BIO-MOTIVATED FEATURES AND DEEP LEARNING FOR ROBUST SPEECH RECOGNITION

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Introduction

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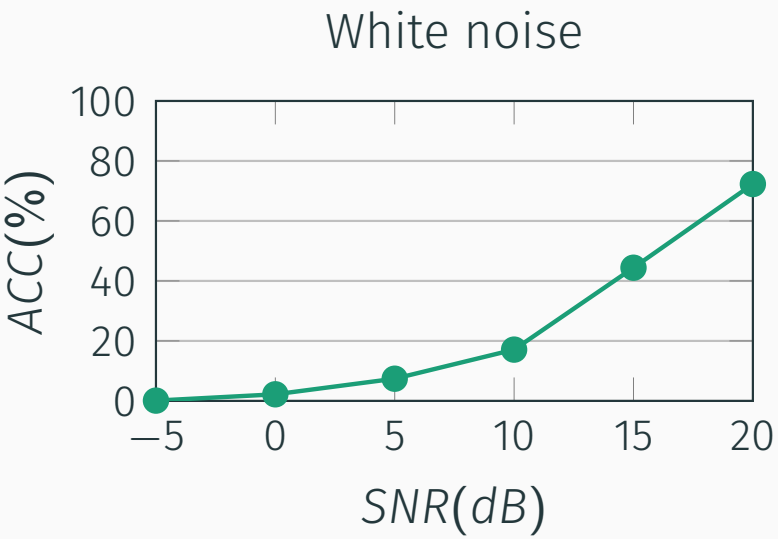

Robust Speech Recognition

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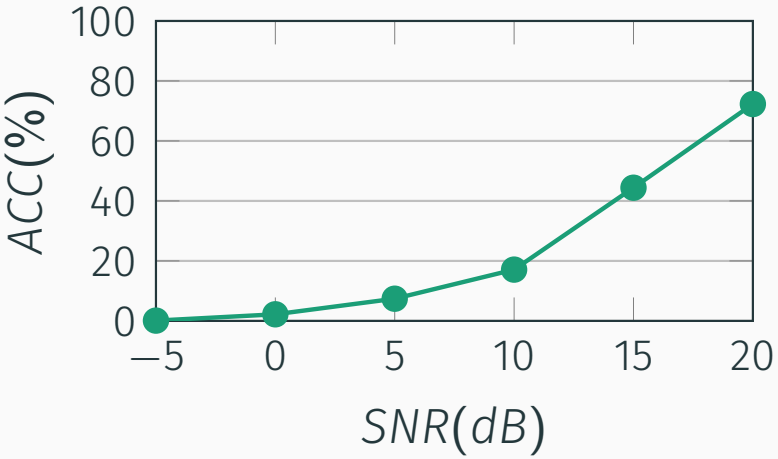
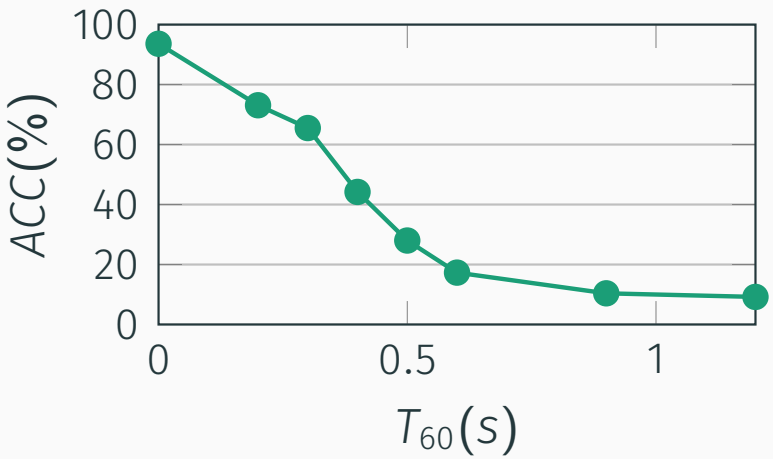
White noise



Reverberation



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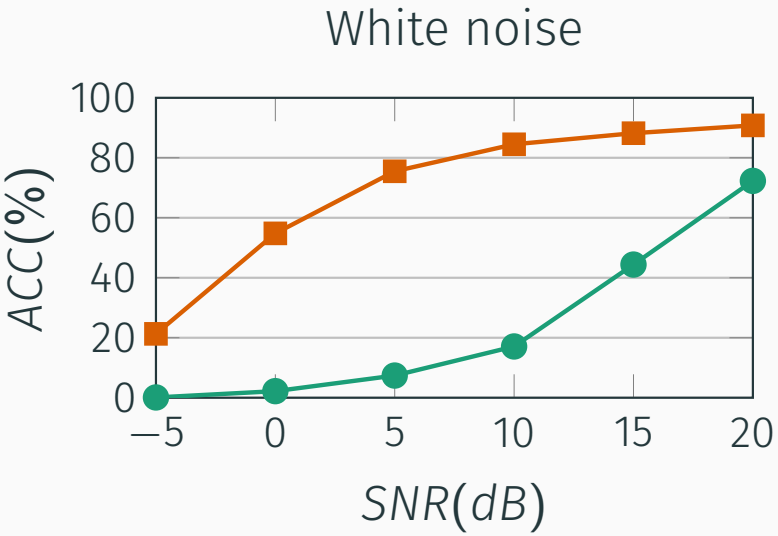

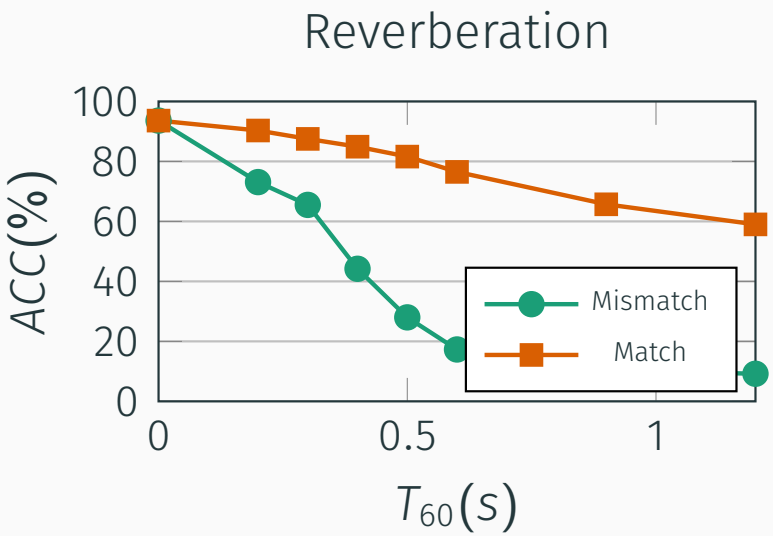

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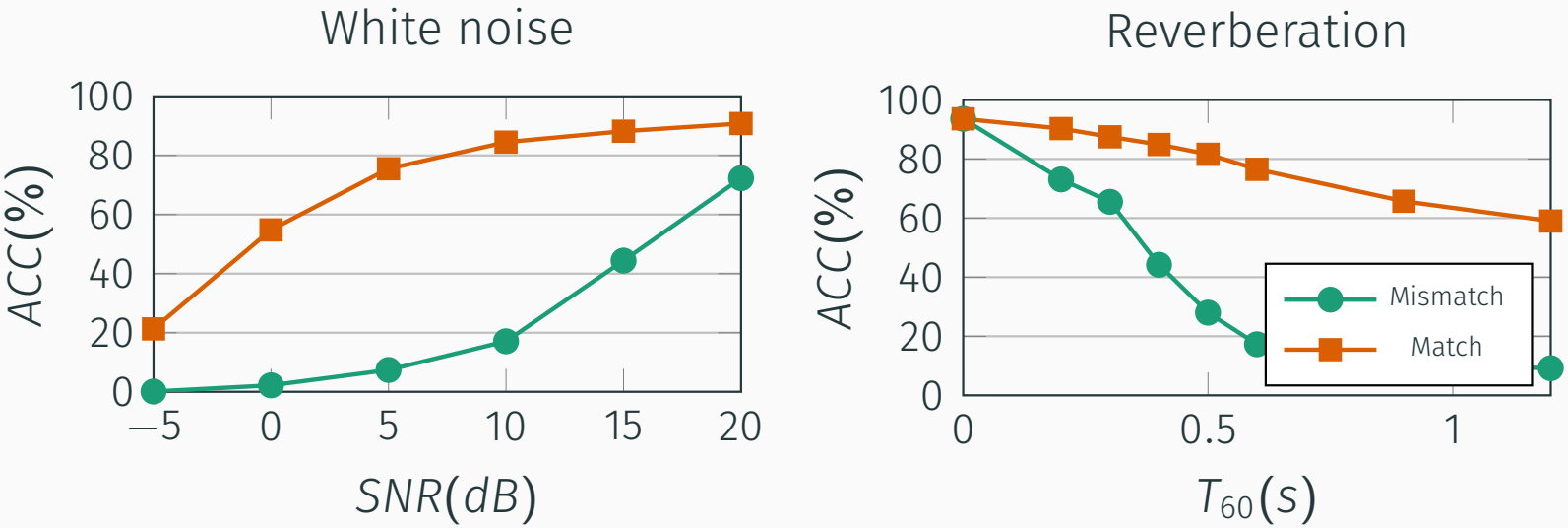

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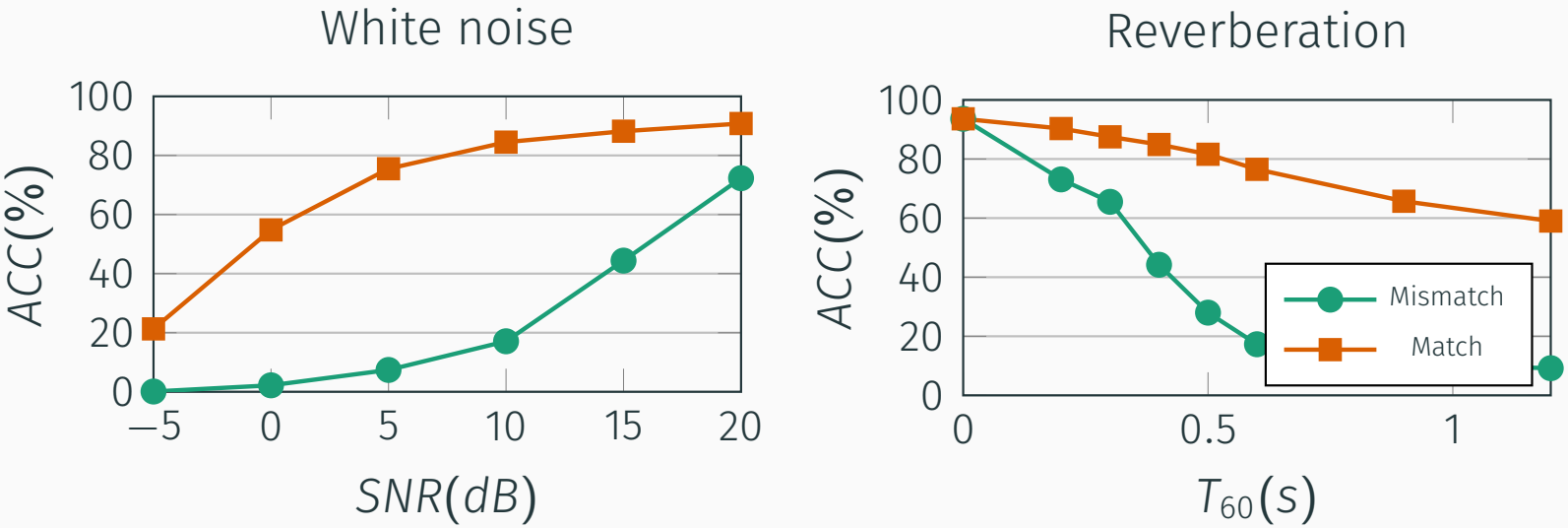

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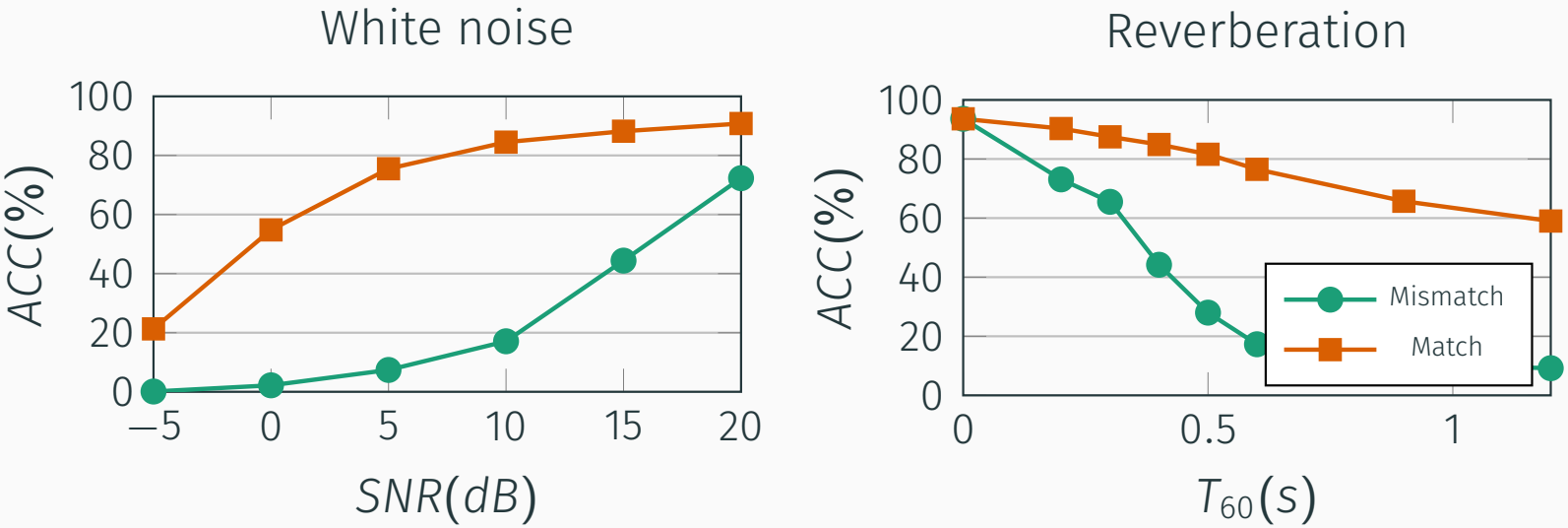

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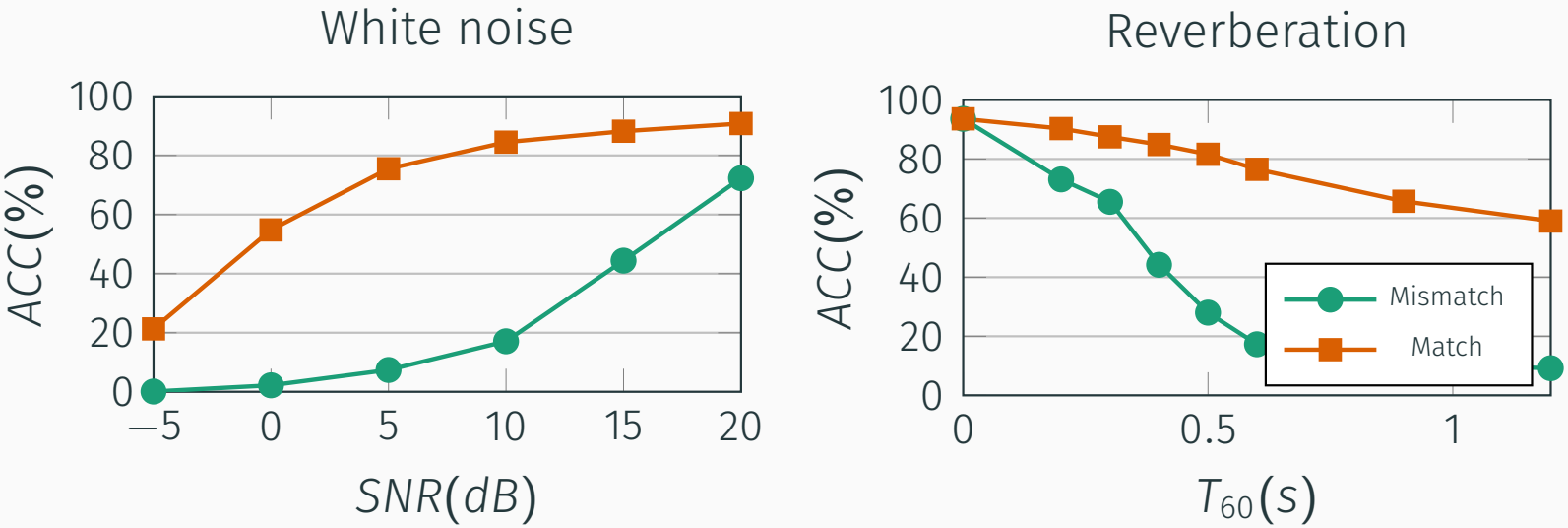

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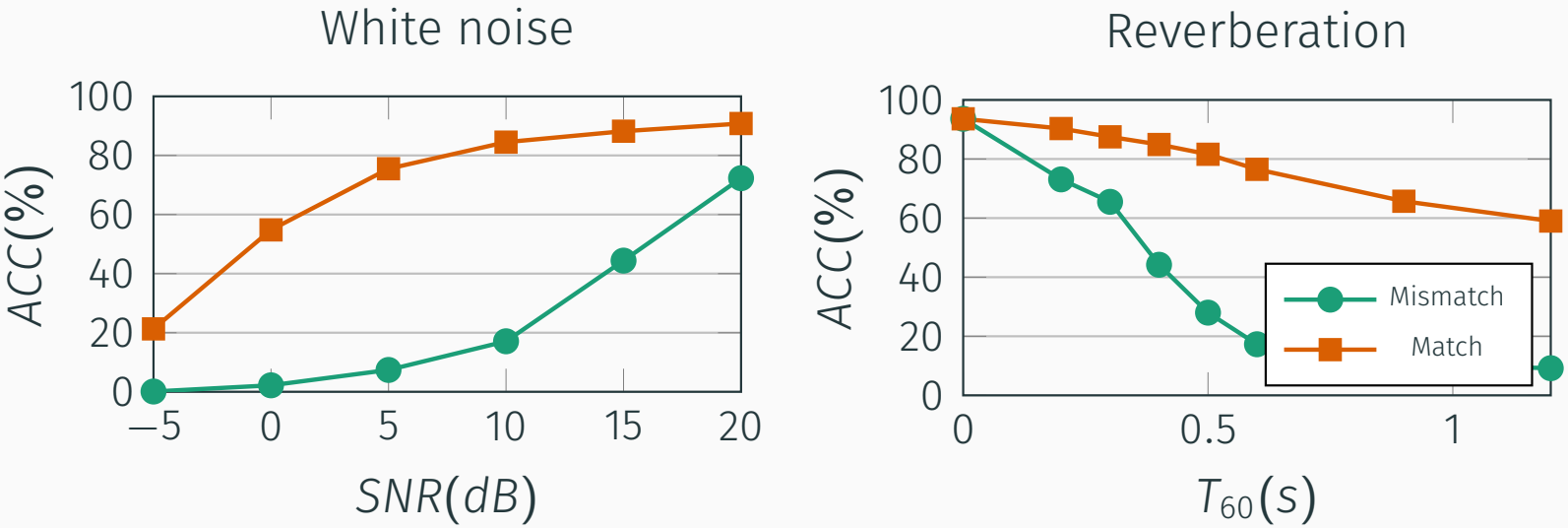

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  - Noise-resistant features: Auditory based.

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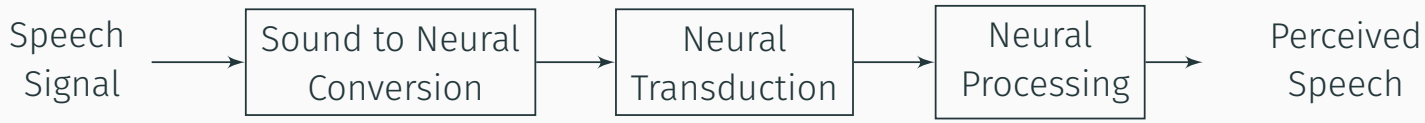

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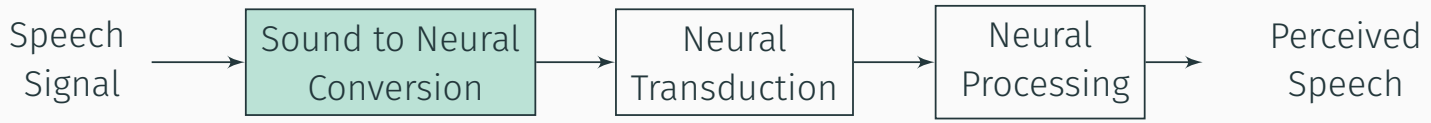

- Frequency Selectivity.
- Auditory Masking

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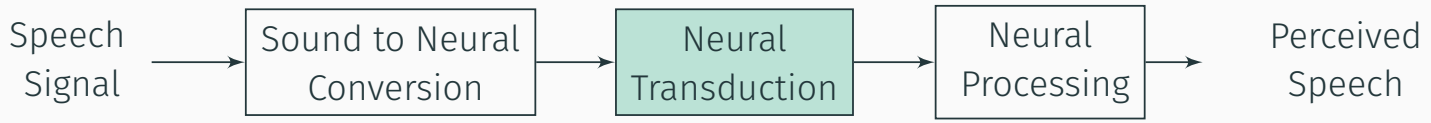

- Neural Coding.
- Synchrony Effect.

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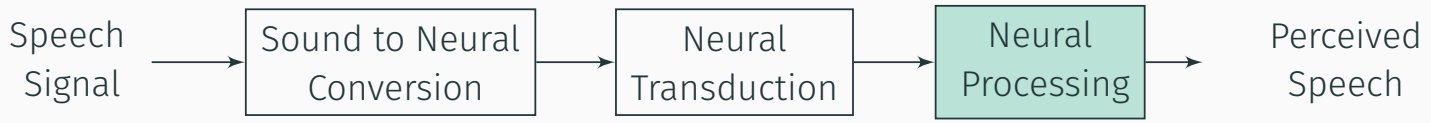

- Not yet well understood.

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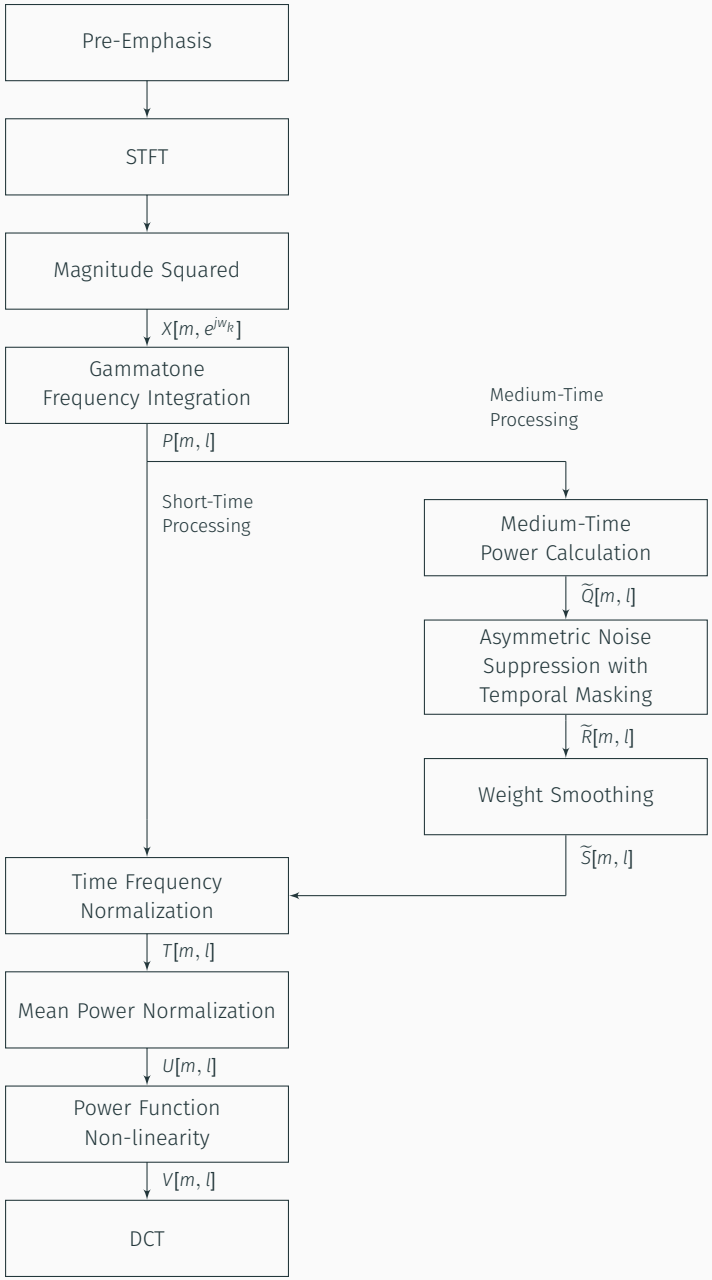
Power Normalized Cepstral Coefficients (PNCC)



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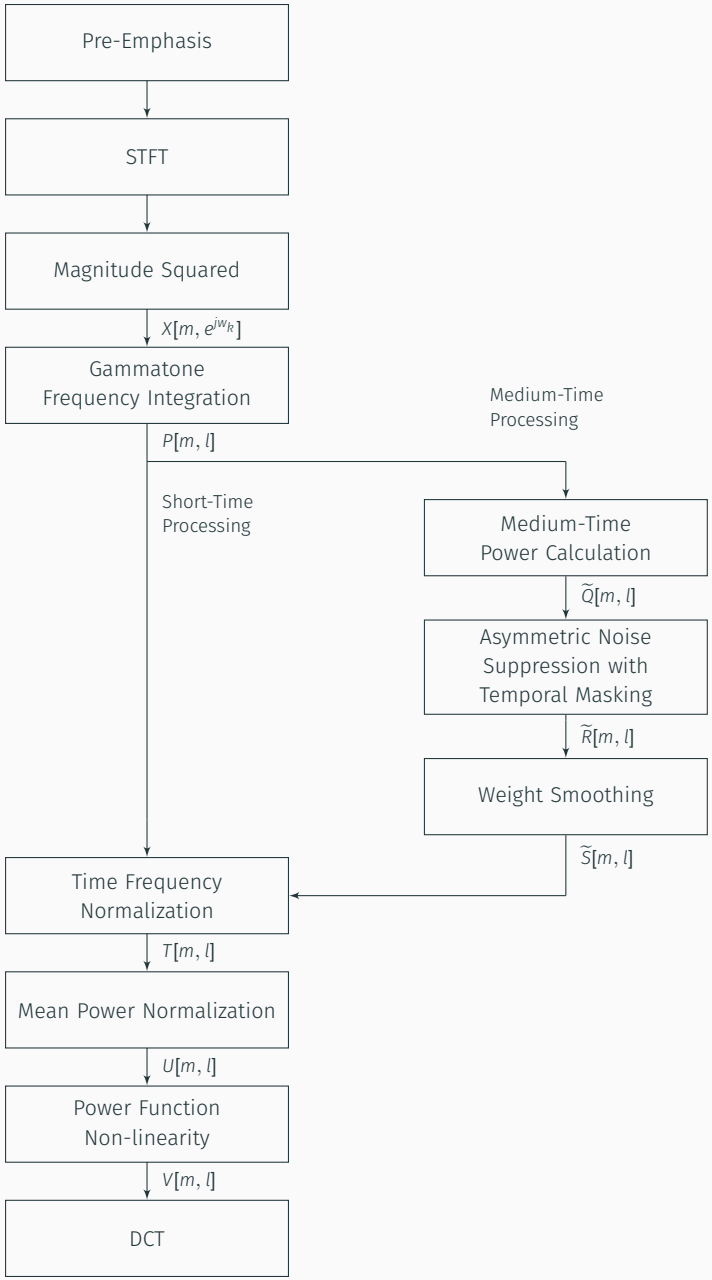

