binaural framework for spectral subtraction dereverberation”. In Forum Acusticum, Aalborg, Denmark, 2011

Audio Demos



Available at:

http://www.wcl.ece.upatras.gr/audiogroup/tools/derev.html

Conclusions

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- Framework for binaural spectral subtraction dereverberation based on bilateral gain adaptation
- Gain Magnitude Regularization for the reduction of overestimation errors

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    - ✓ Selection of the adaptation scheme and the GMR parameters according to the application scenario
    - ✓ Significant reverberation reduction and preservation of overall speech quality and binaural cues

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- Framework for binaural spectral subtraction dereverberation based on bilateral gain adaptation
- Gain Magnitude Regularization for the reduction of overestimation errors
  - ✓ Selection of the adaptation scheme and the GMR parameters according to the application scenario
  - ✓ Significant reverberation reduction and preservation of overall speech quality and binaural cues

However...

Loss of speech naturalness → Need for native binaural methods that take into account the binaural properties of the auditory system

Future work

Thank you for attention!