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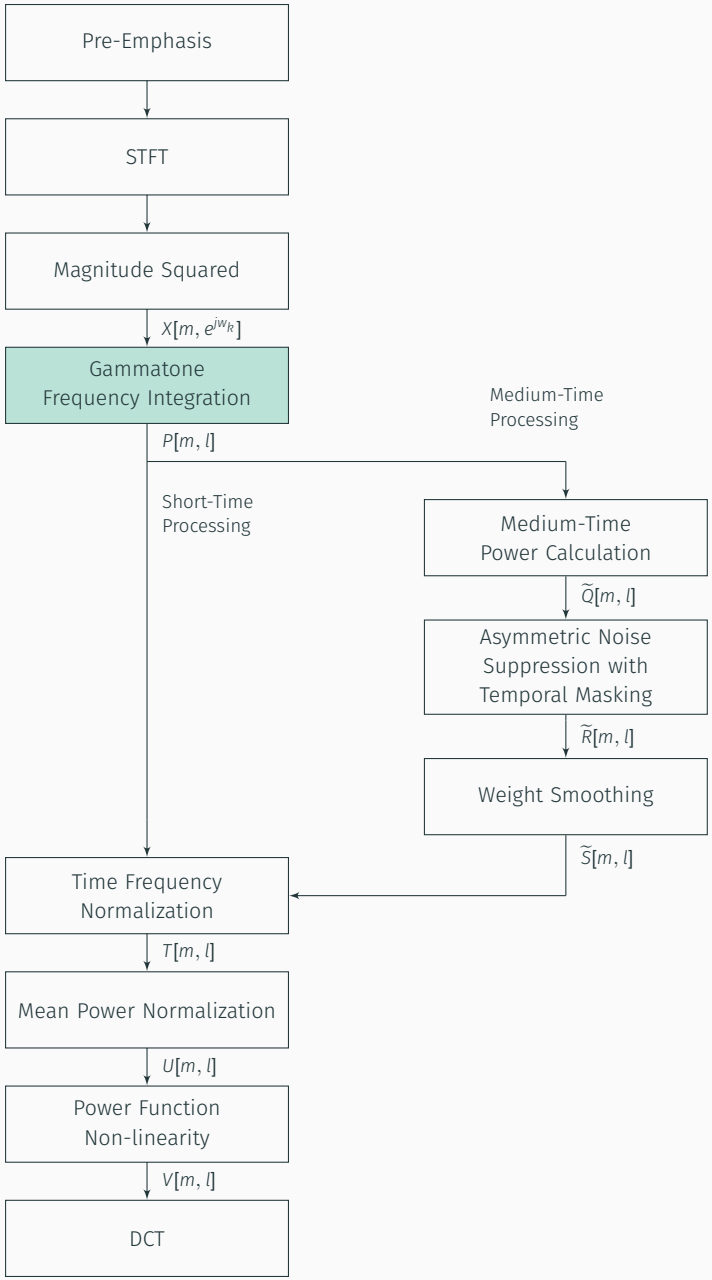

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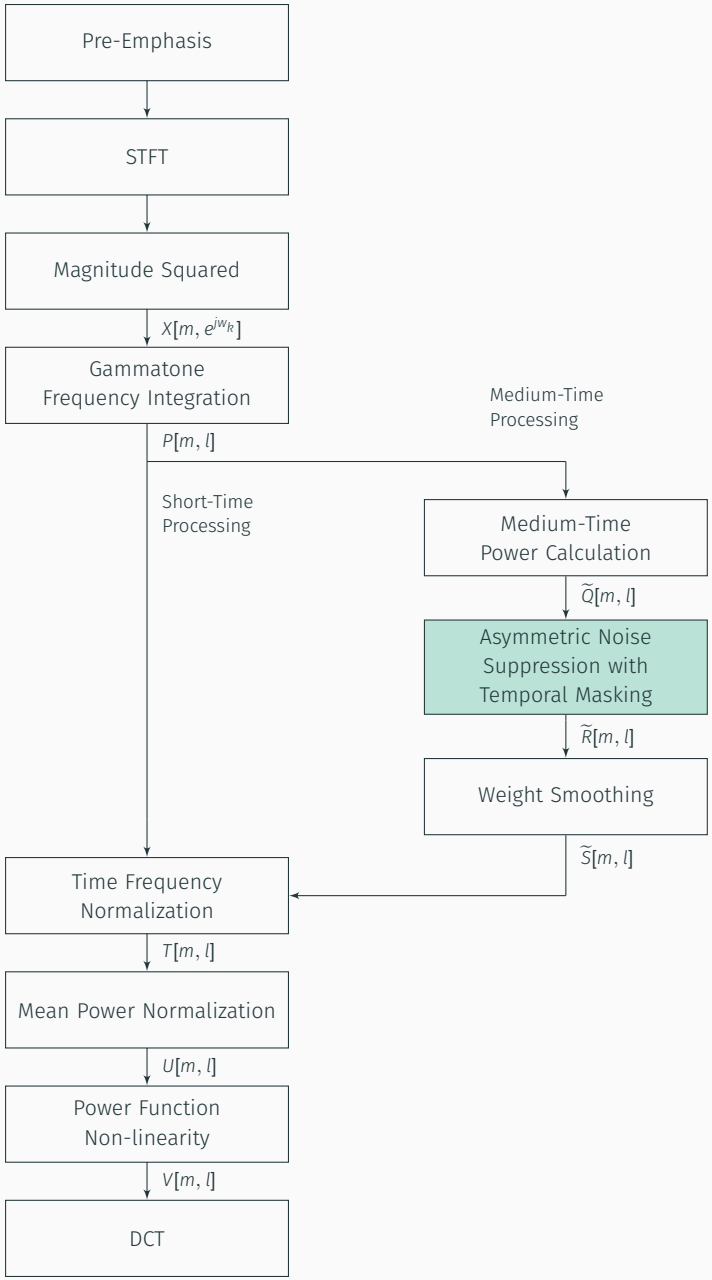

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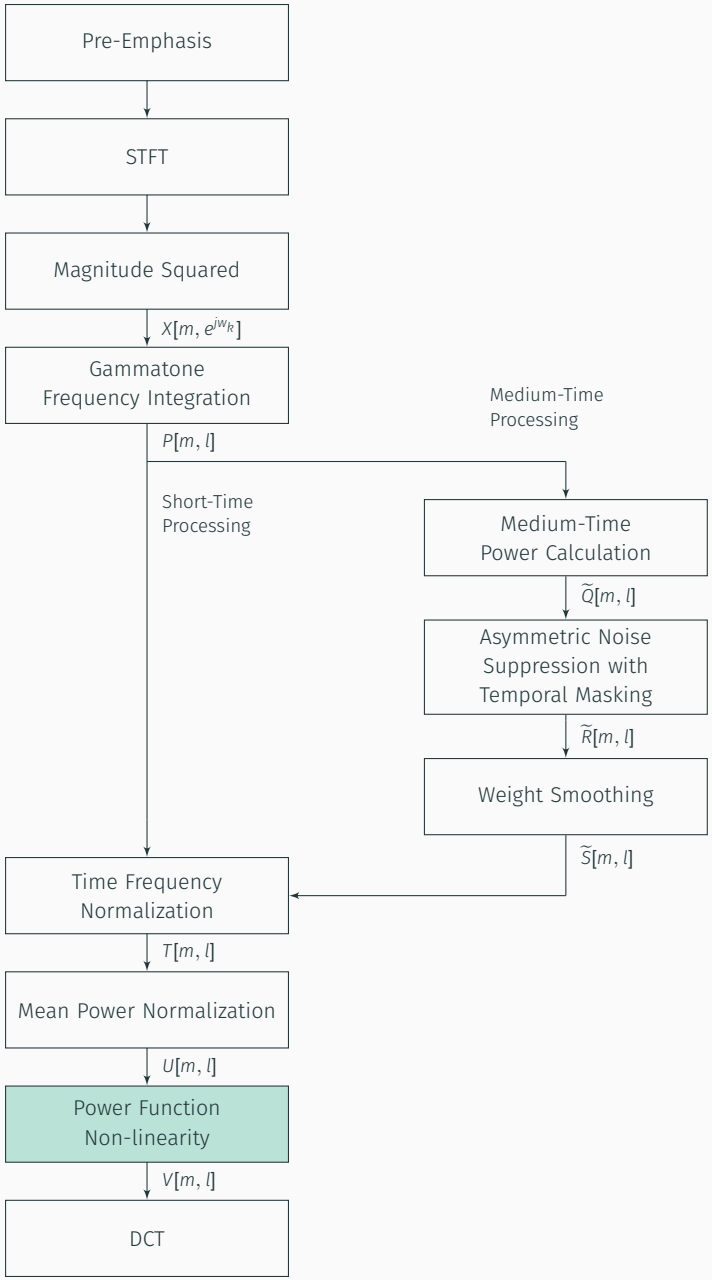

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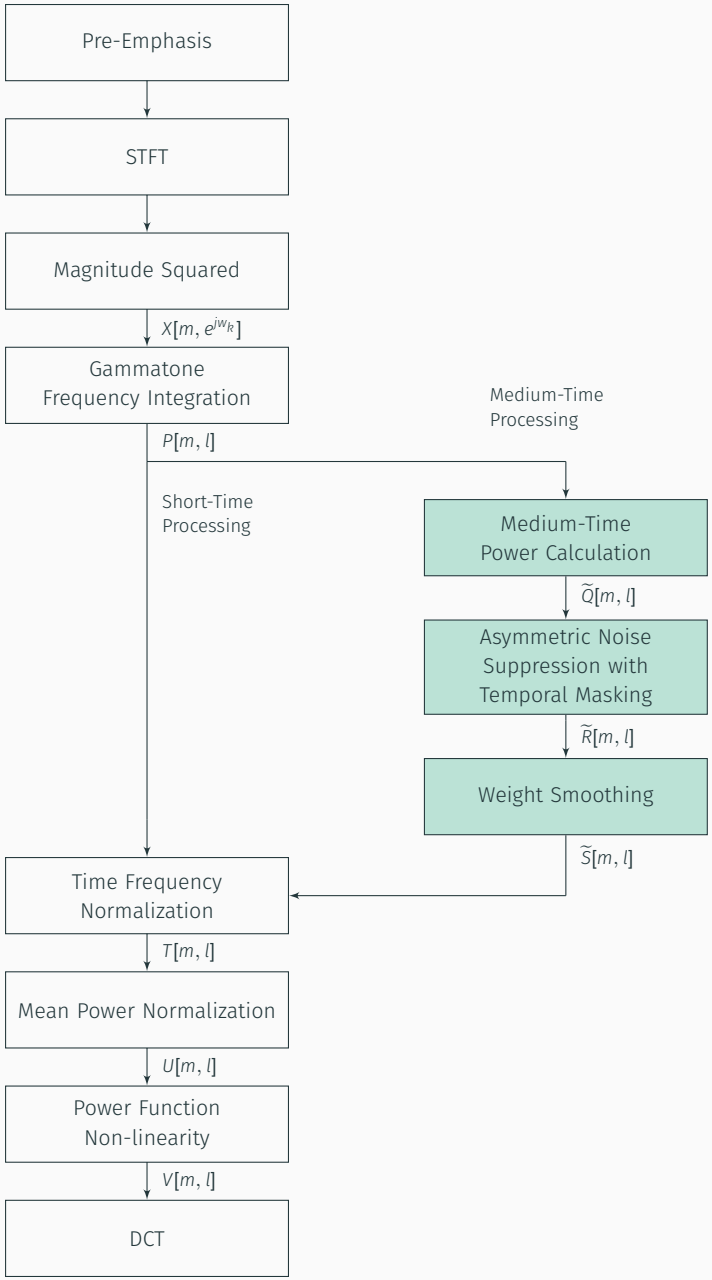

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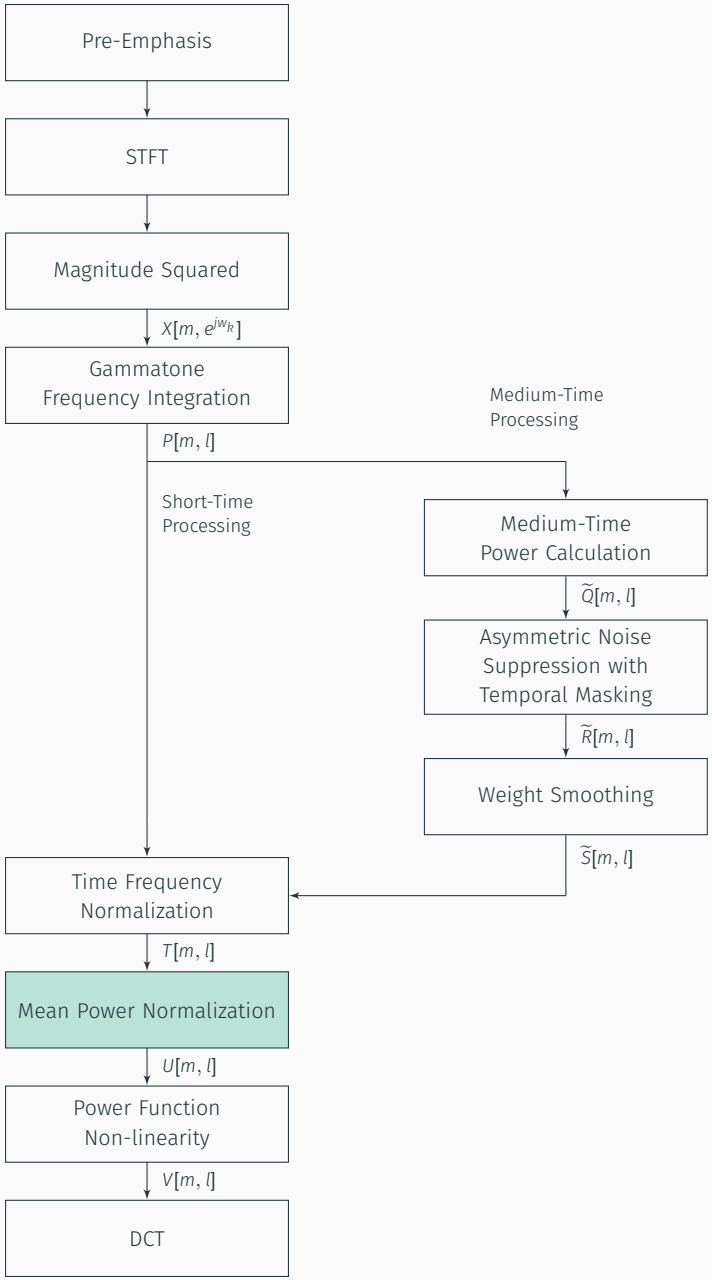

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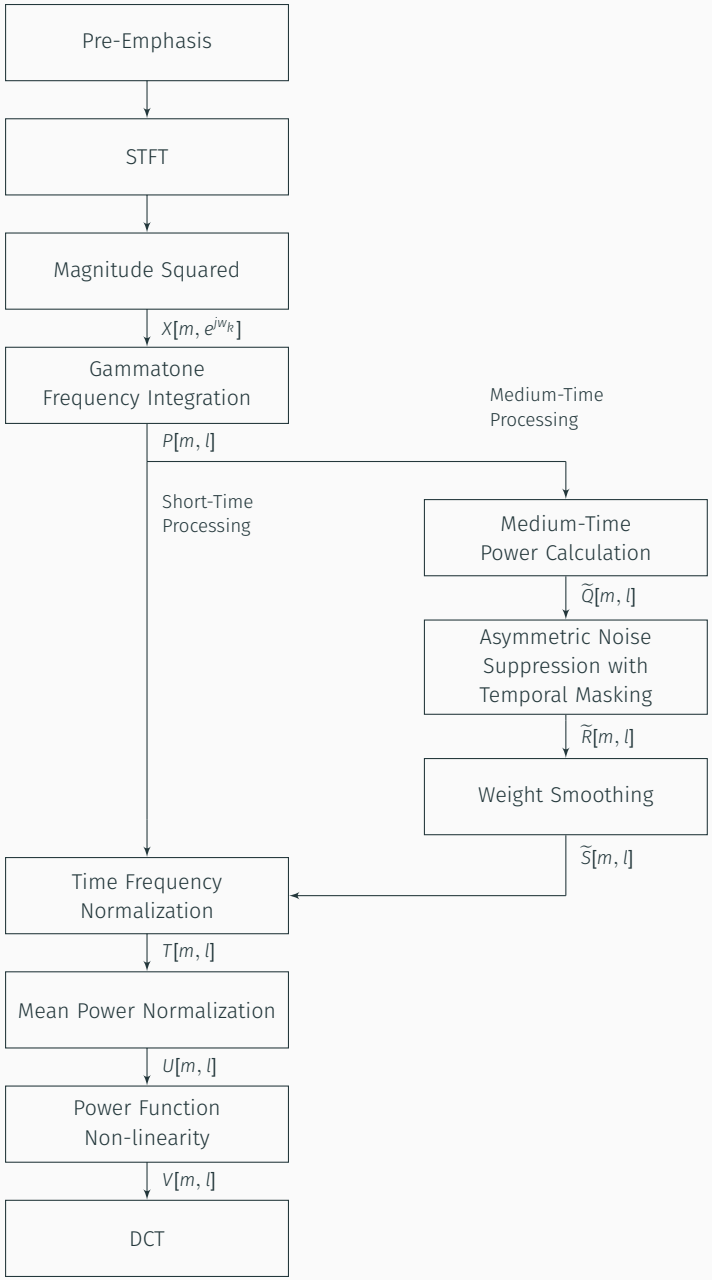

- Pragmatic implementation of auditory principles:
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- Not represented:

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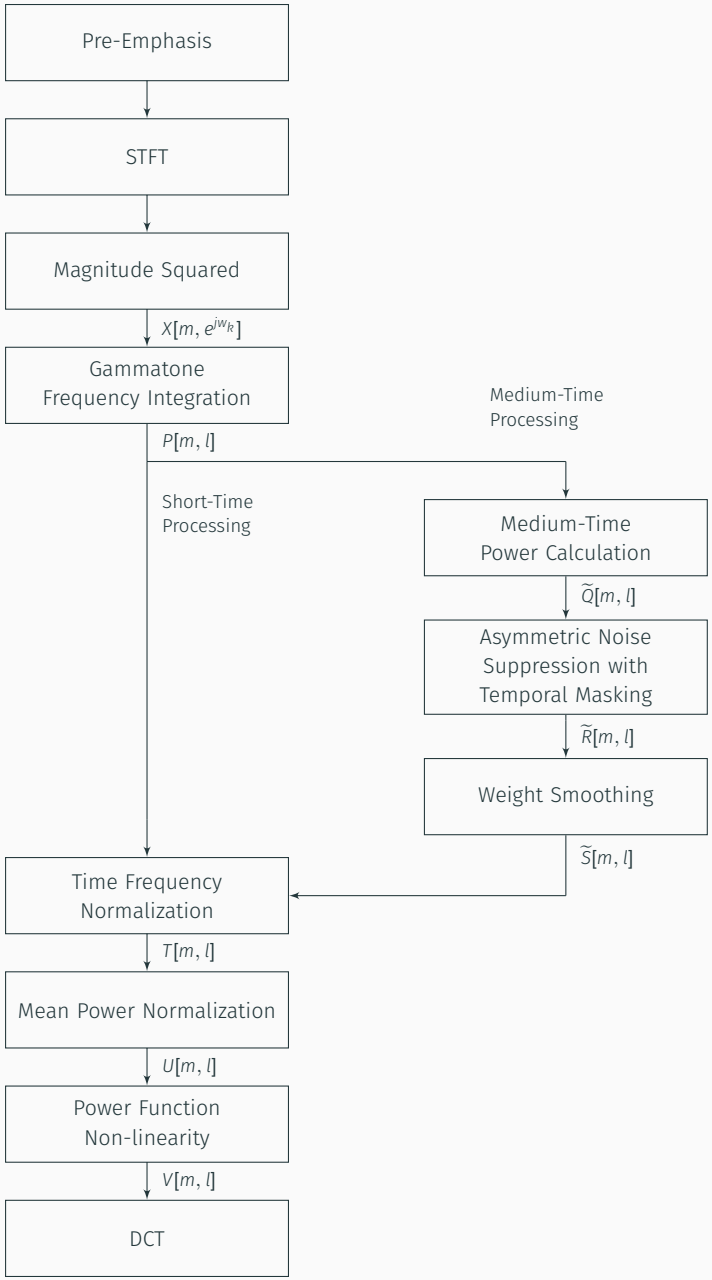

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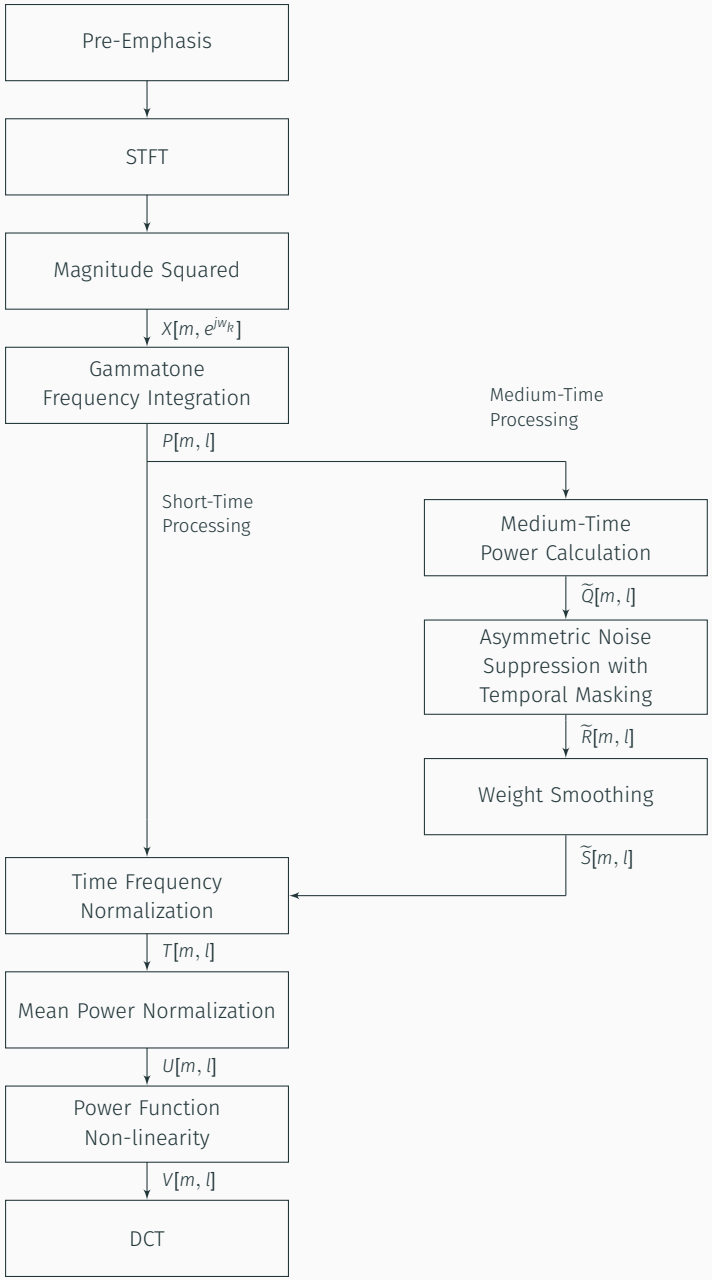

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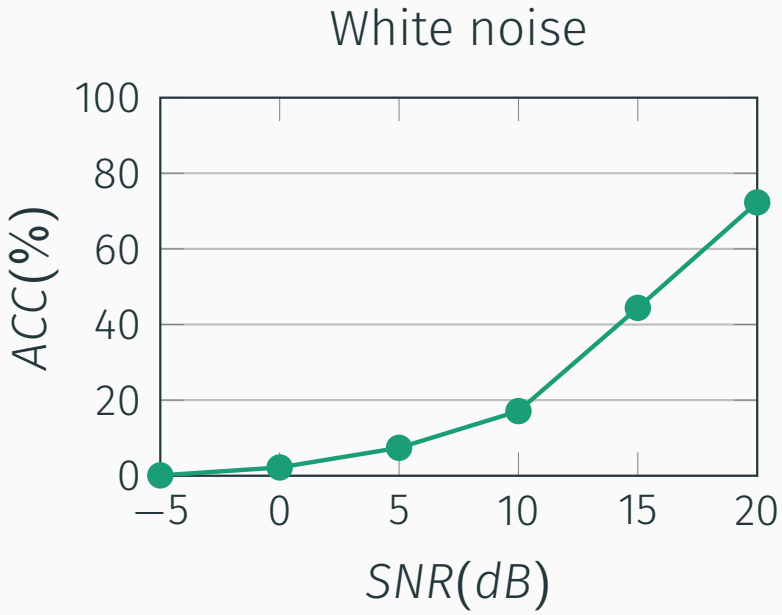
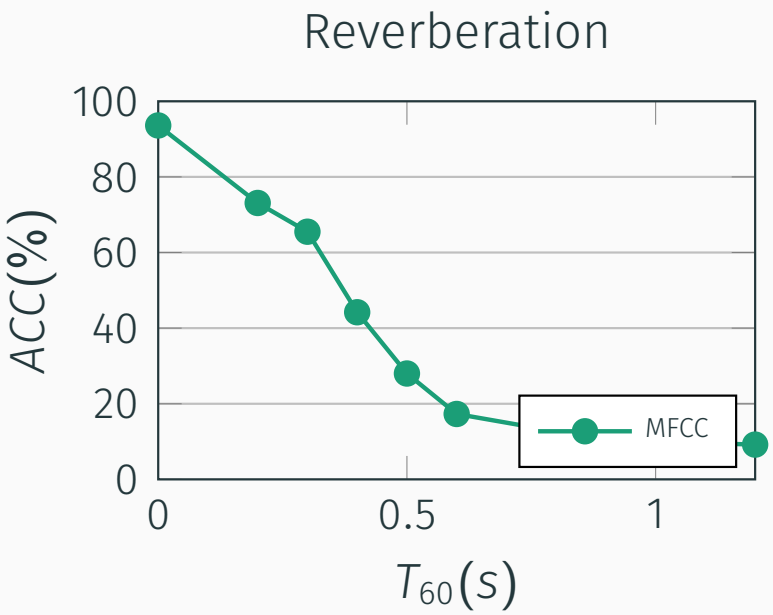
  - Detailed timing structure.

PNCC Results





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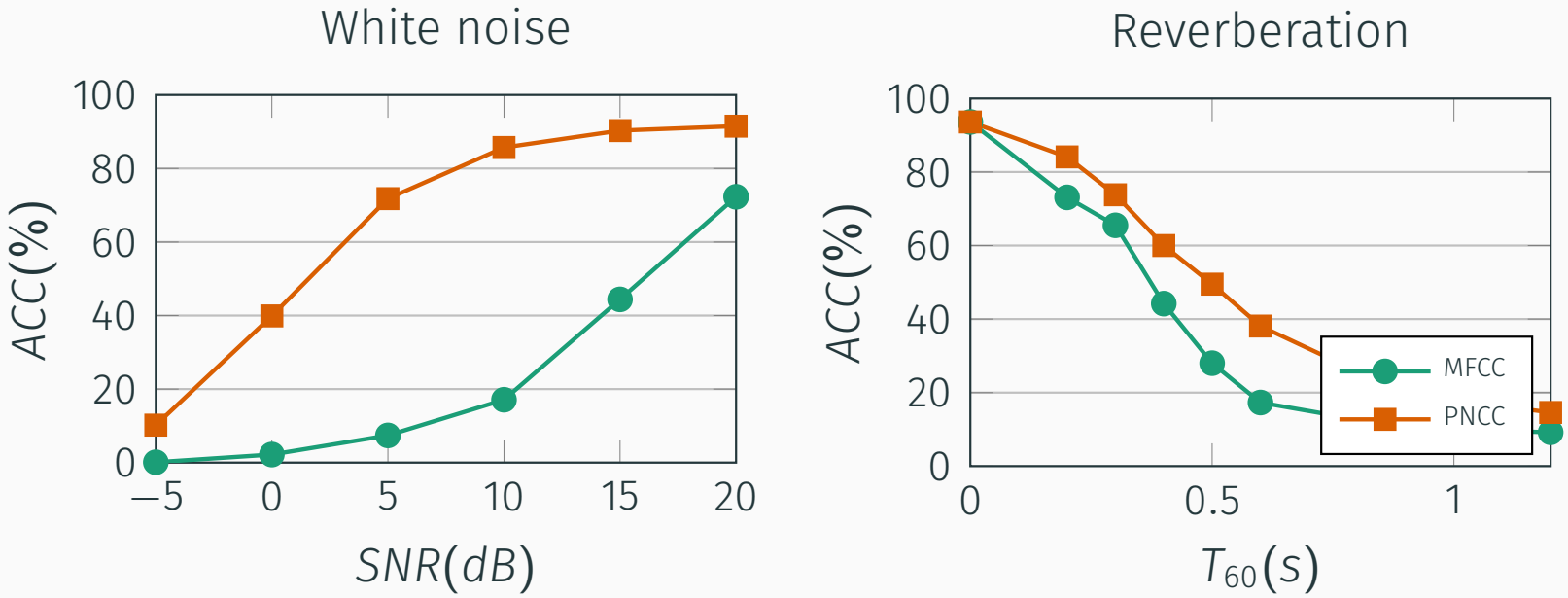

It is our main baseline.

Power-Normalized Cochleograms

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- Structuring Element (SE) design based on the masking properties of the HAS.

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The perception of one sound is affected by the presence of another sound.

From Fastl and Zwicker (2007).

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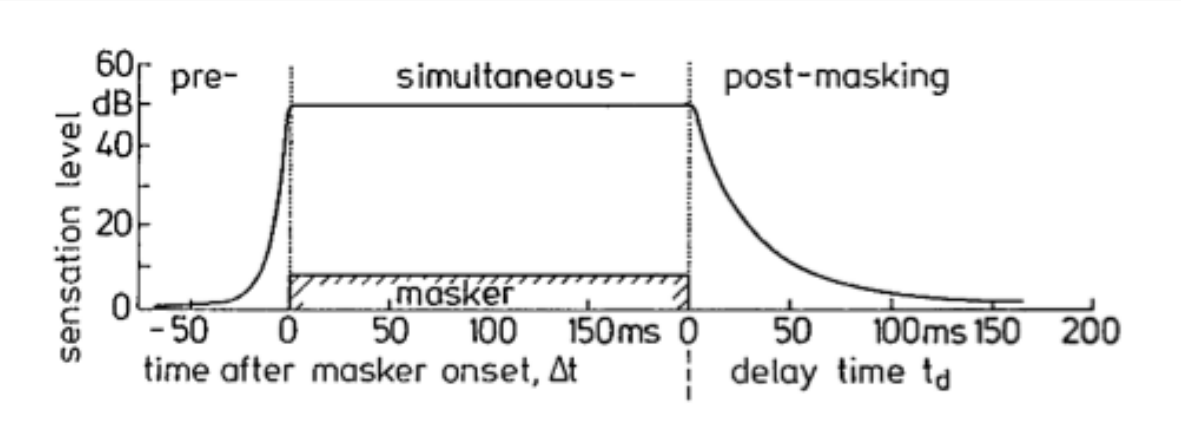

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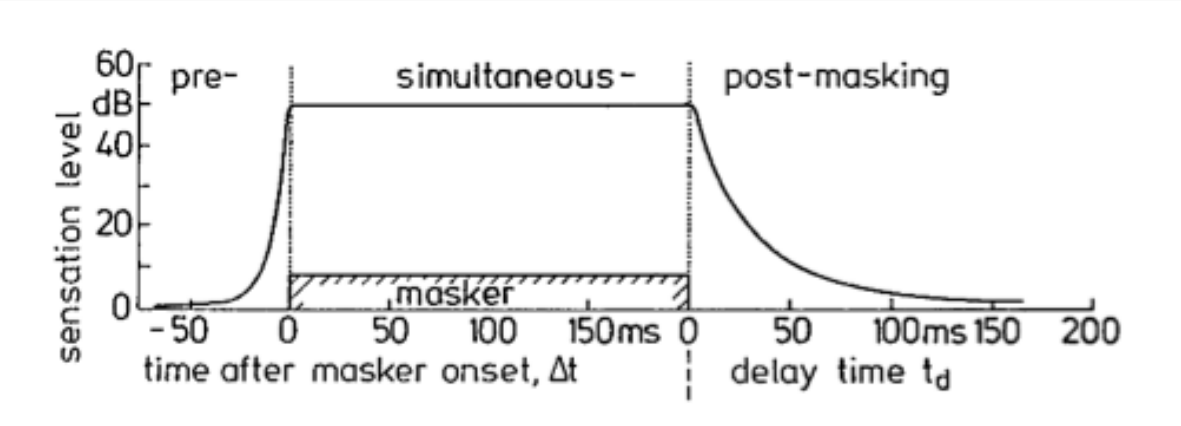

- Simultaneous or spectral masking.

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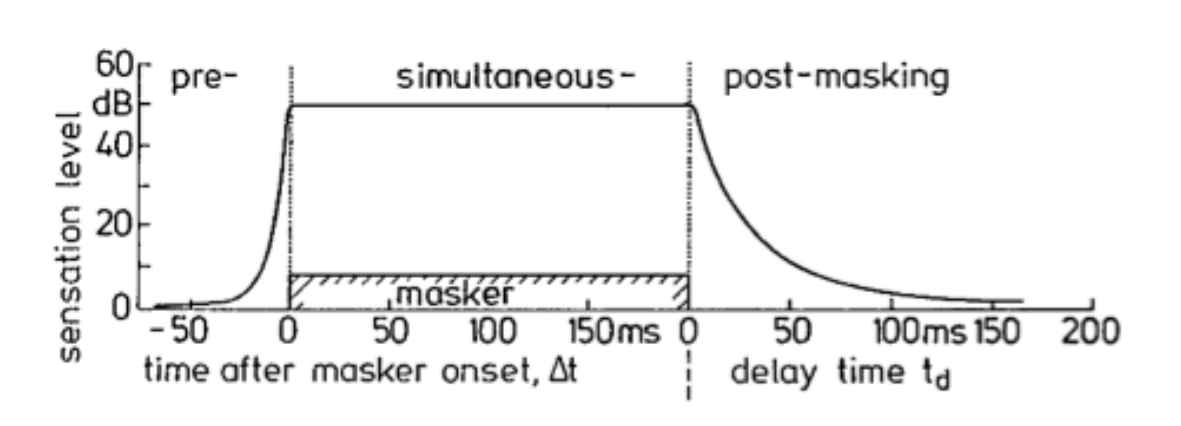

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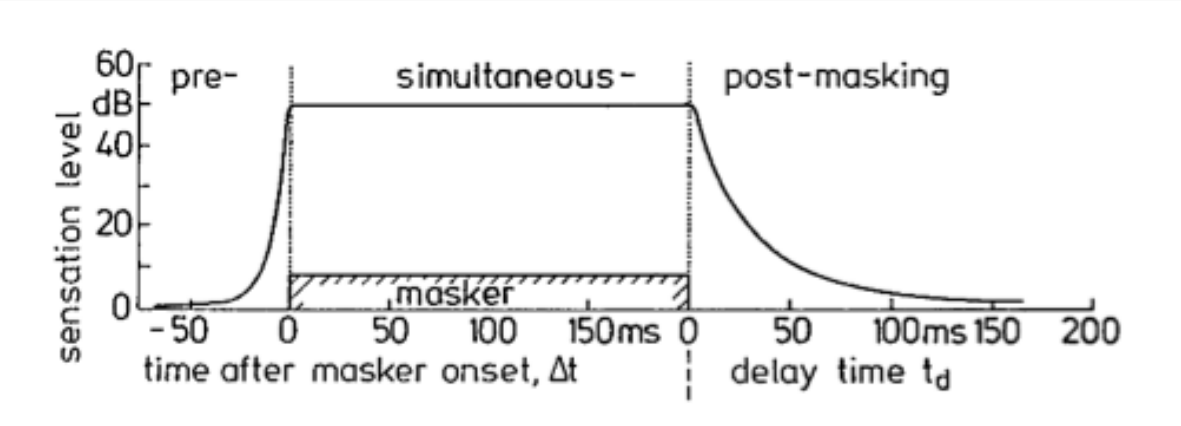

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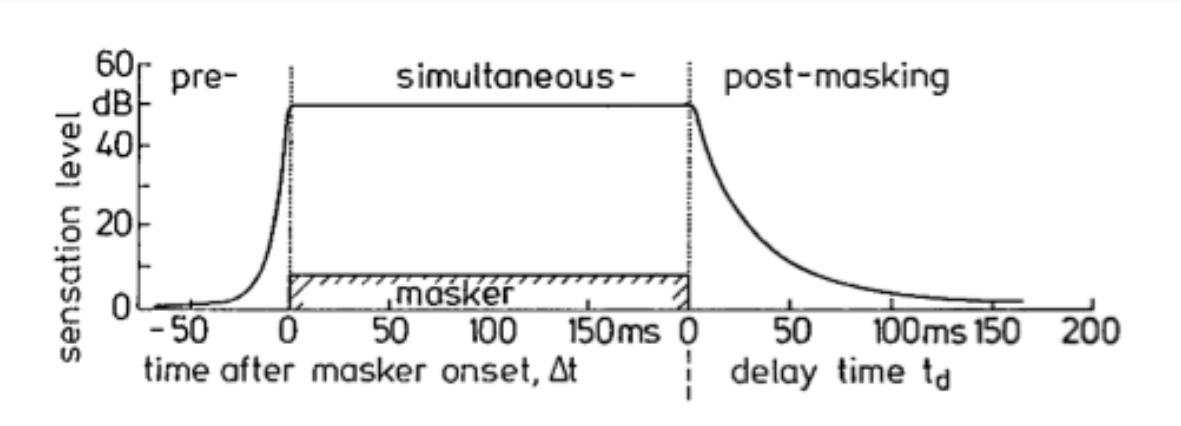

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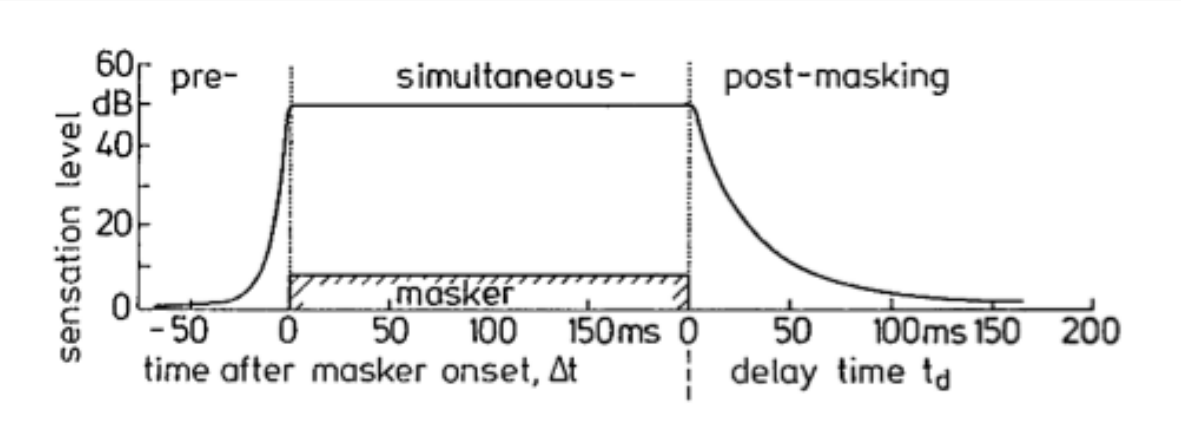

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Simultaneous Masking Model

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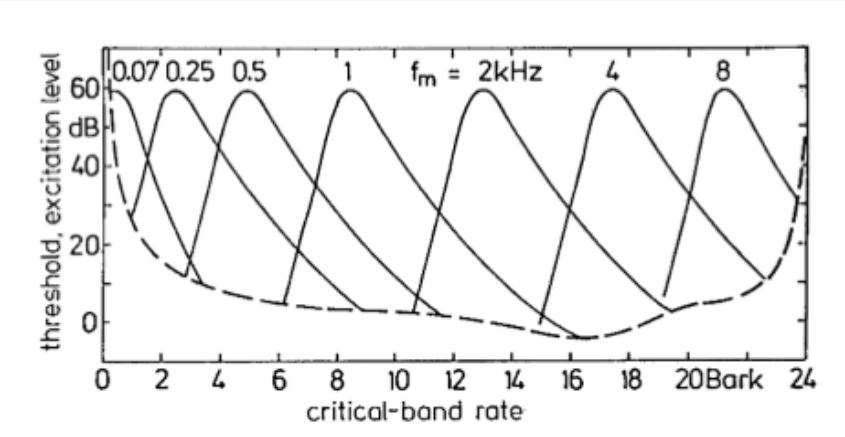

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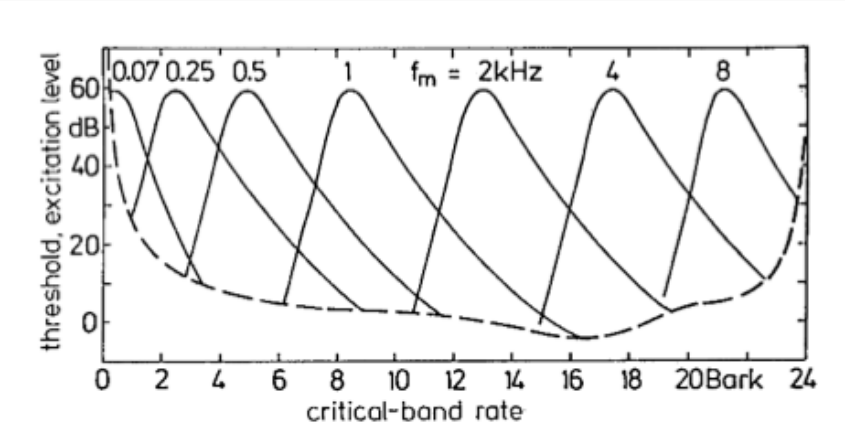
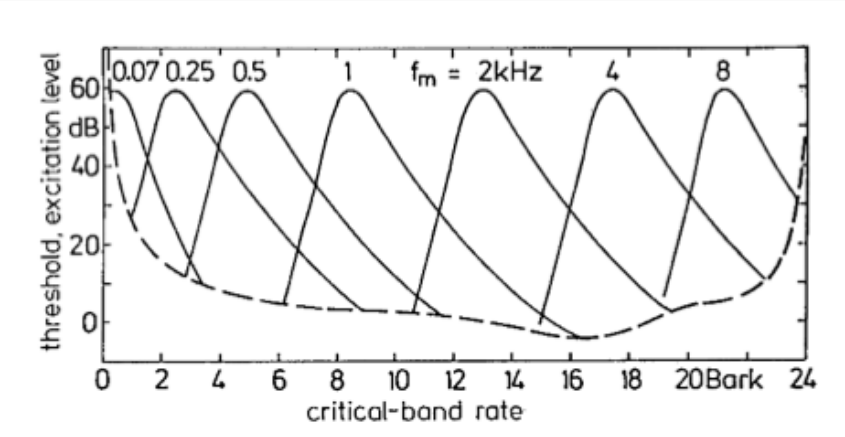


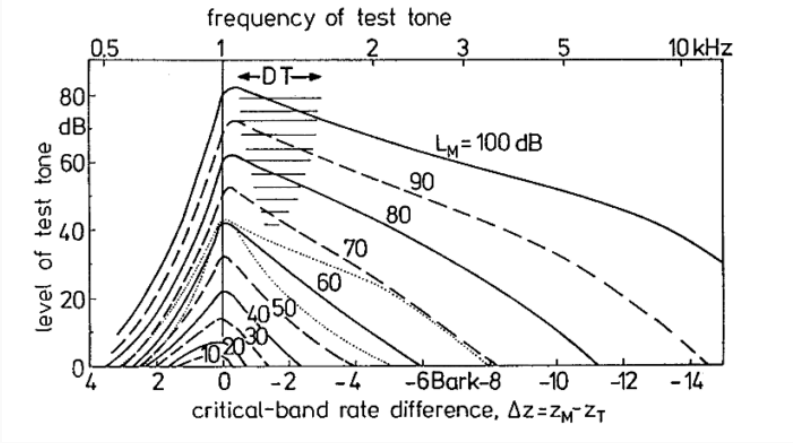
- Represented in bark scale.

Simultaneous Masking Model

Masking curves presented by Fastl and Zwicker (2007).



- Represented in bark scale.
- Varying intensity levels can also have an effect on masking.



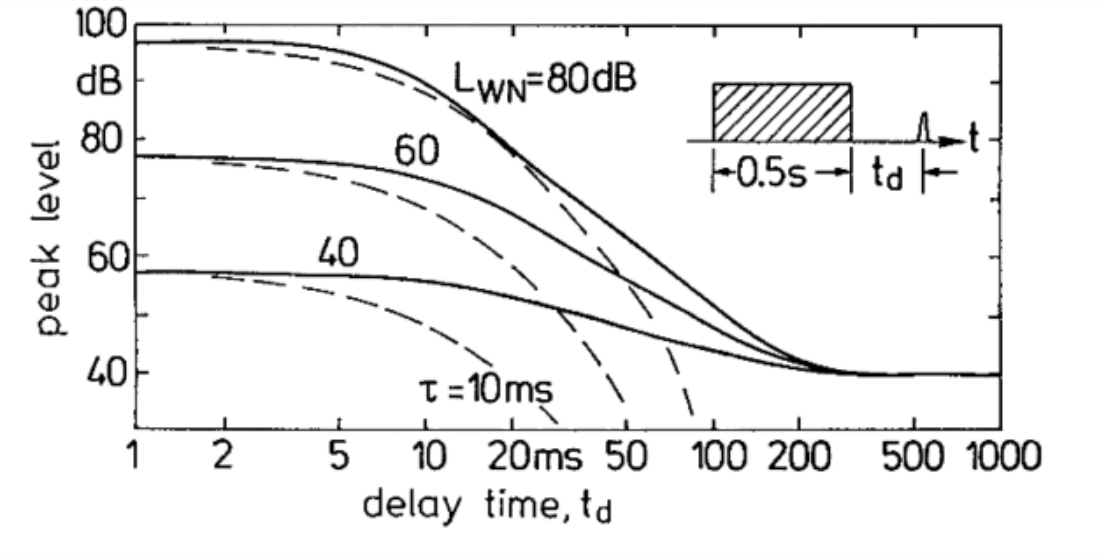
Temporal Masking Model

- Linear model for premasking.

From Fastl and Zwicker (2007).

Temporal Masking Model

- Linear model for premasking.
- Logarithmic model for postmasking (Jesteadt et al., 1982).



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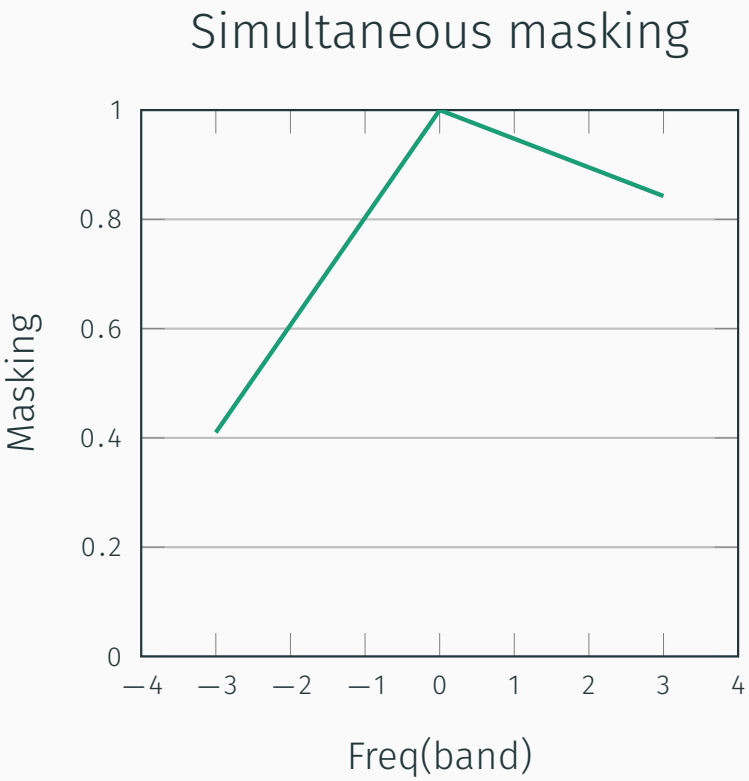
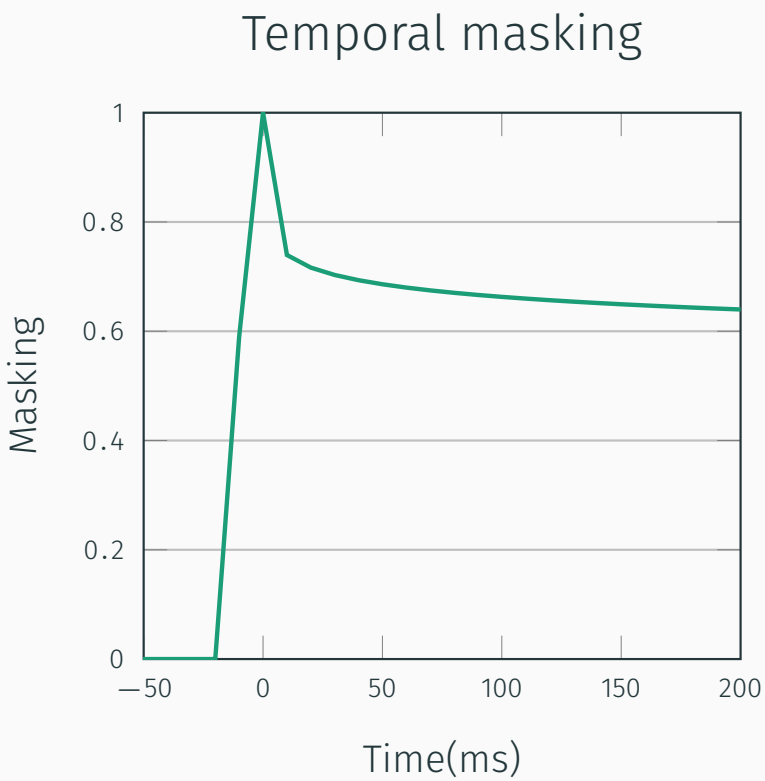
Masking Models





Morphological Filtering

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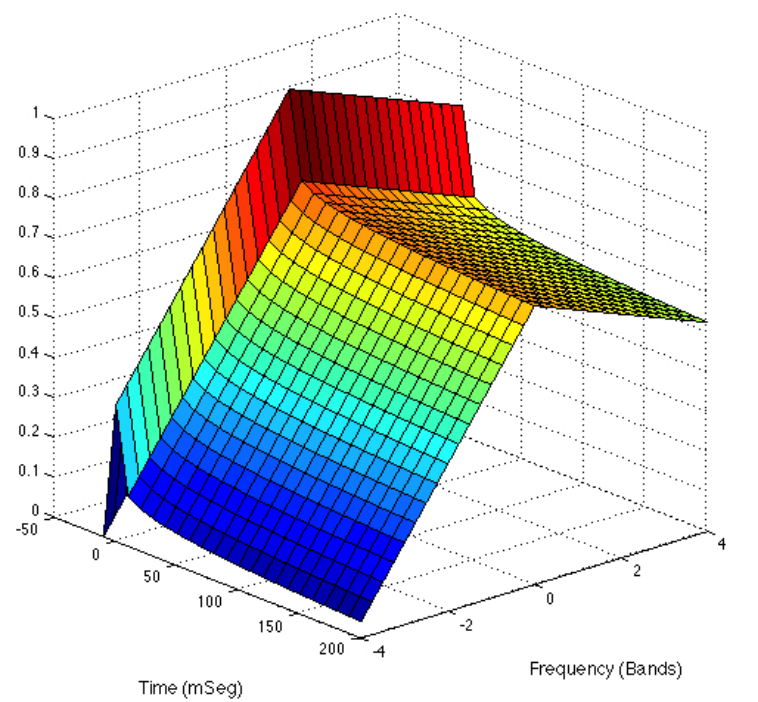
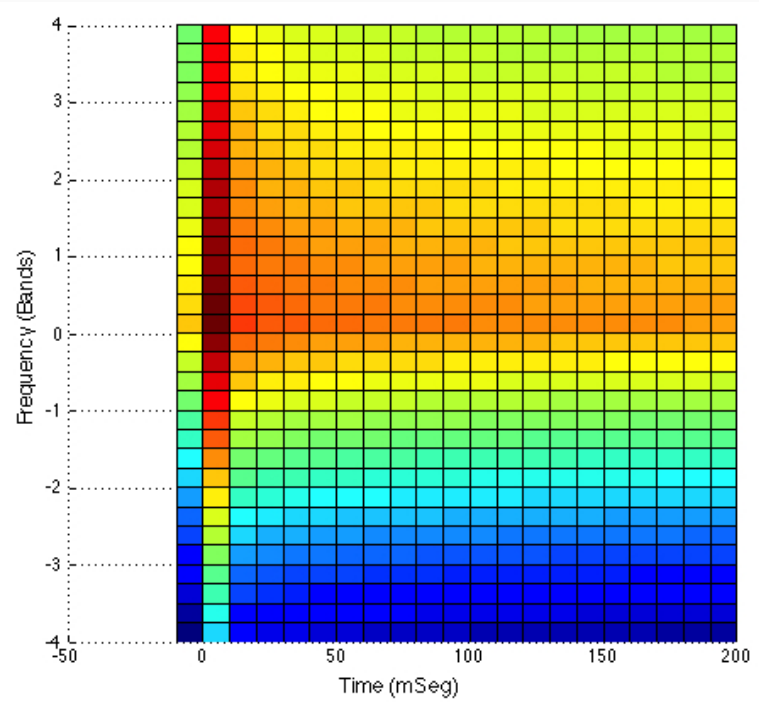
Piecewise-lineal SE





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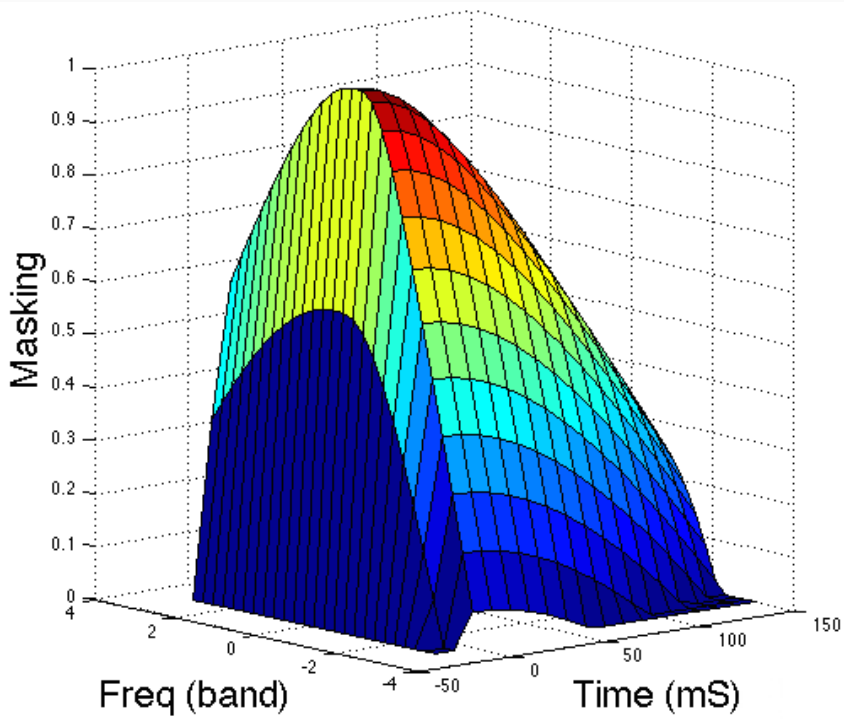
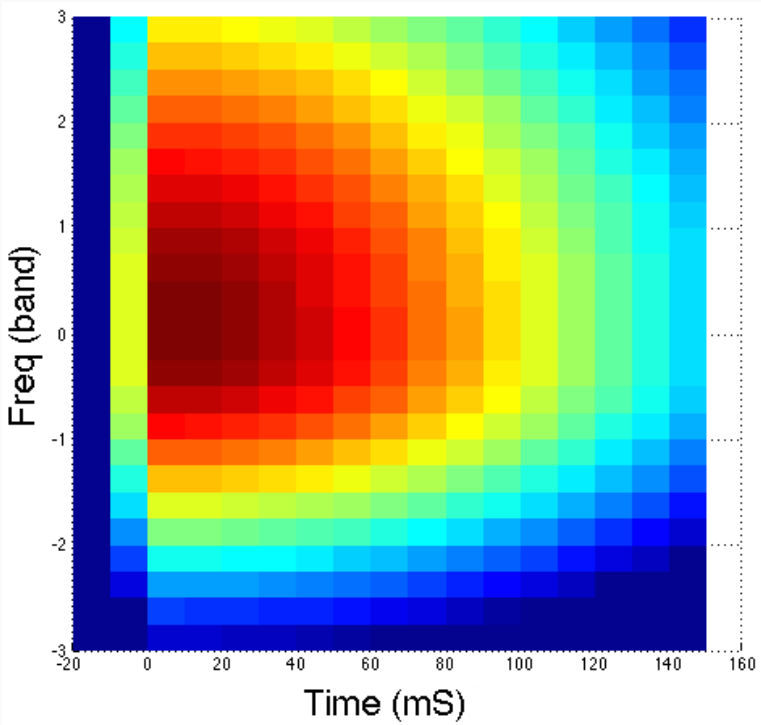
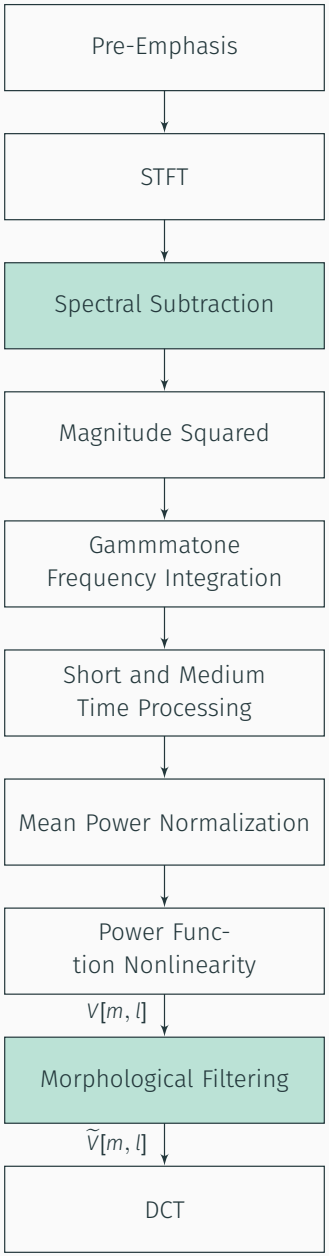
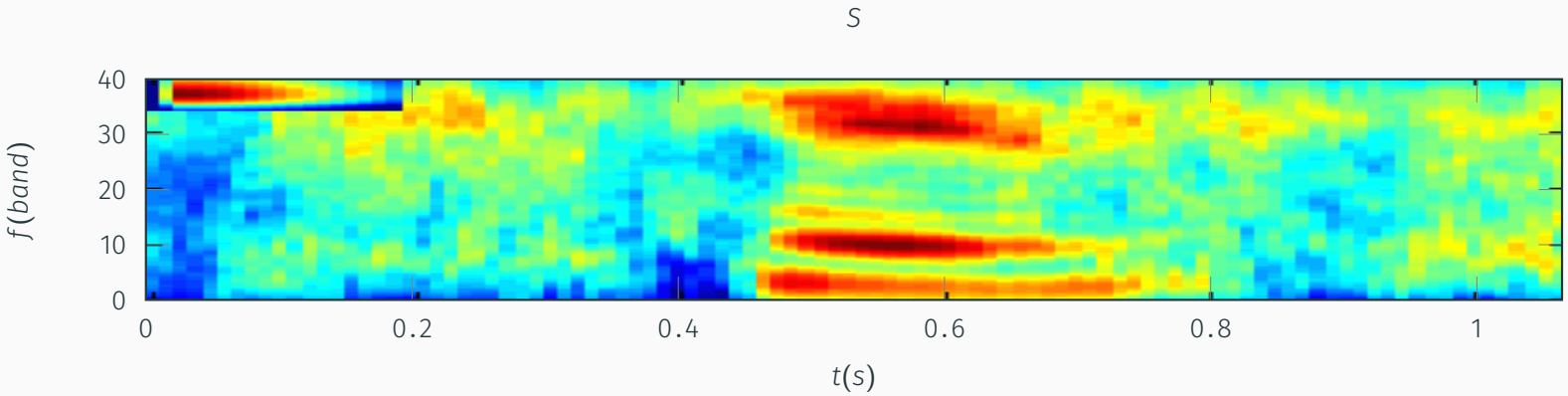




PNCC Spectro-temporal Representation



Filtering Process



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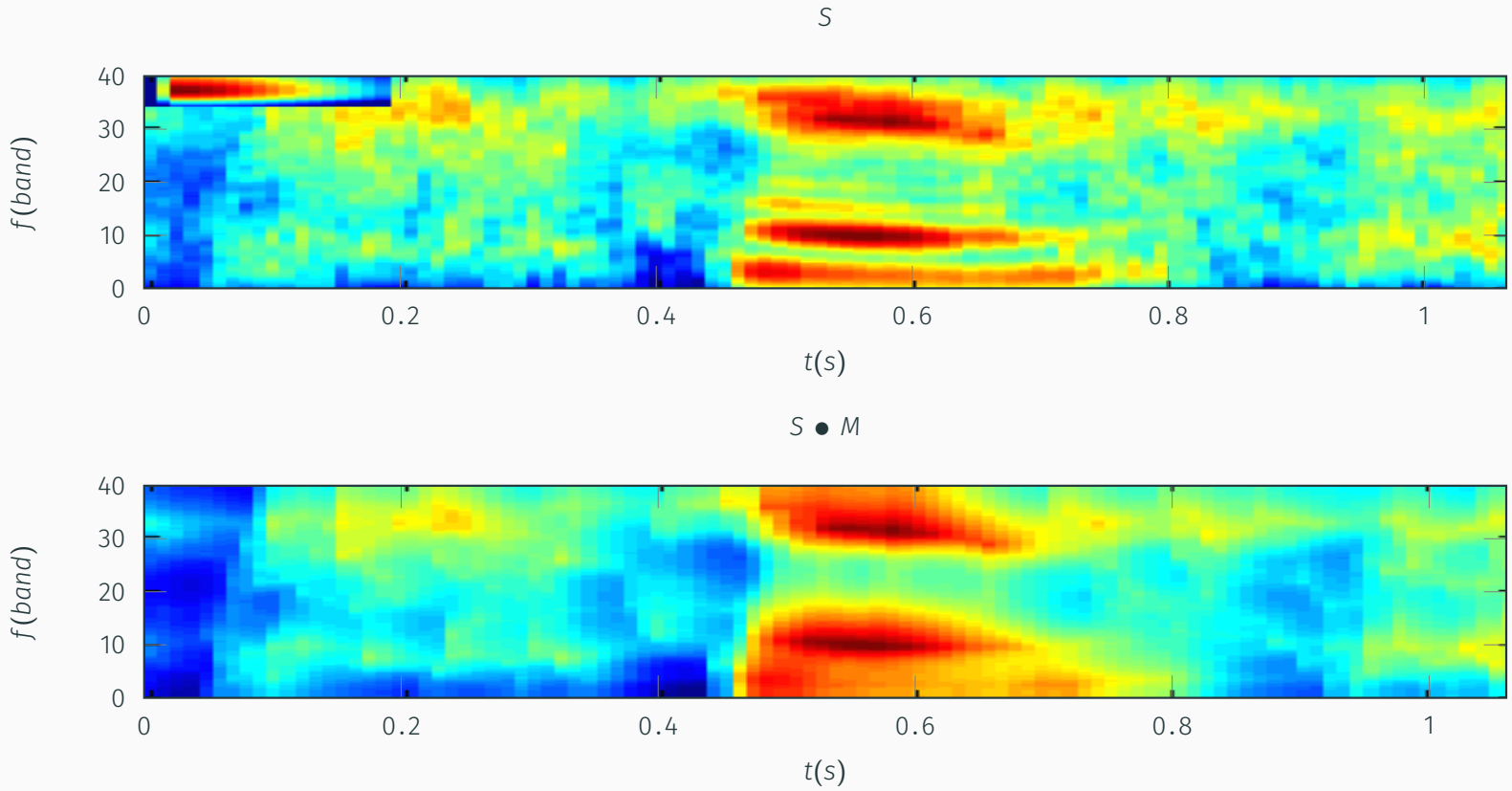
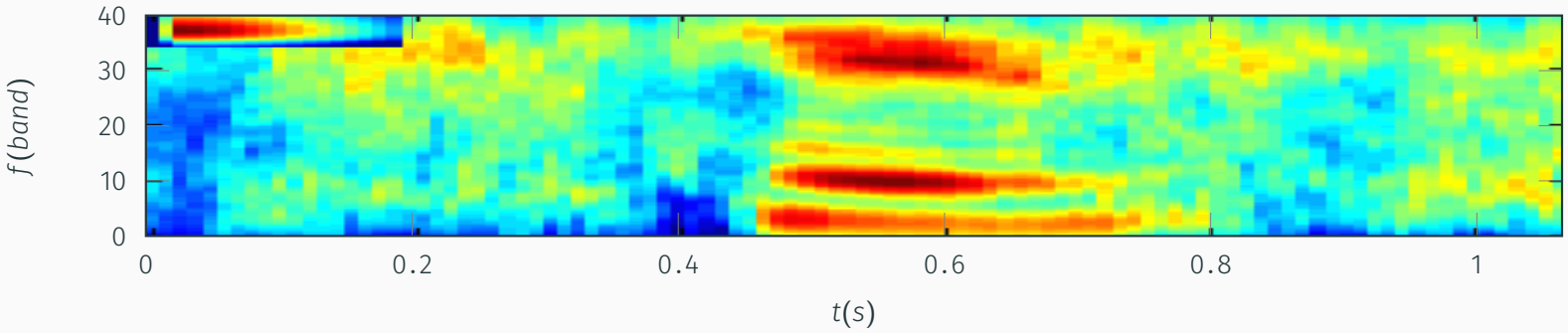
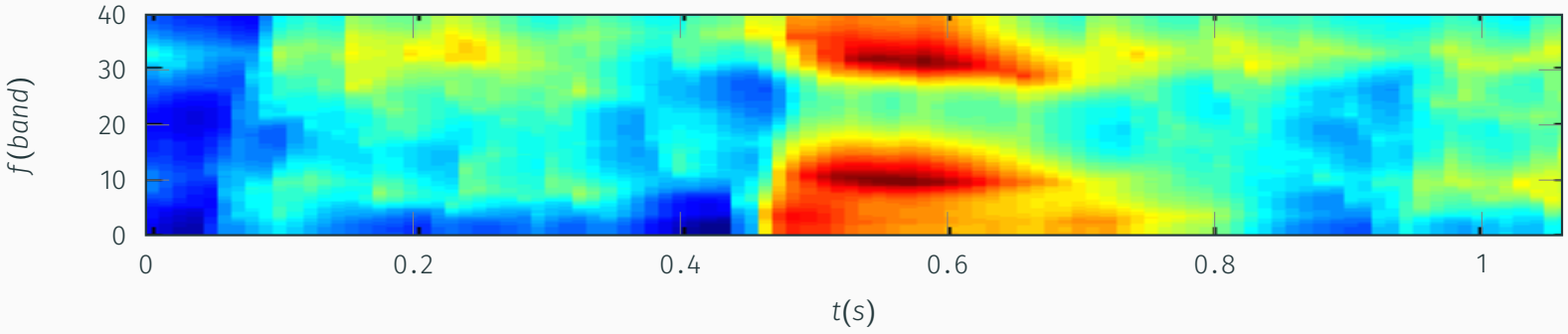


Filtering Process

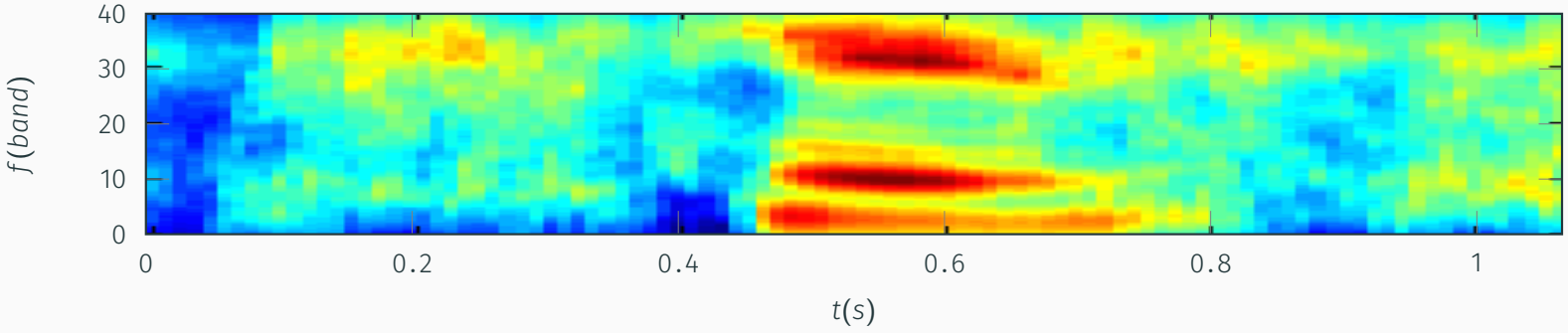
S



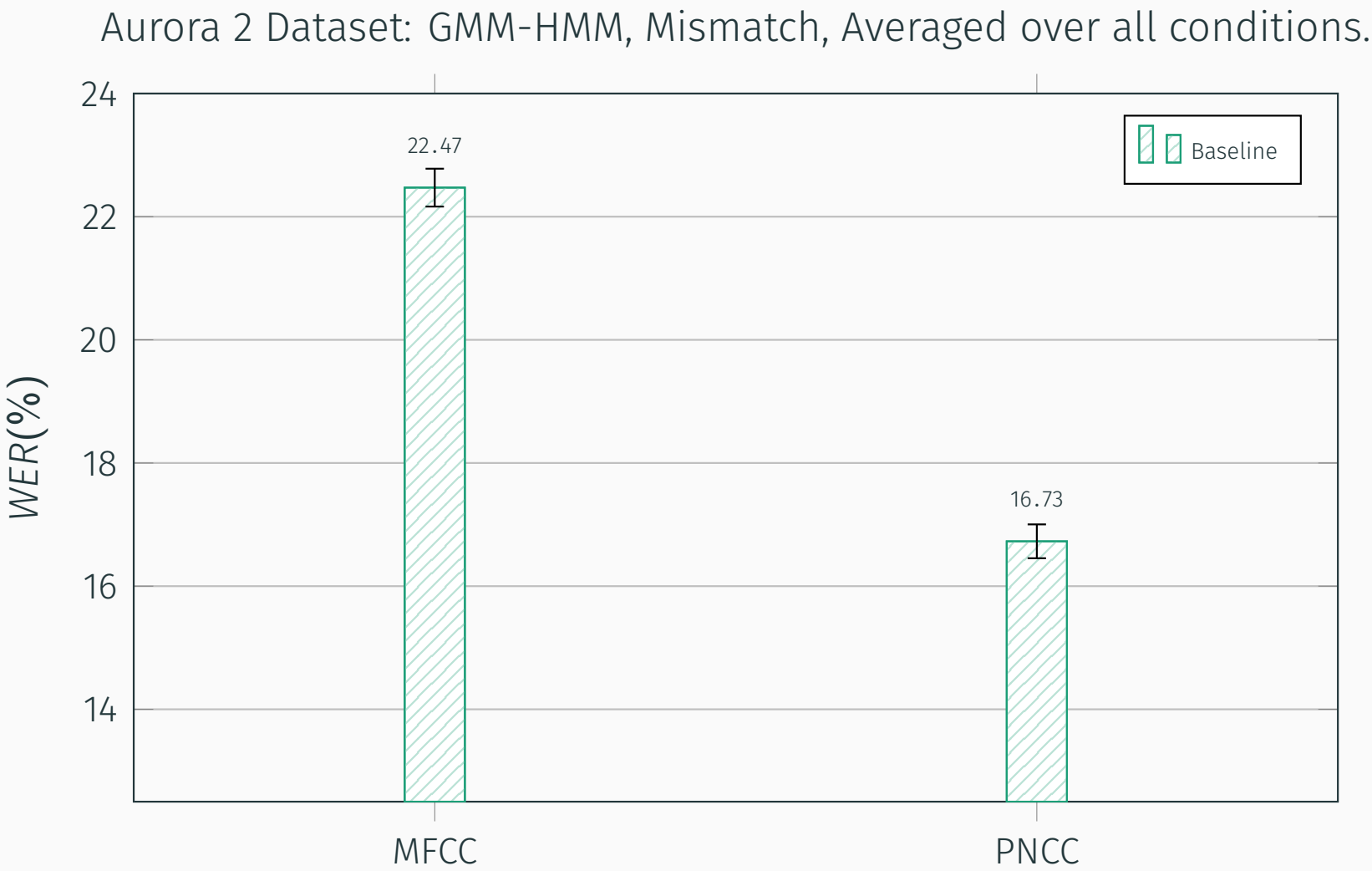
$S \bullet M$



$S' = \lambda S + (1 - \lambda) S \bullet M$ with $\lambda = 0.5$

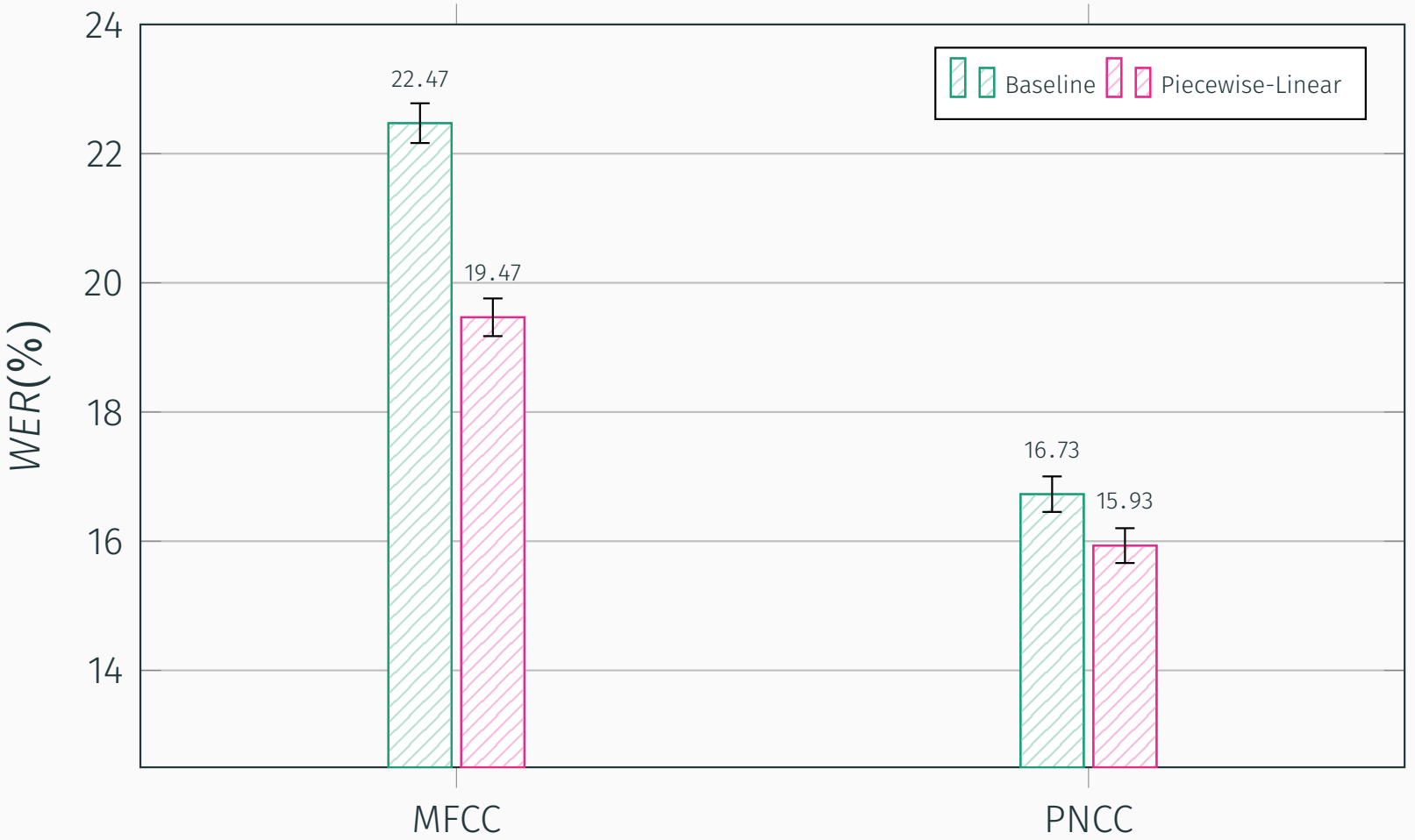


Results: Aurora 2



Results: Aurora 2

Aurora 2 Dataset: GMM-HMM, Mismatch, Averaged over all conditions.



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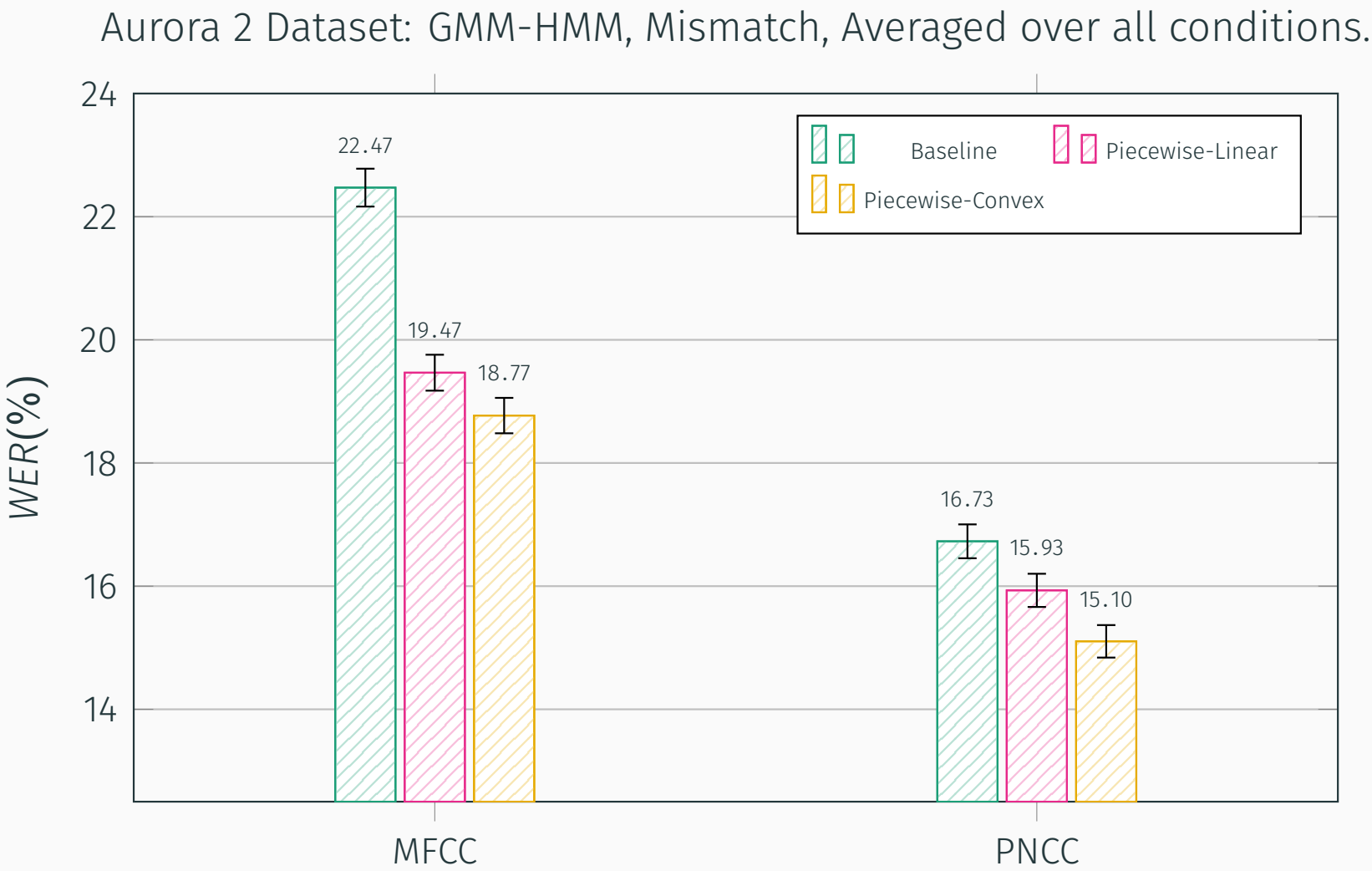

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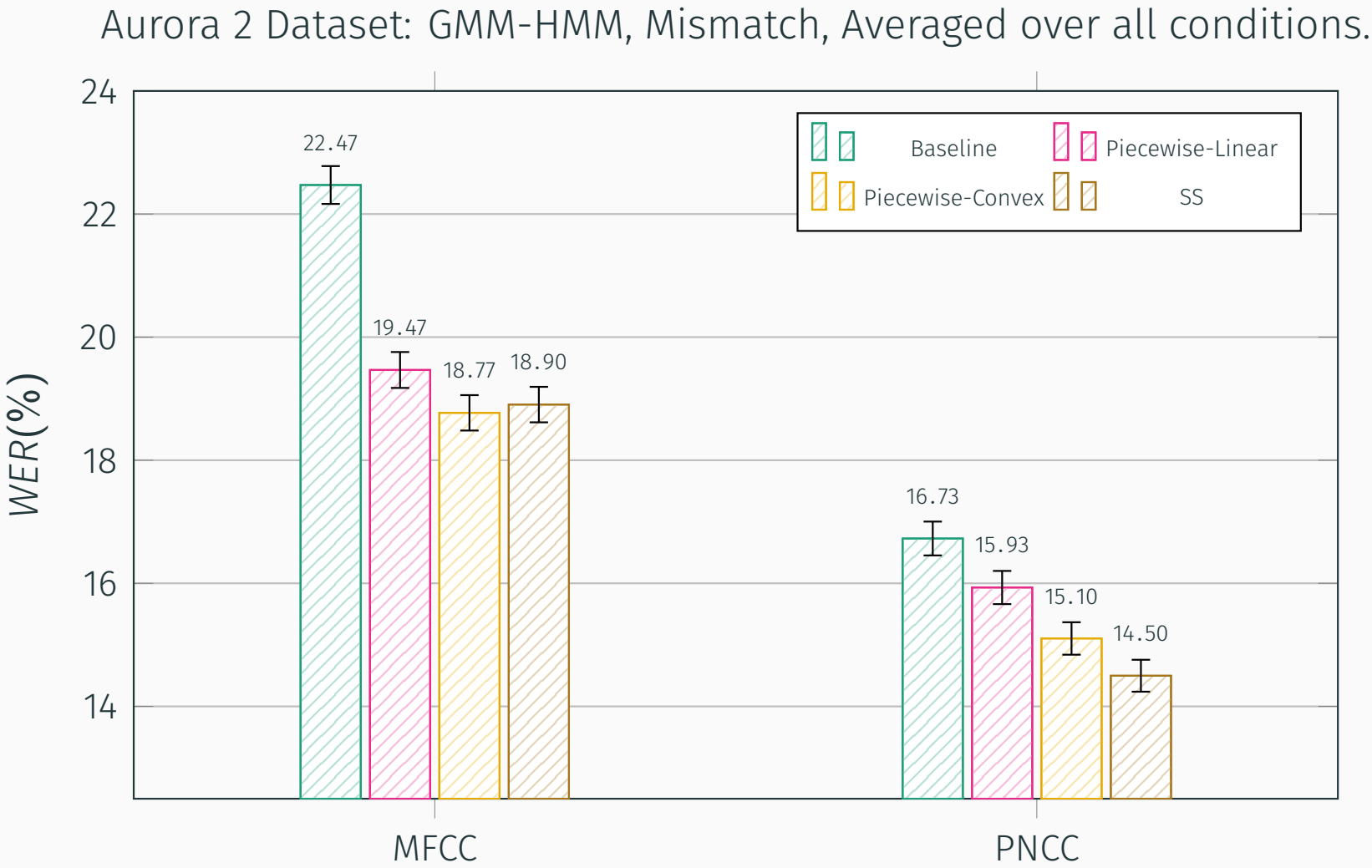

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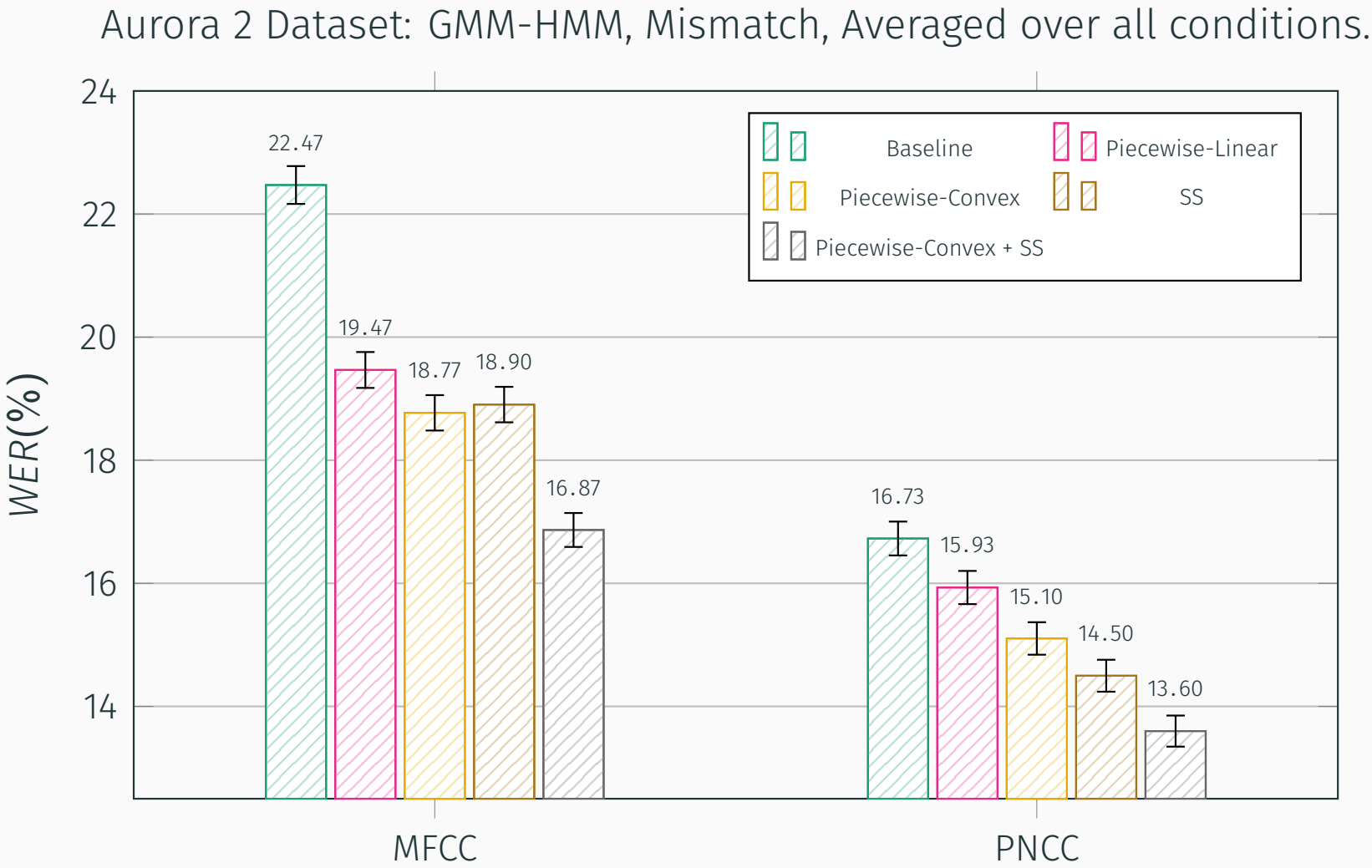
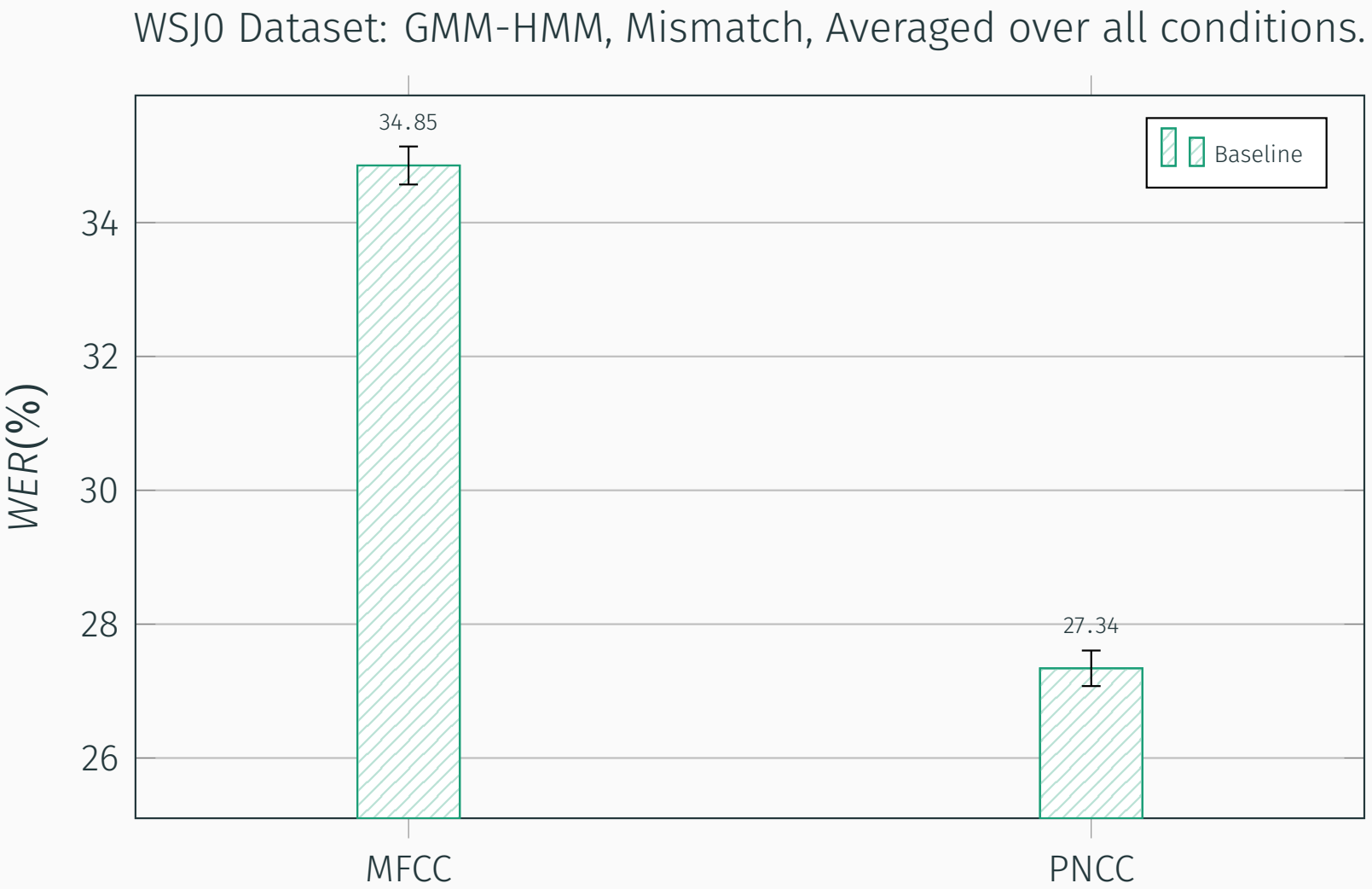


Results: WSJ0



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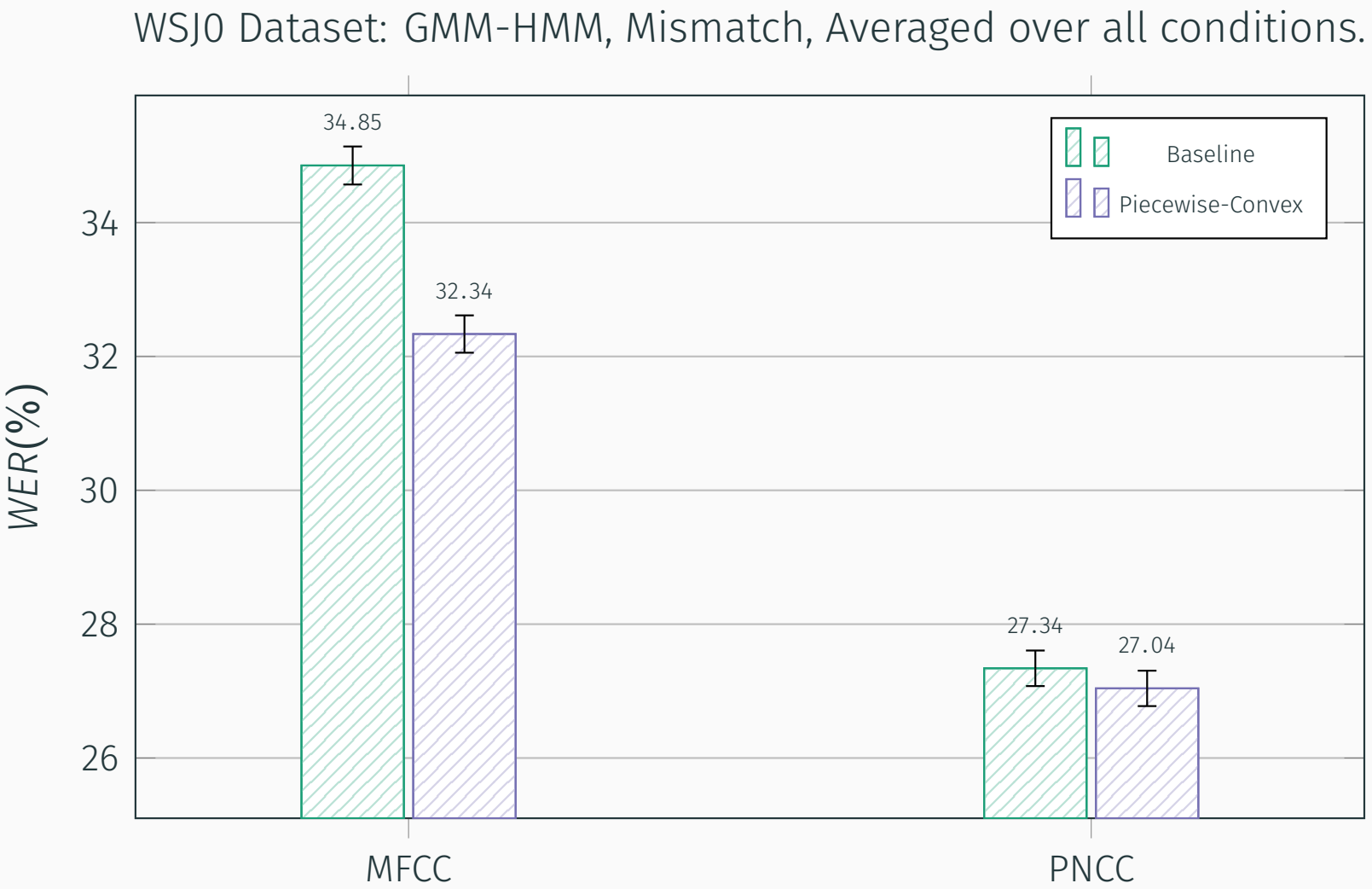

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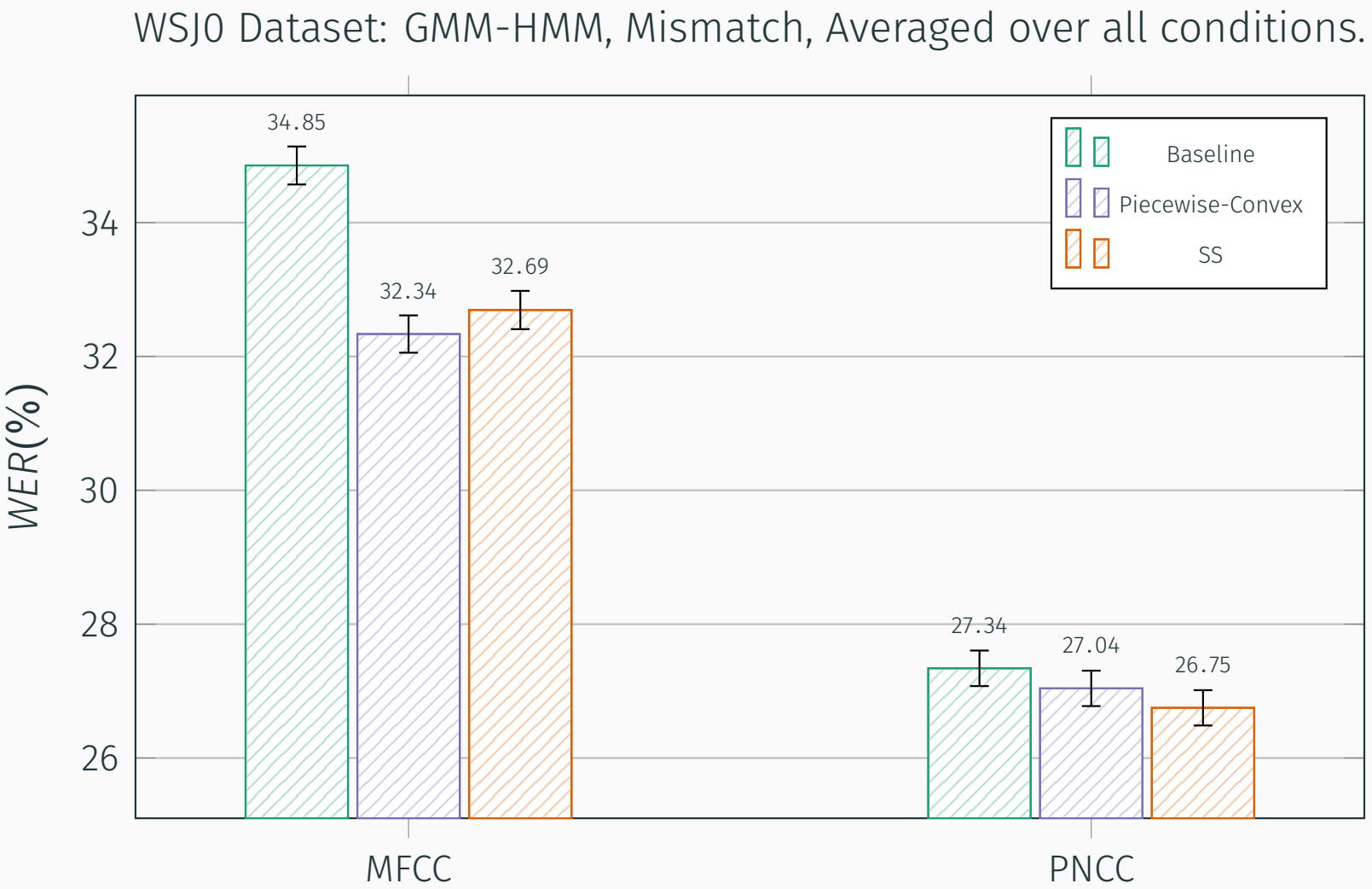

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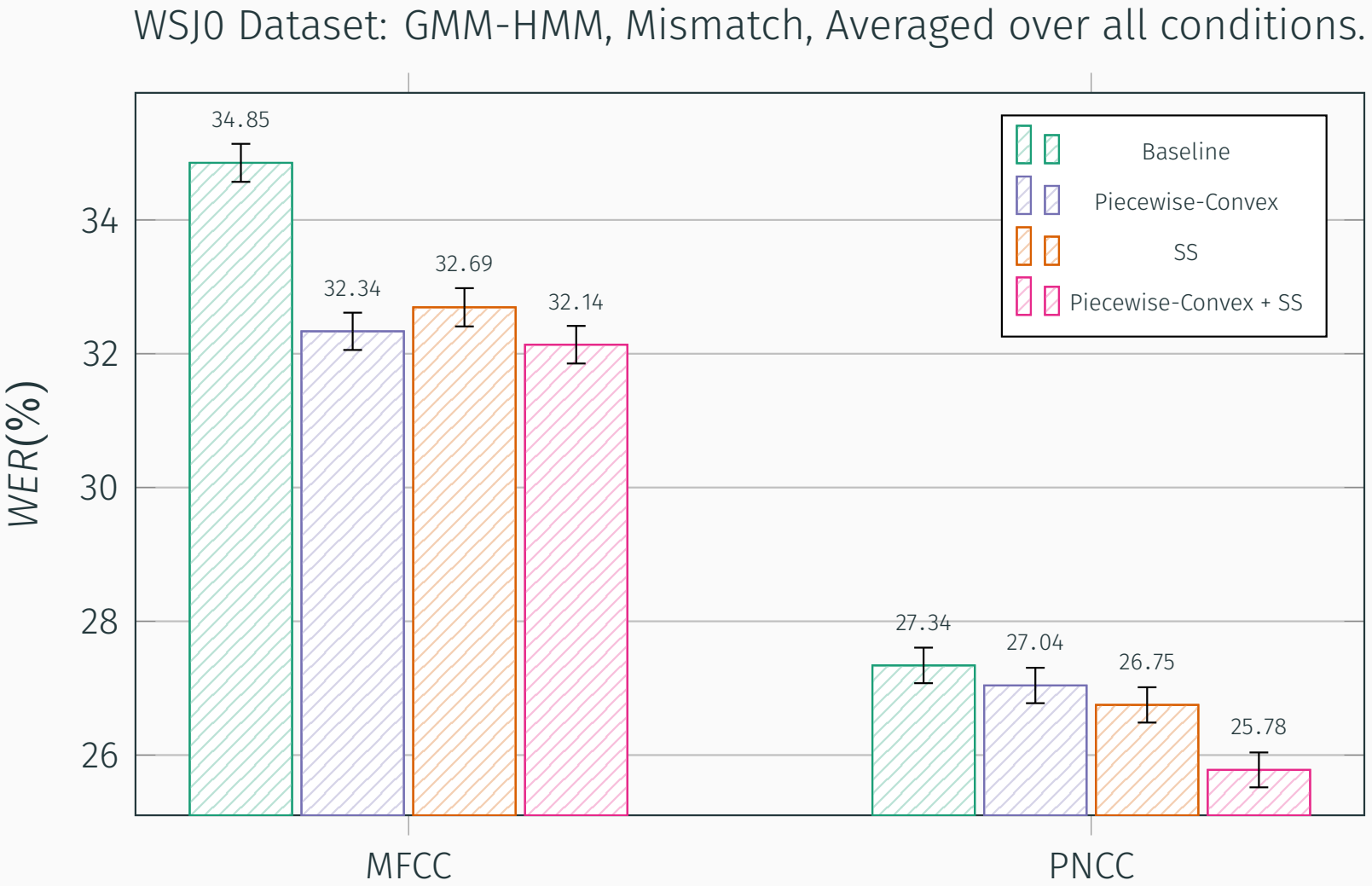

Synchrony-Based Features

Synchrony Effect

- The response of an auditory-nerve fiber roughly follows the shape of the input signal.

From Rose et al. (1971).

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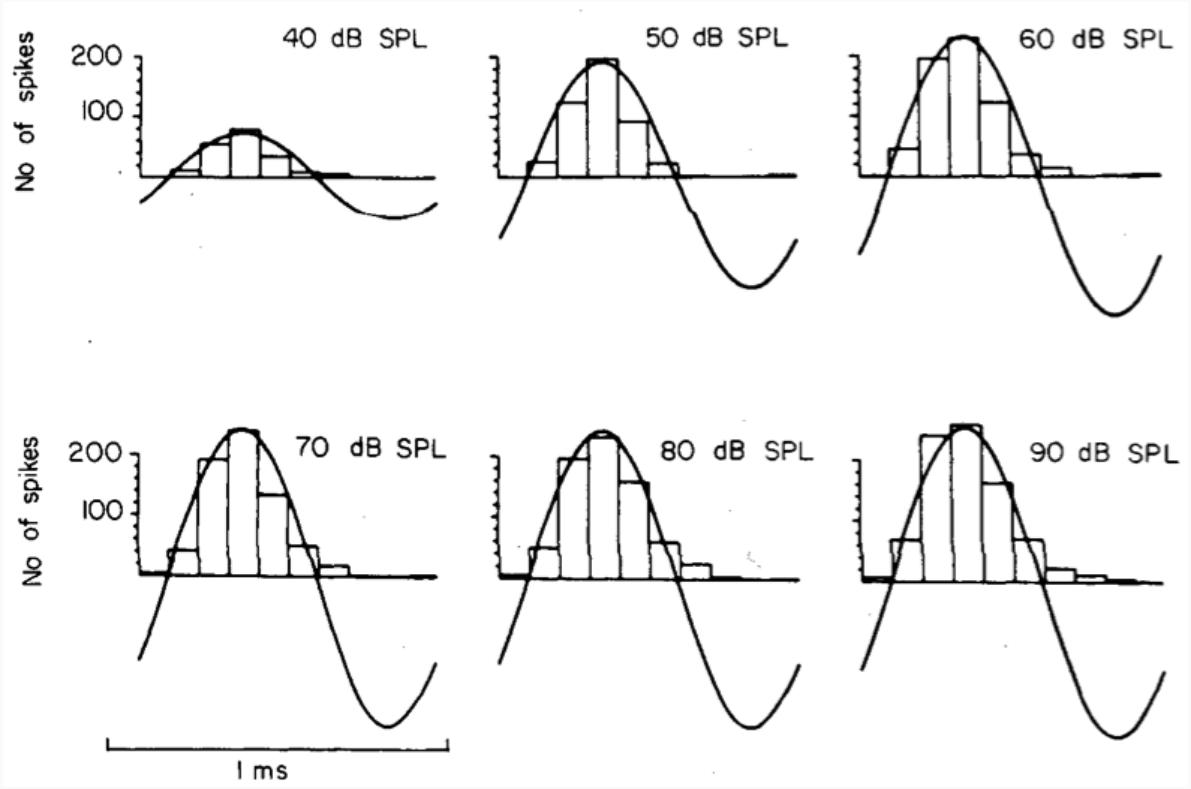

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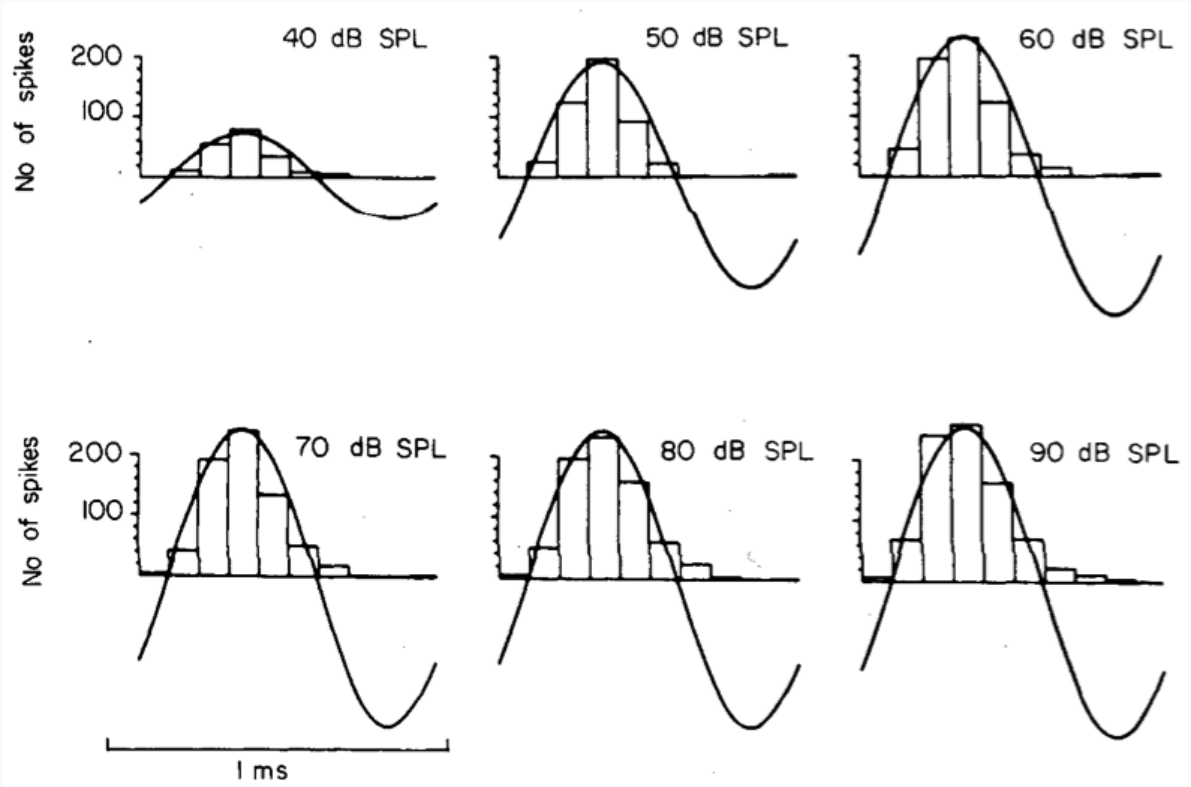

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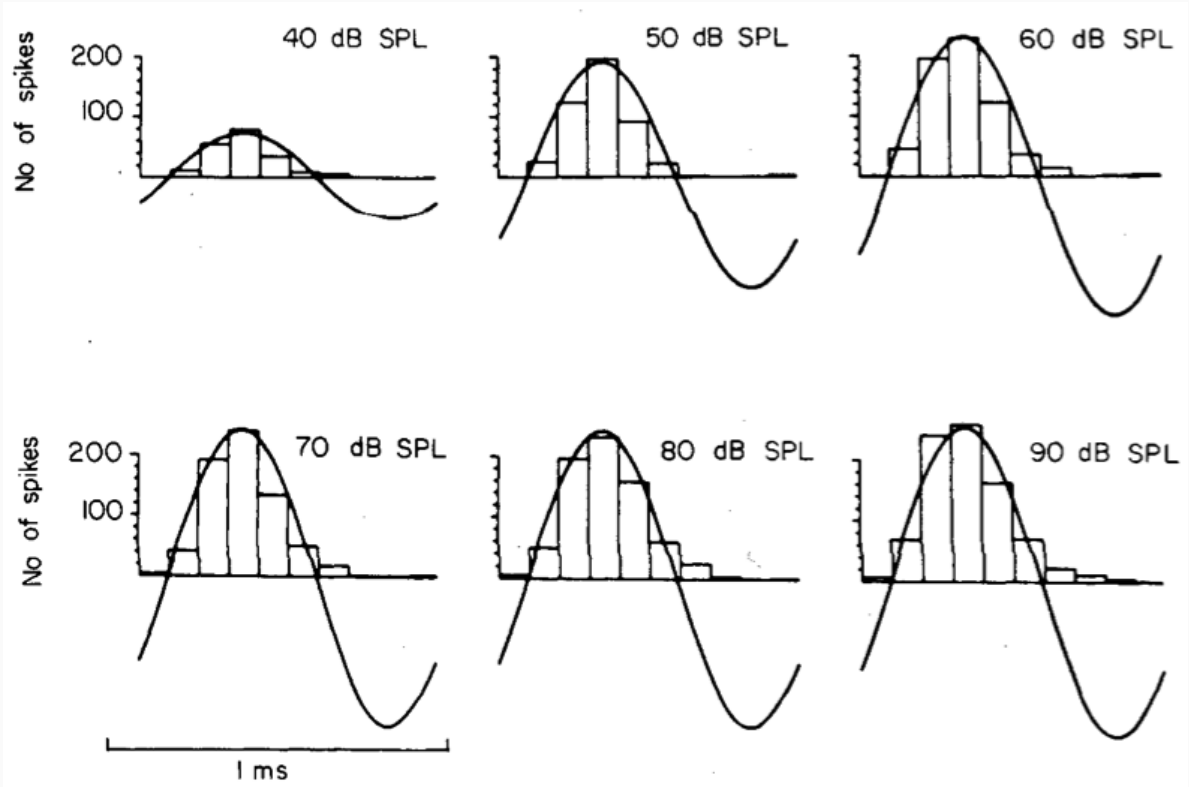

- Compare arrival times of signals to the ears
- Role in the robust interpretation.

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- Knowing the presented vowel and the Characteristic Frequency (CF) of the measurement fibers, two responses can be computed.

Mean Rate (MR)

MR is simply the mean activity for each fiber over time.

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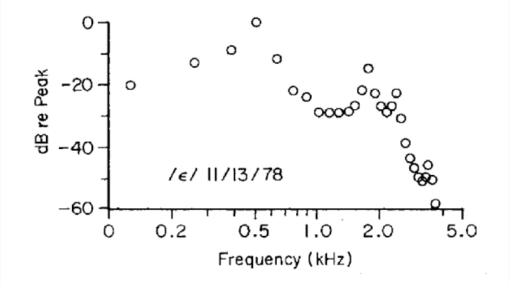

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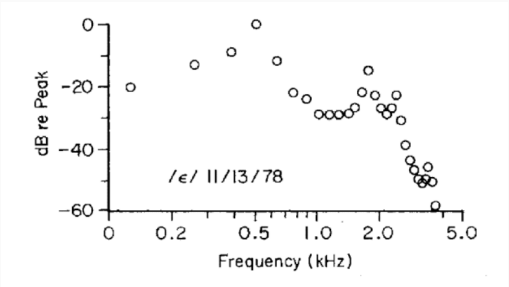

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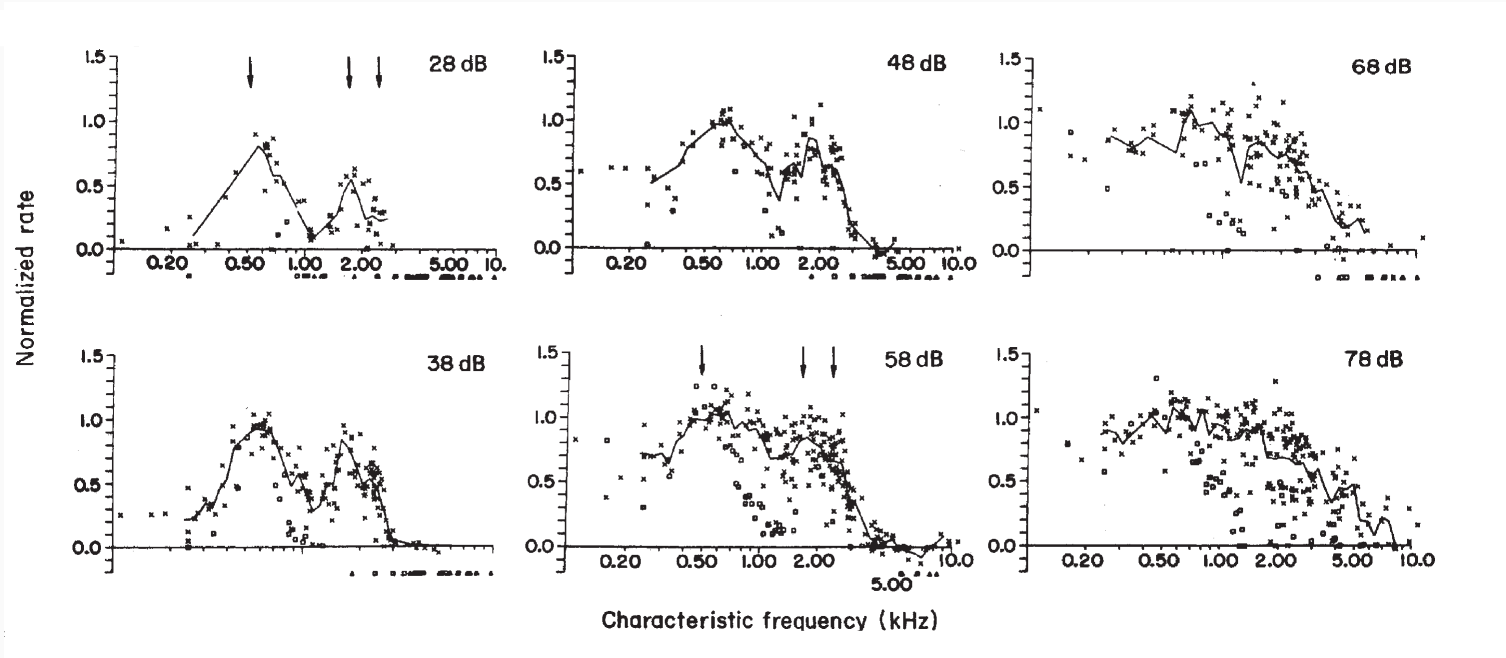

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Describes how the auditory nerve activity is synchronized with the nearest harmonic of the fundamental frequency of the vowel.

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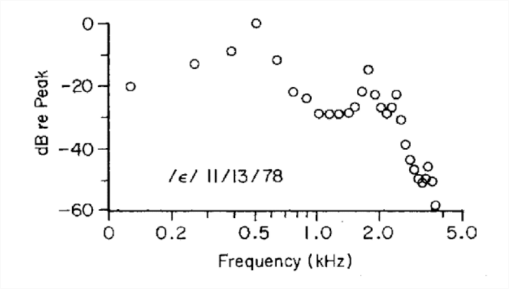

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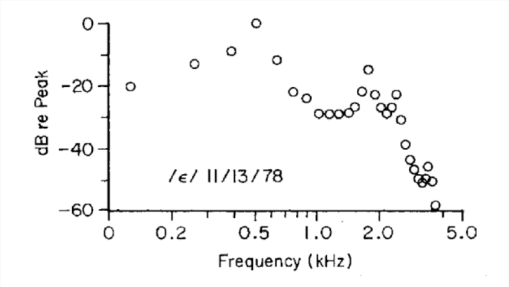

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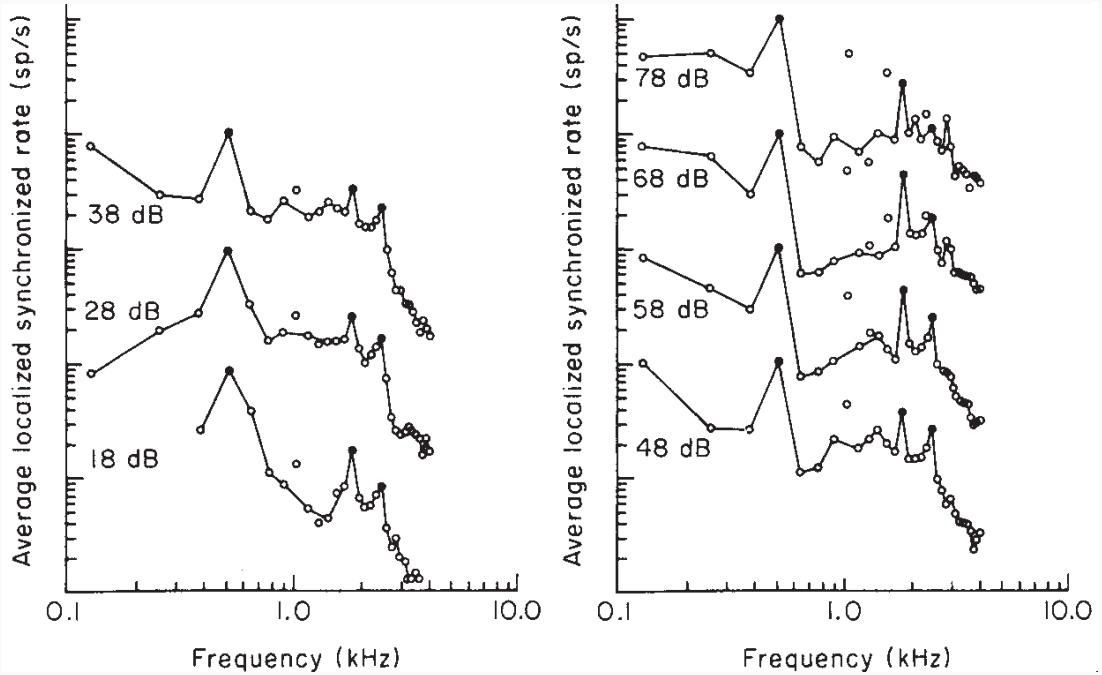

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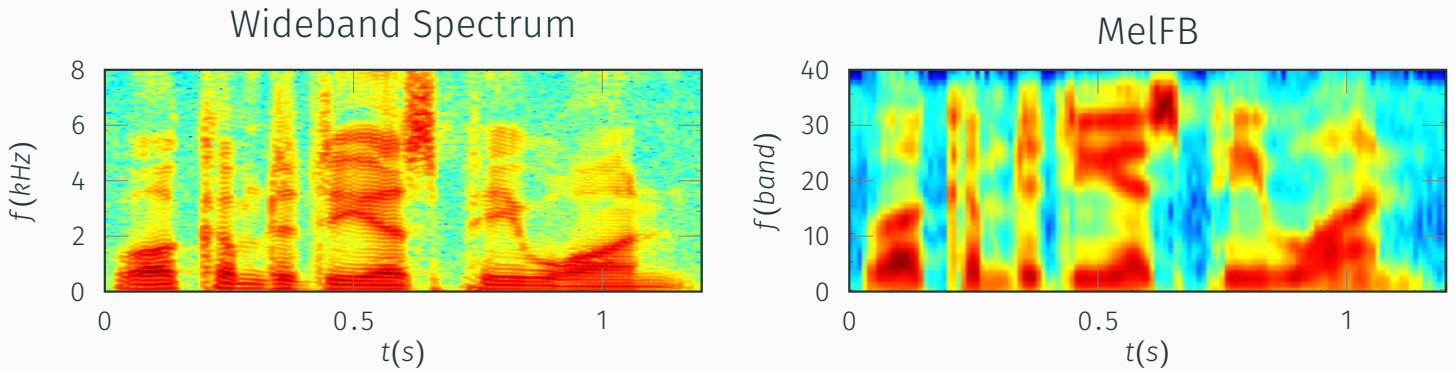

Synchrony Features

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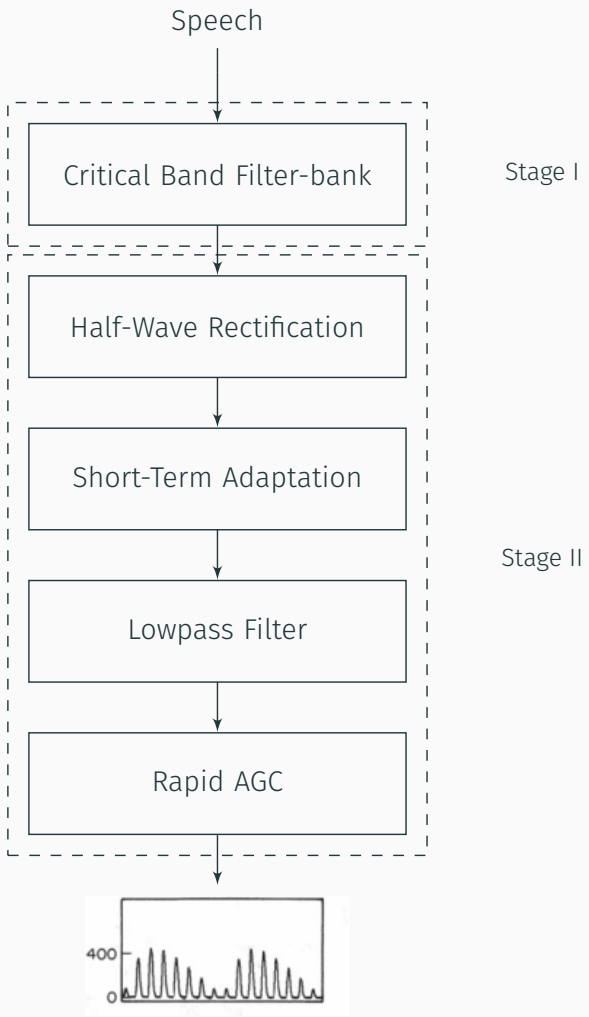

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- Synchrony response disappears below 1000 Hz, linear transition between MR and ALSR over 300 to 1200 Hz.

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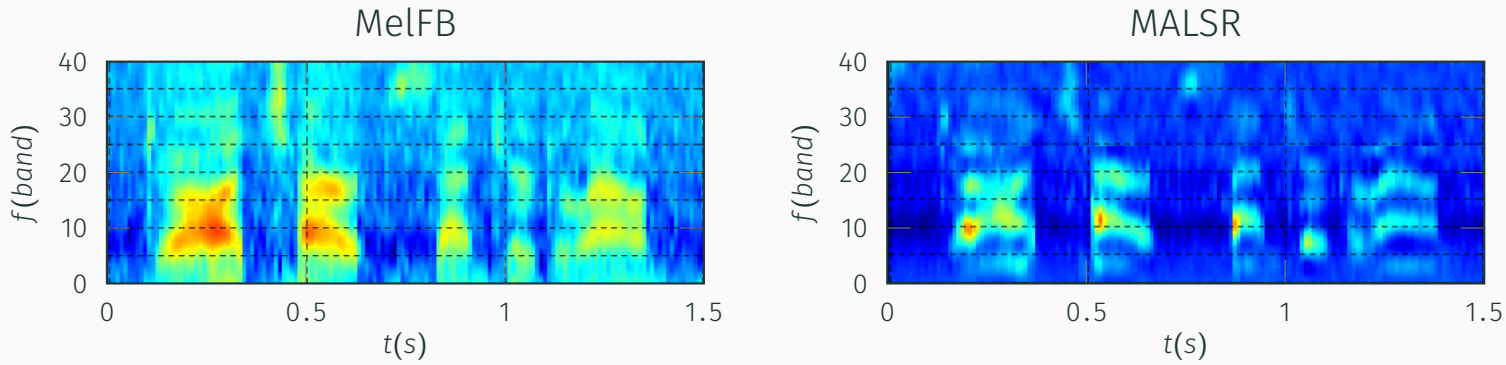

White Noise, 10 dB SNR.

Modified GDS (MGSD)

- Based on the Generalized Synchrony Detector (GSD) (Seneff, 1990).

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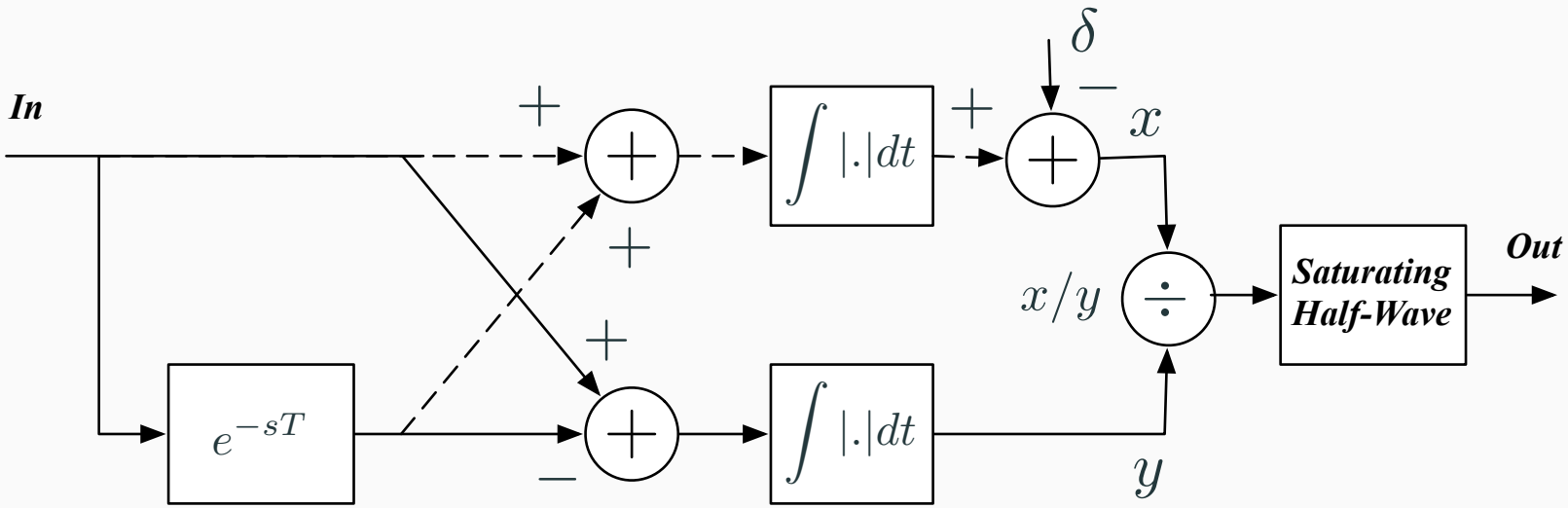

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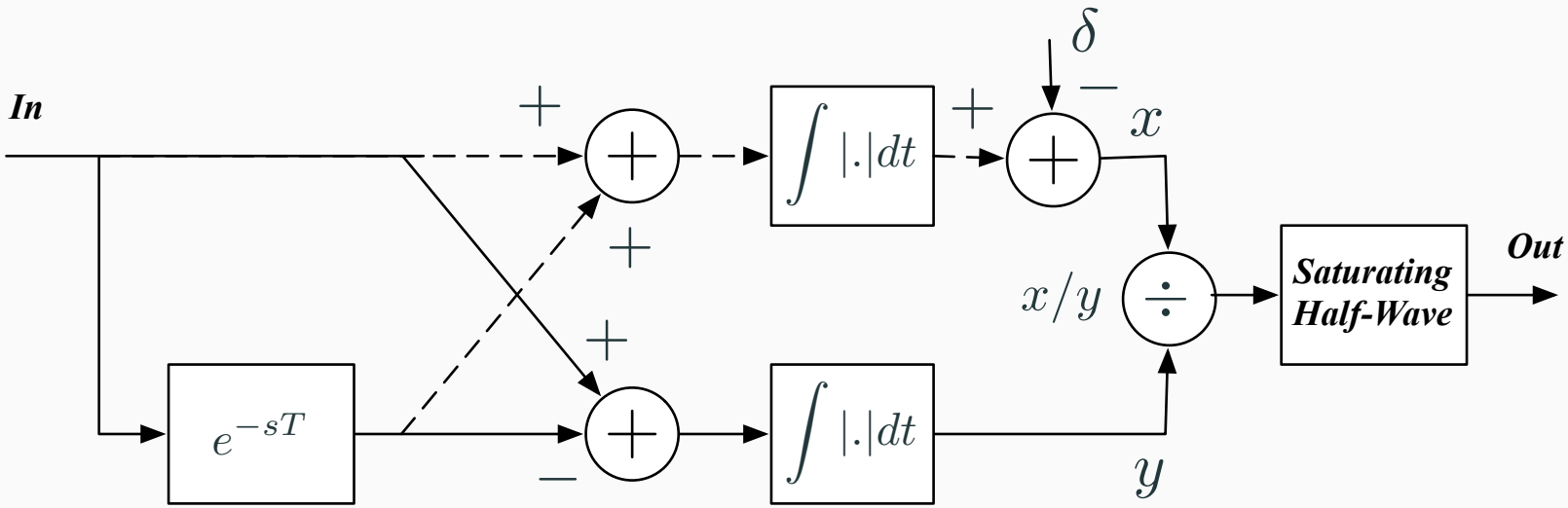

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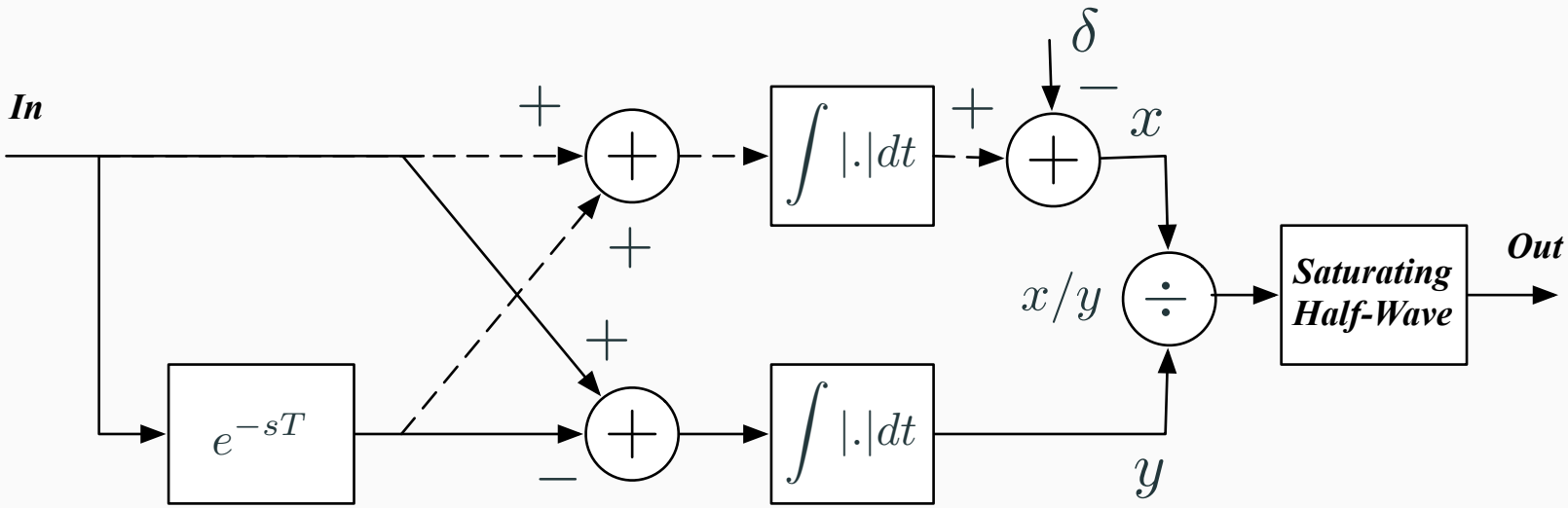
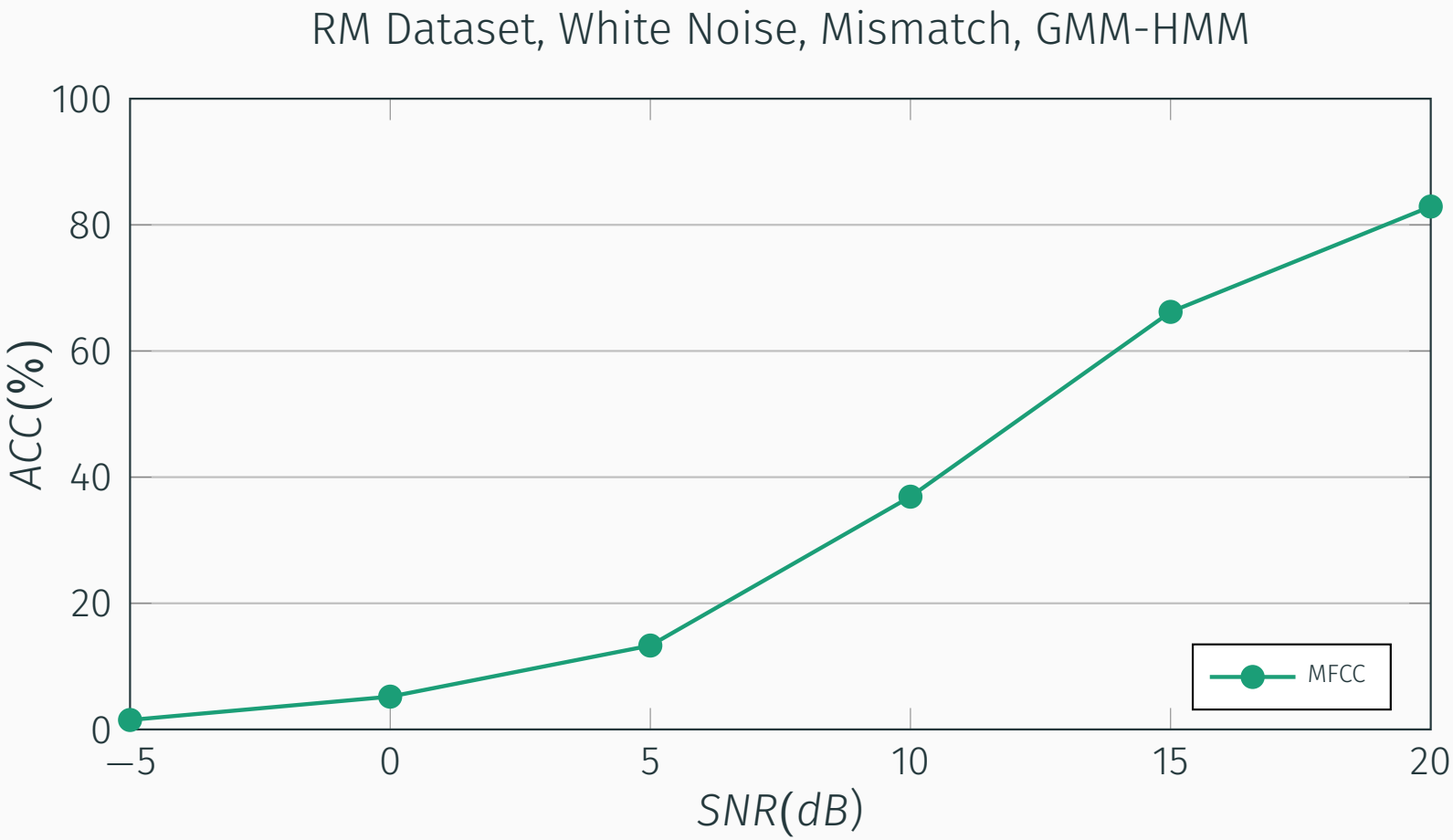


- Time domain.
- Low computational complexity.

Results: MR, MASLR, MGSD



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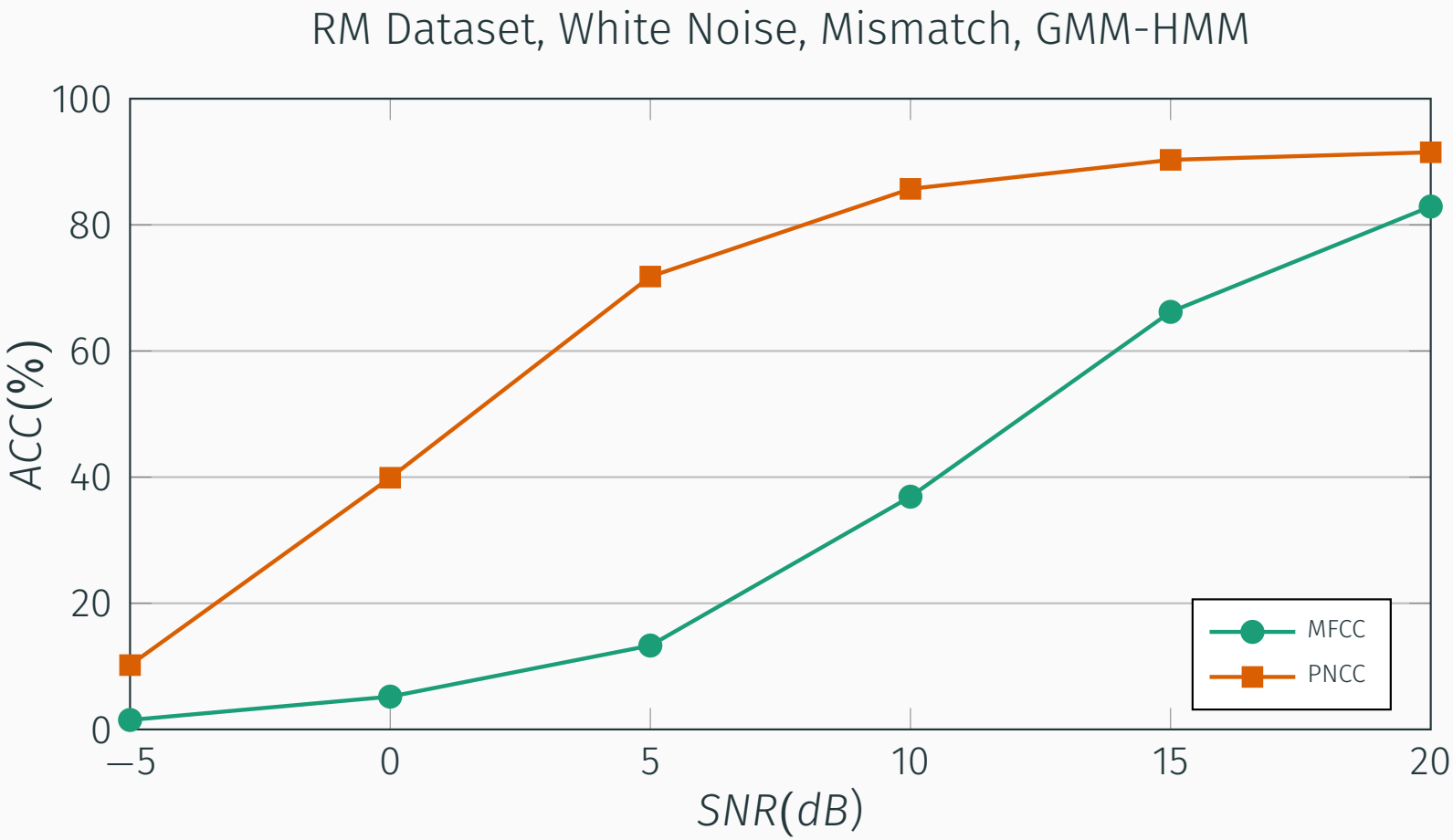

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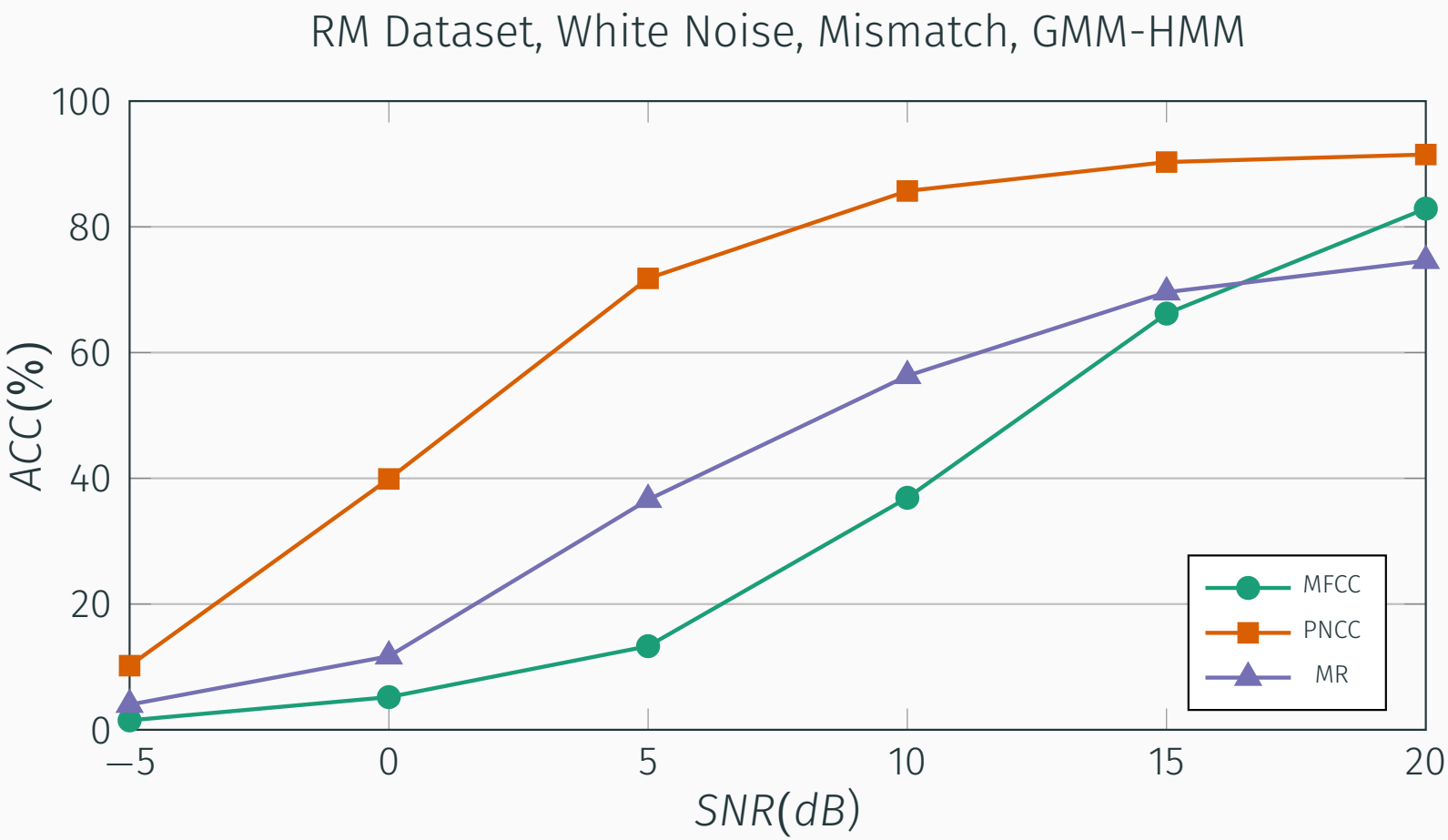

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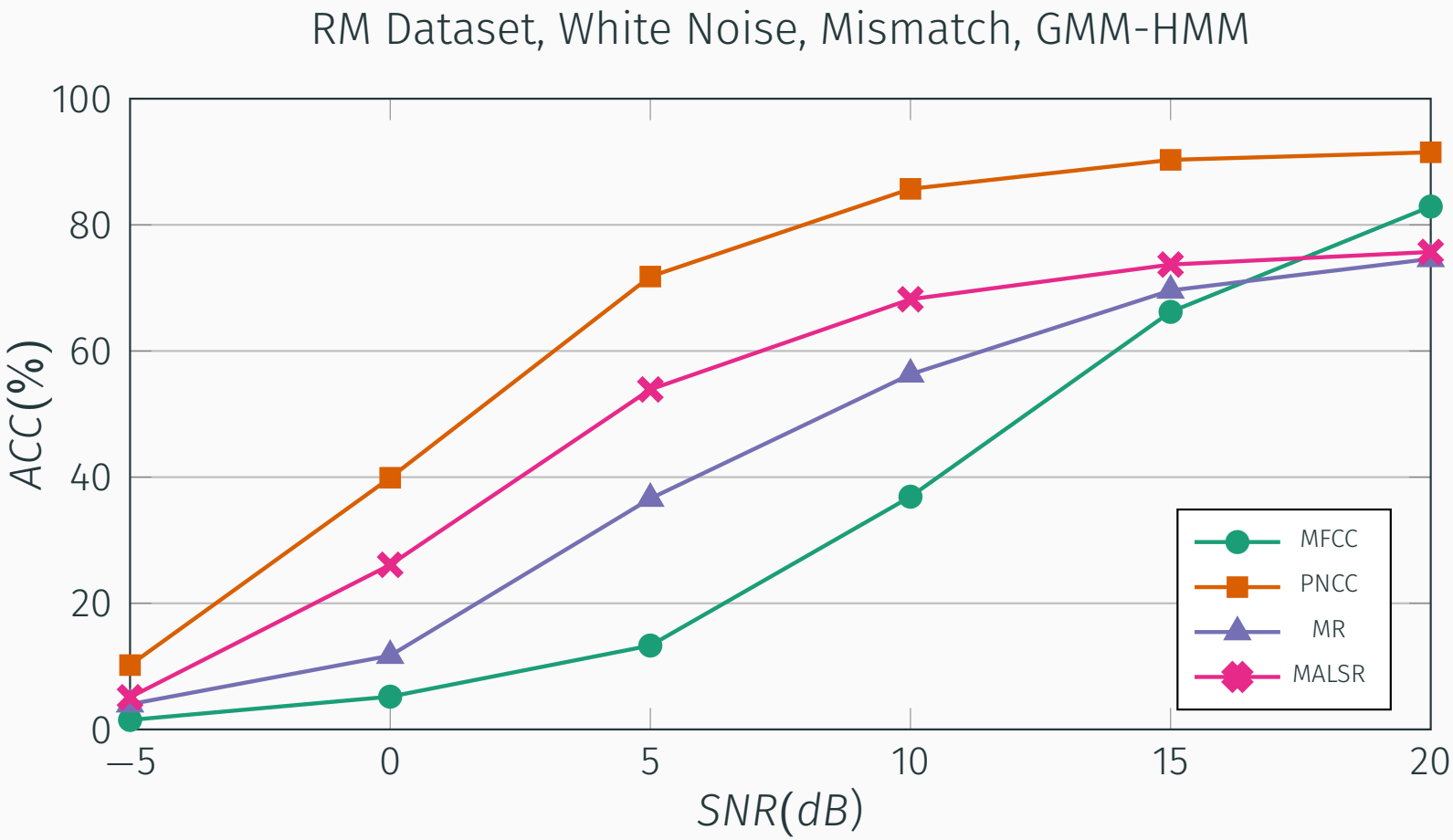

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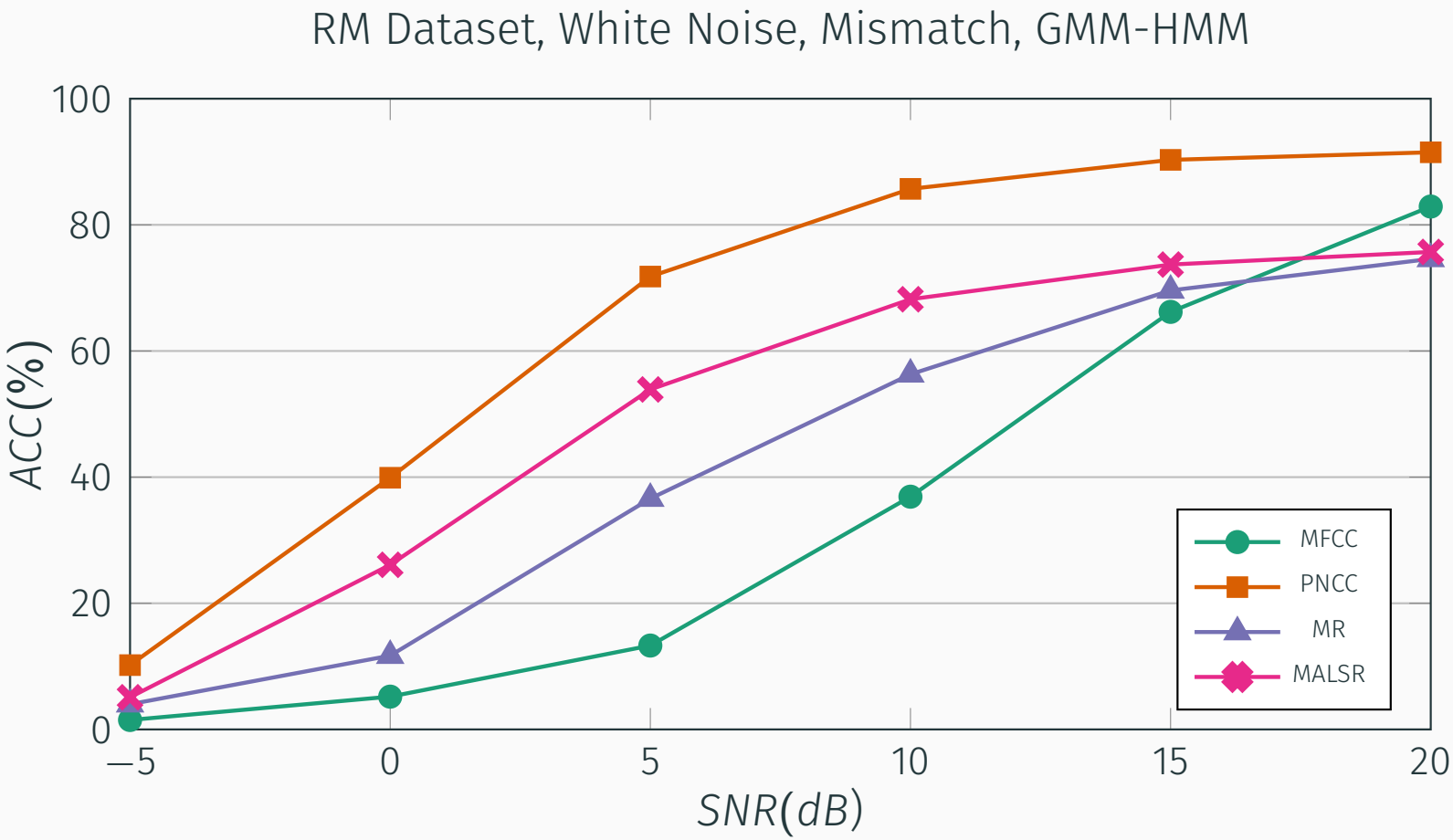

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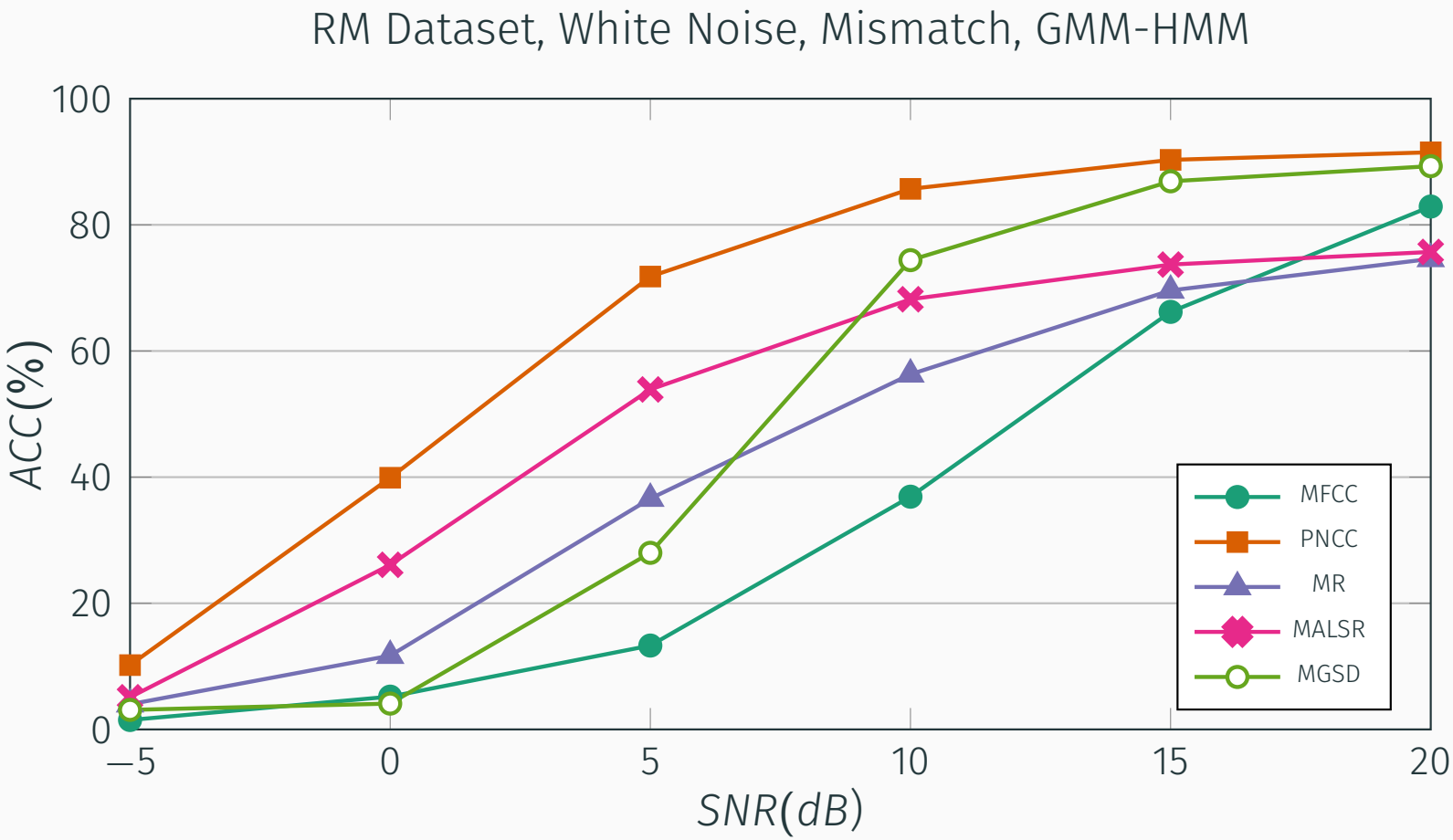
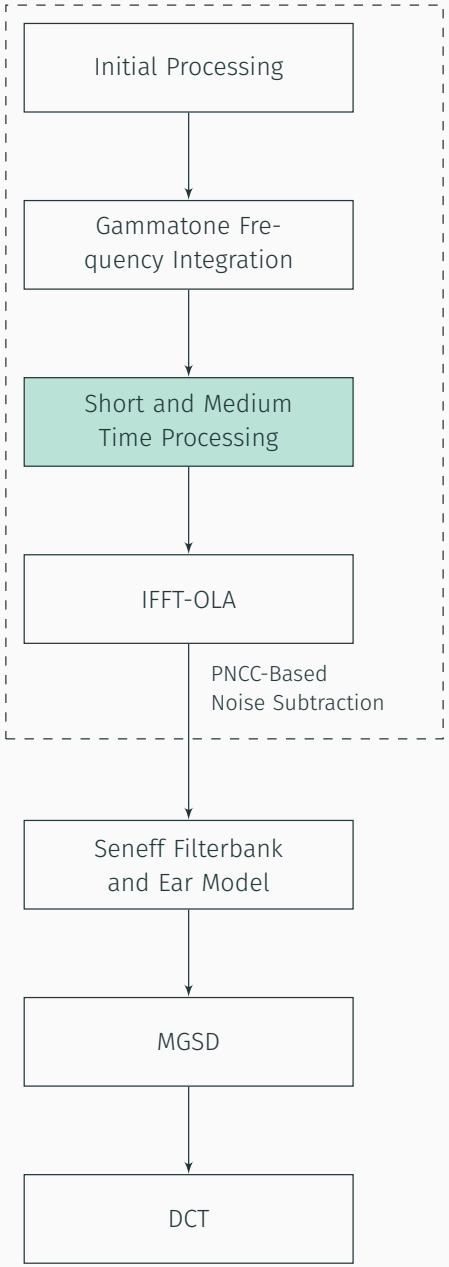
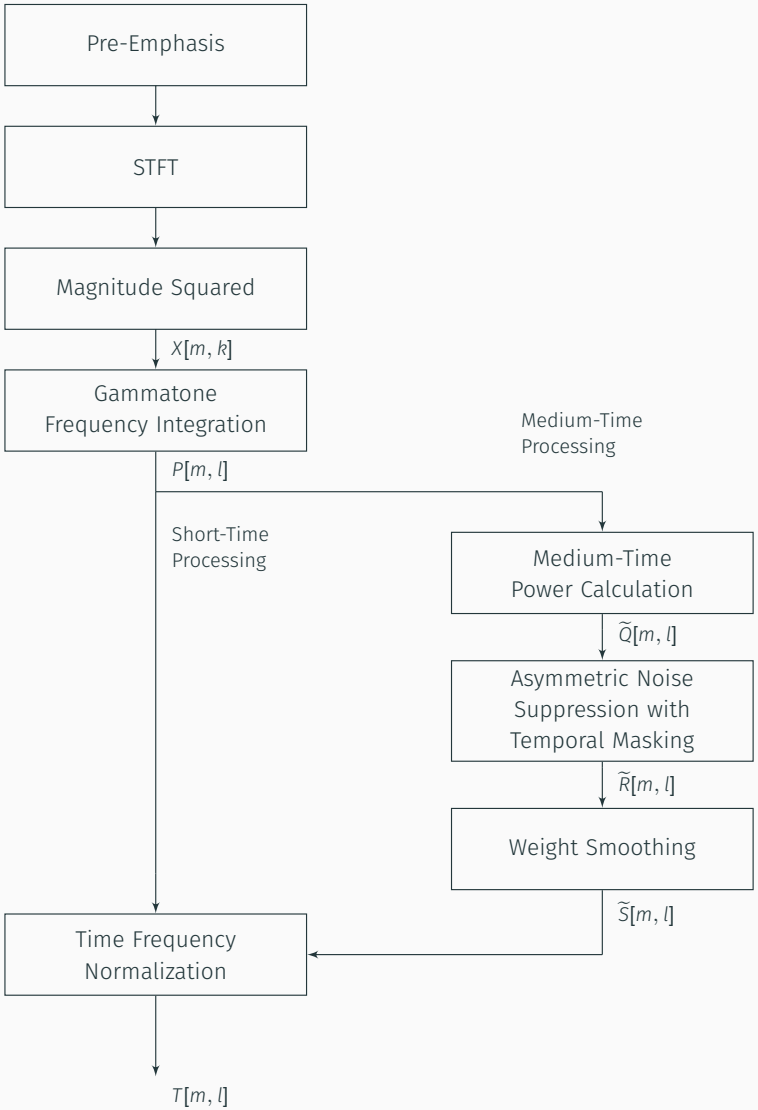


PNCC Integration



PNCC-Based Noise Reduction (PNCC-NR)



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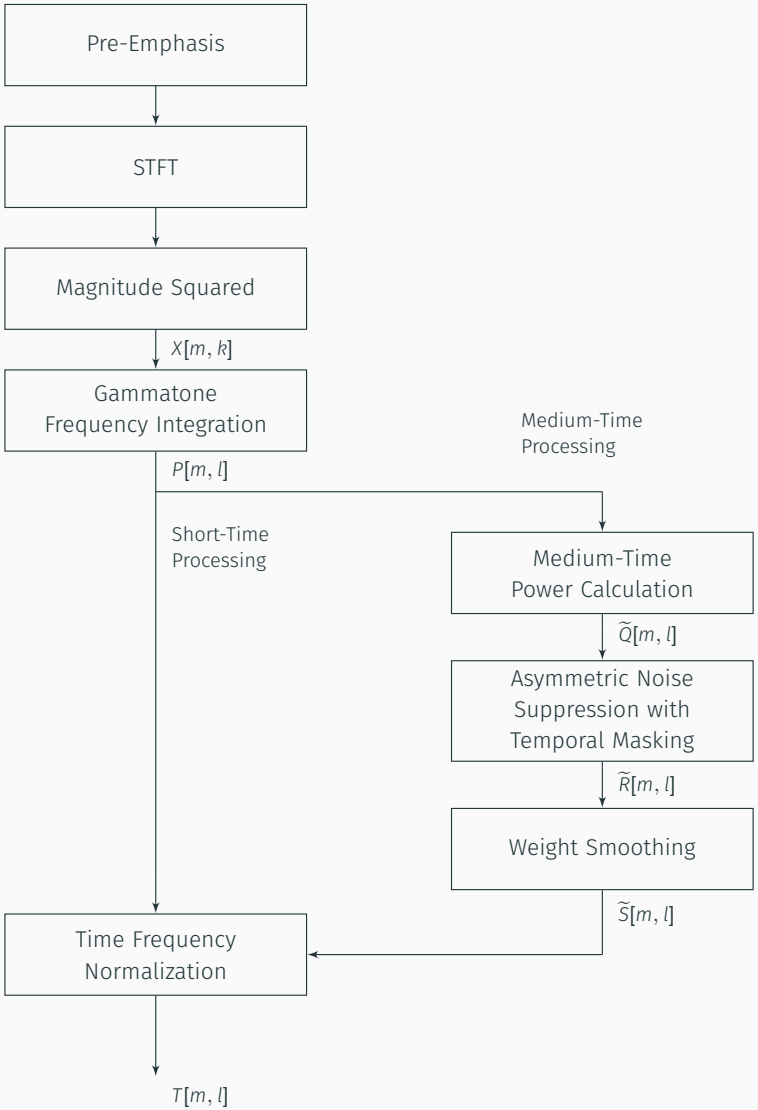

1. $x[n]$ pass through the PNCC pipeline.

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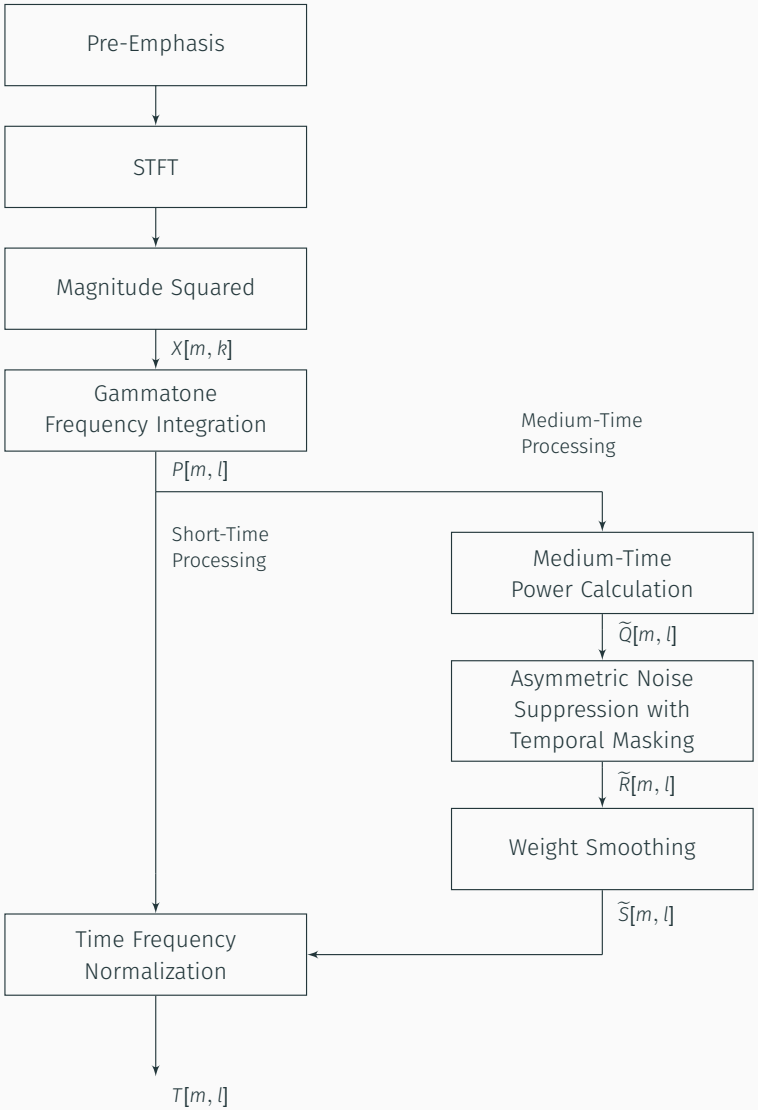

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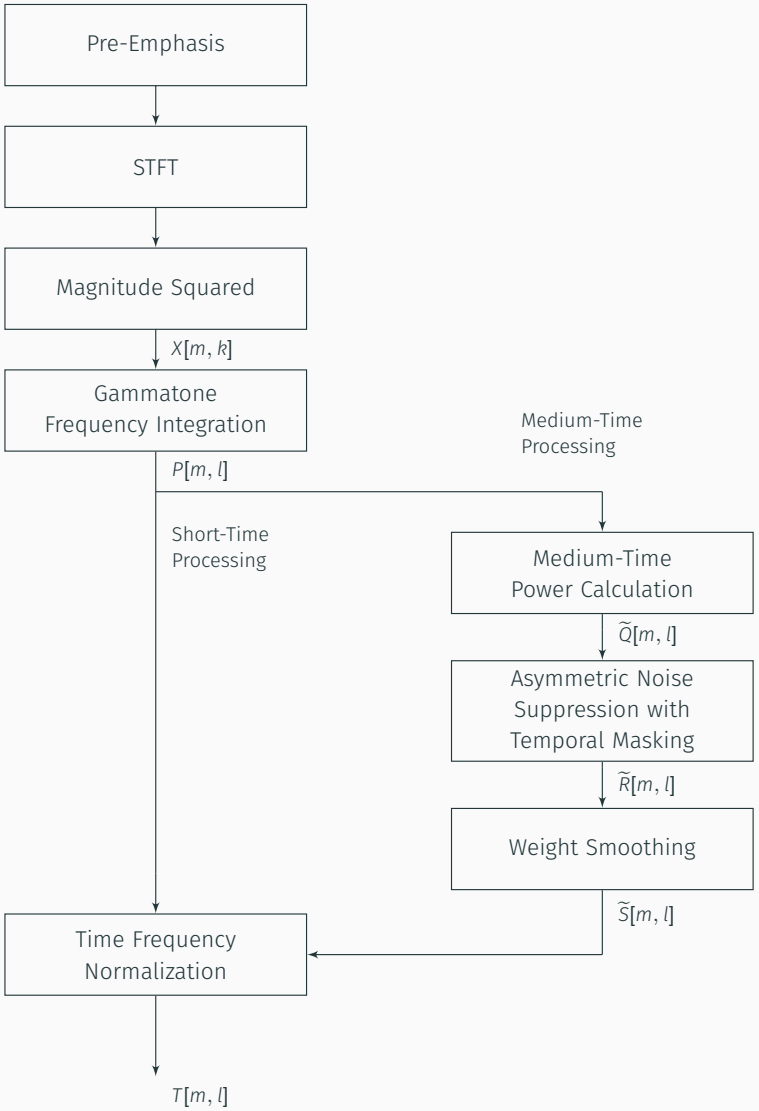

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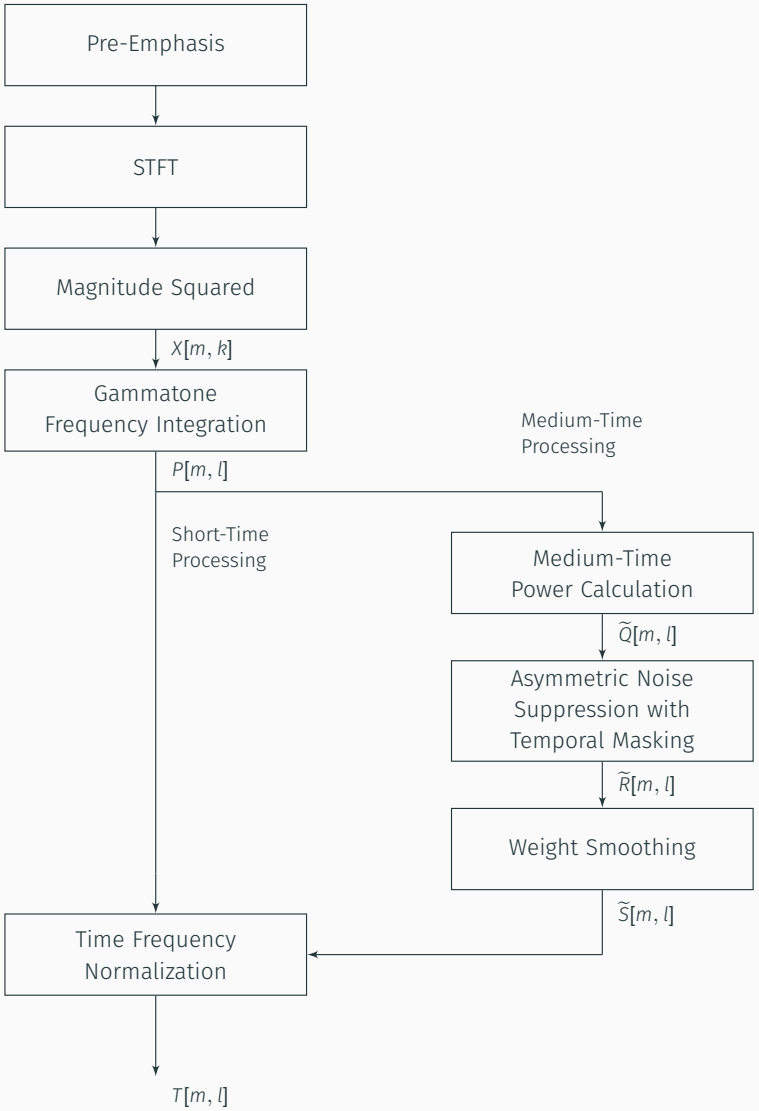

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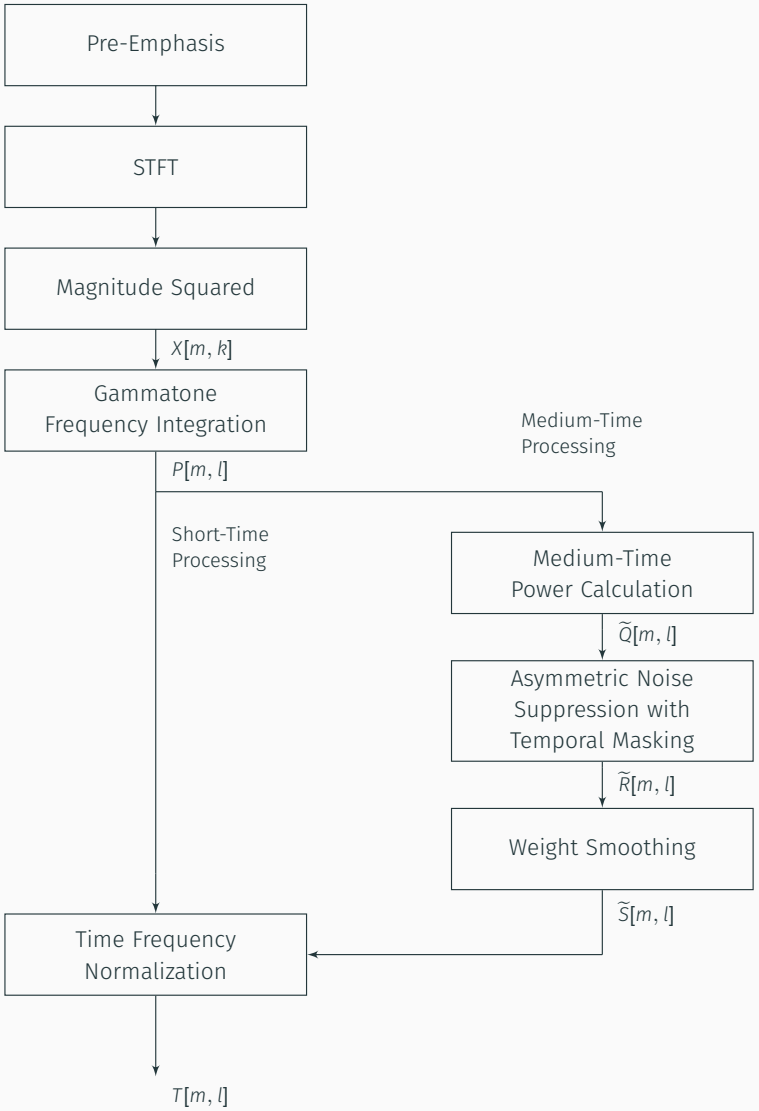

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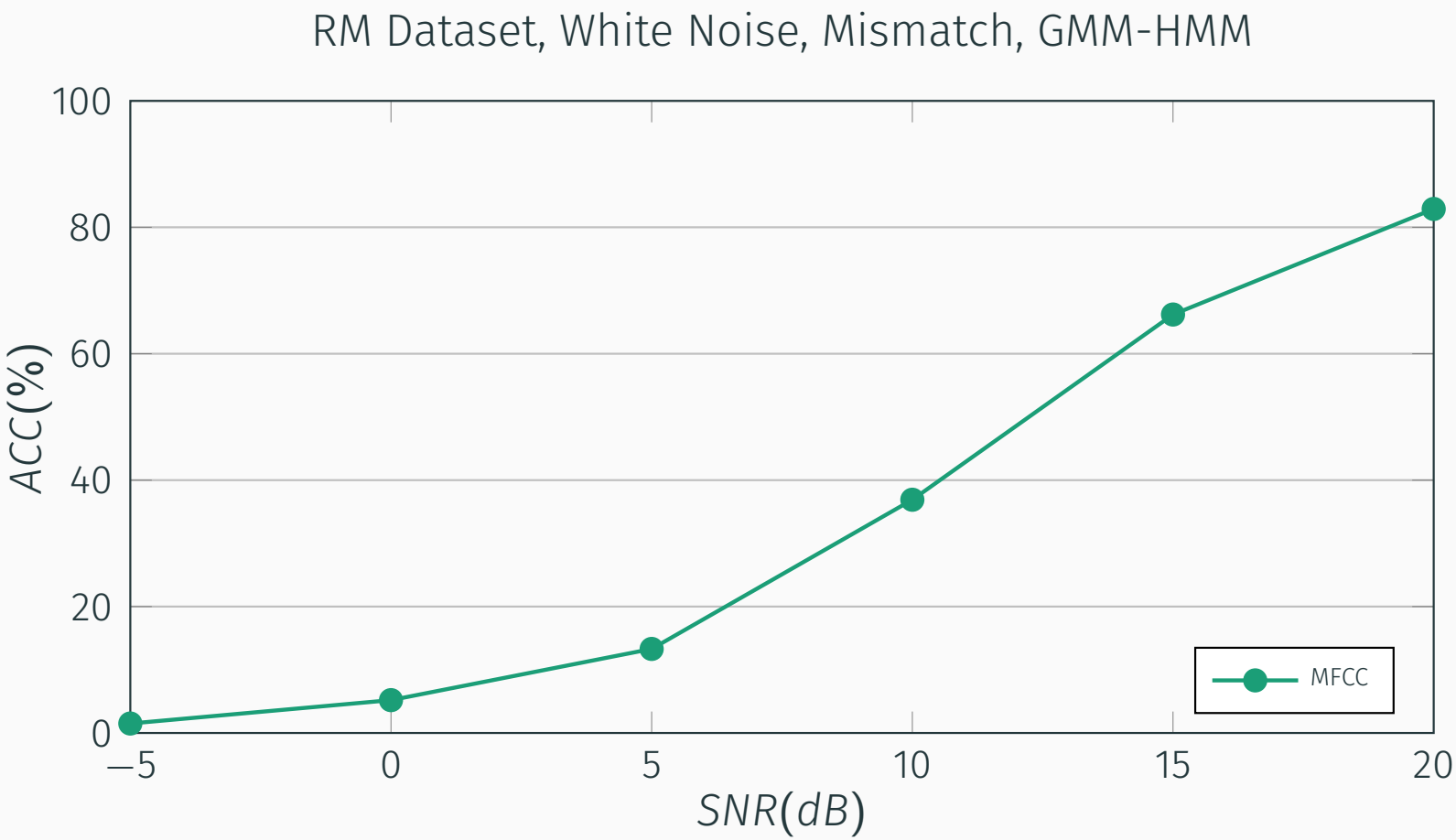
5. $\hat{x}[n]$ is re-synthesized from $\widetilde{X}[m,k]$ by applying and IFFT and using OLA.

PNCC-NR Results



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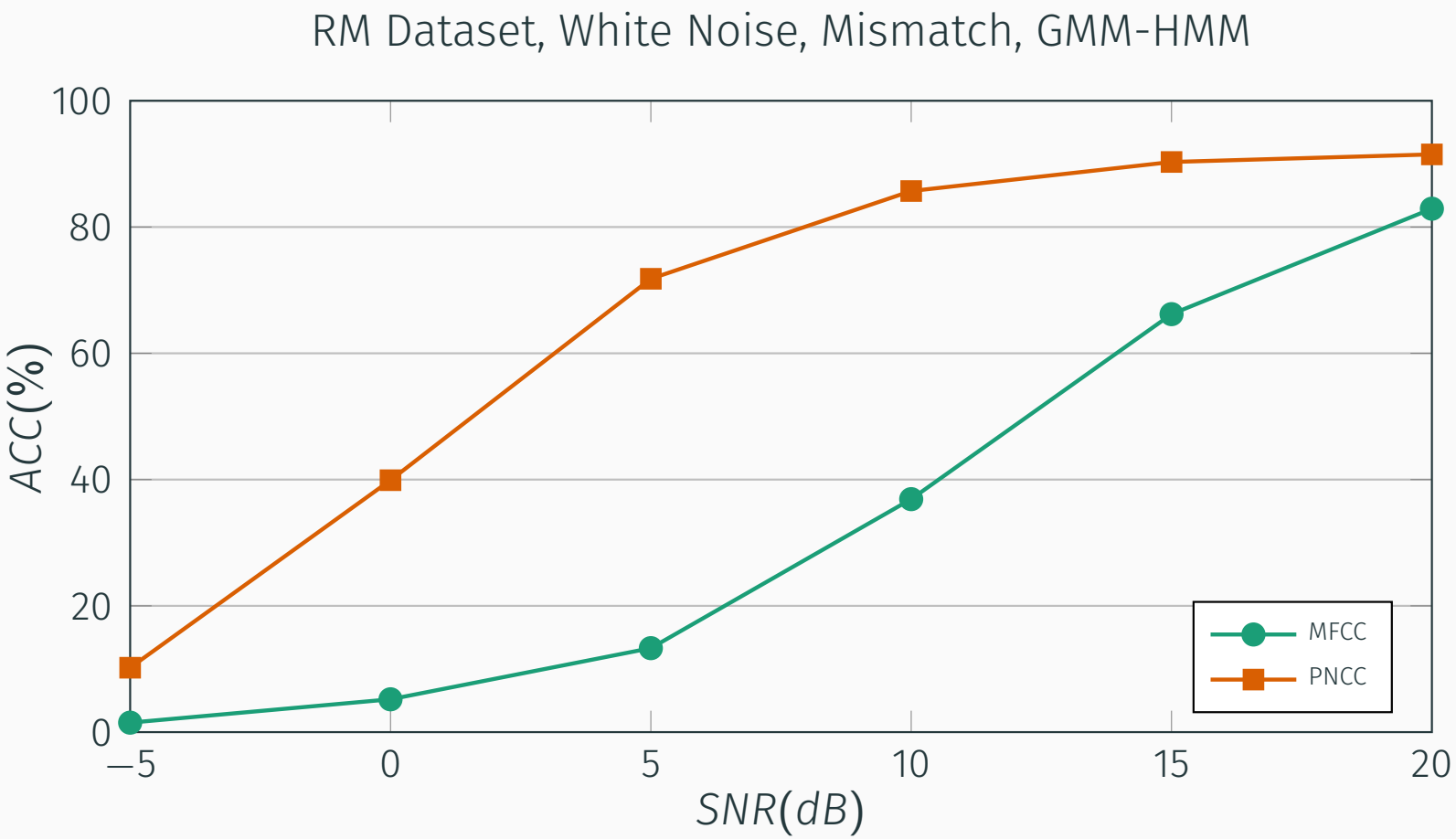

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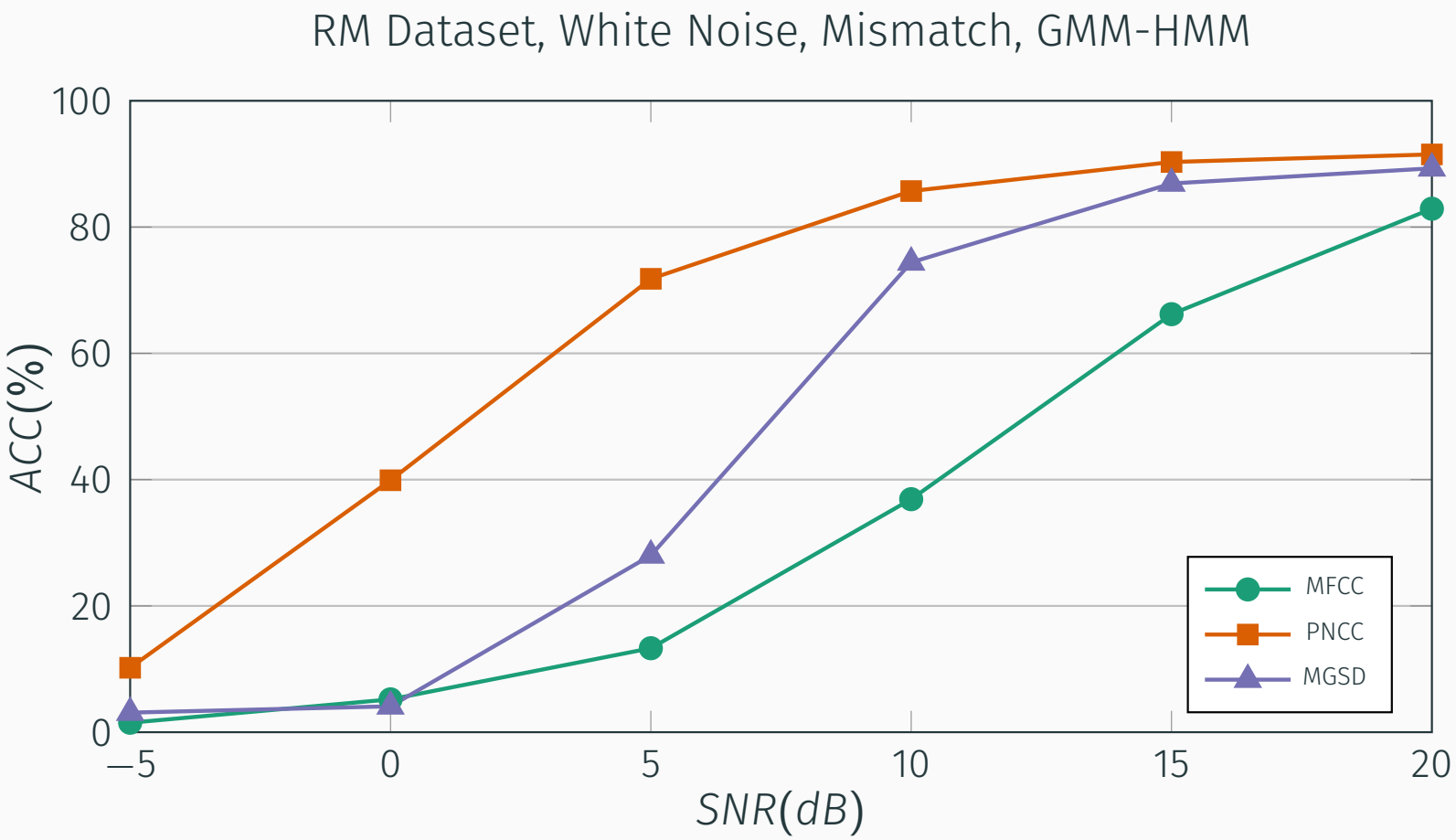

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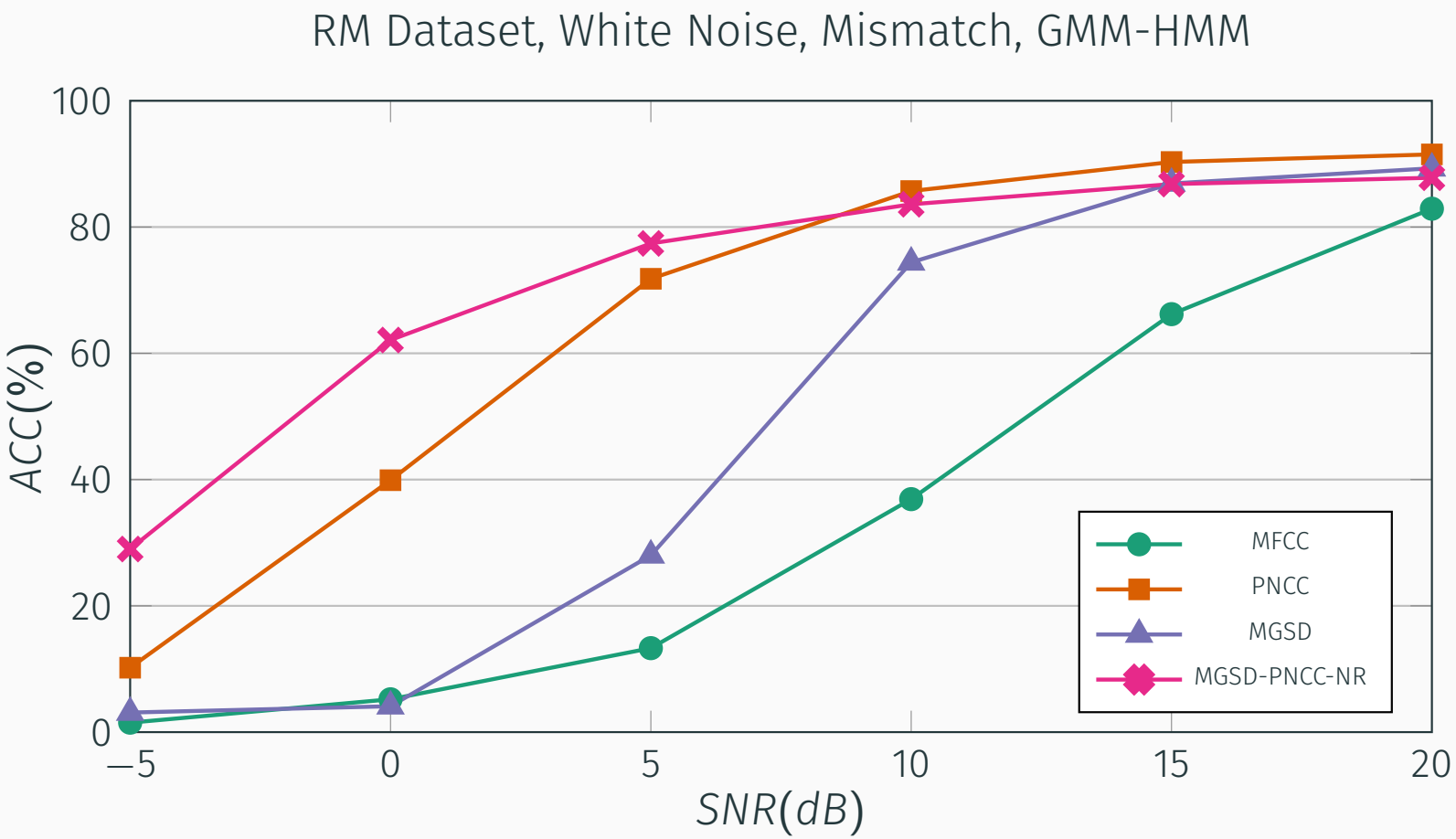

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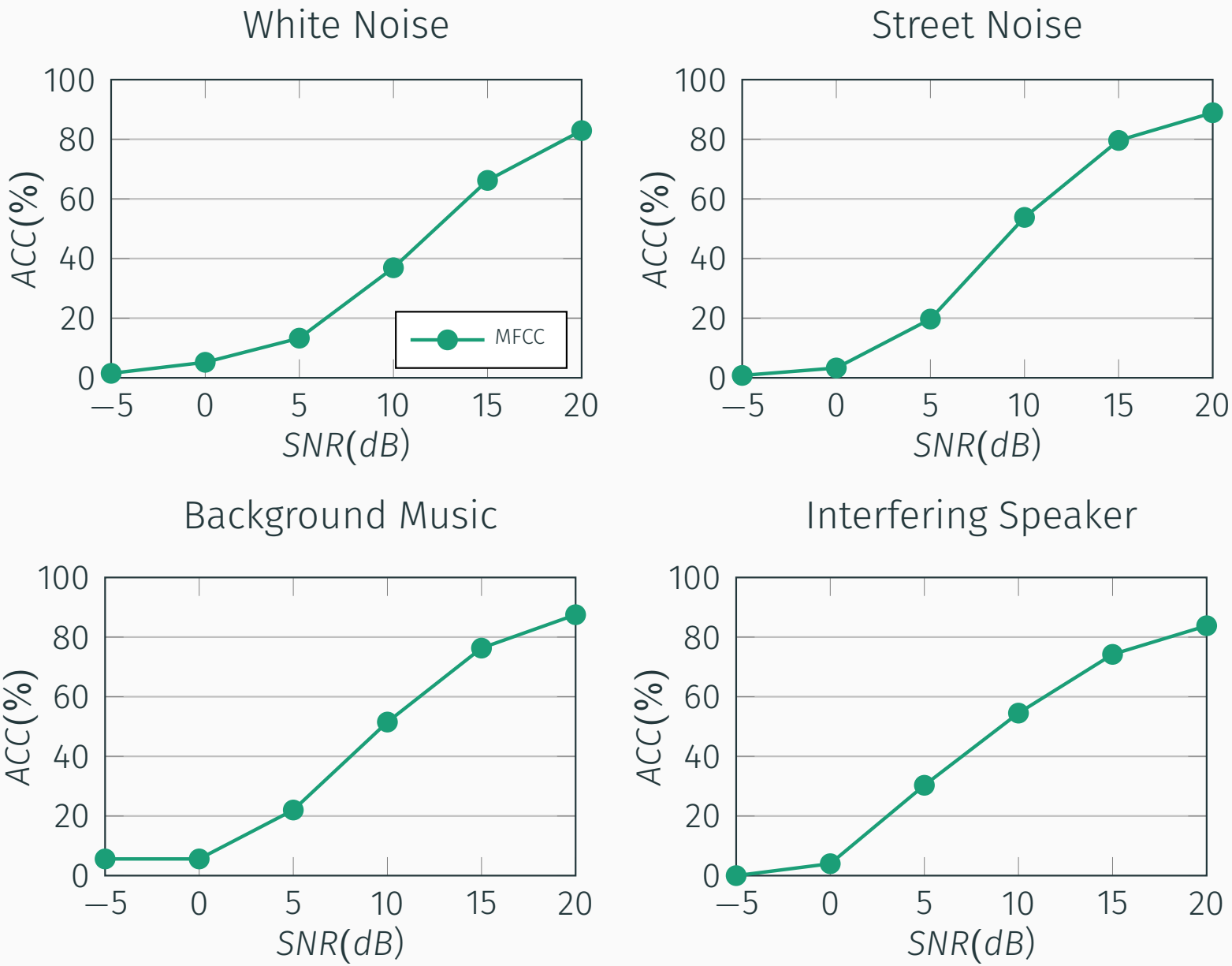

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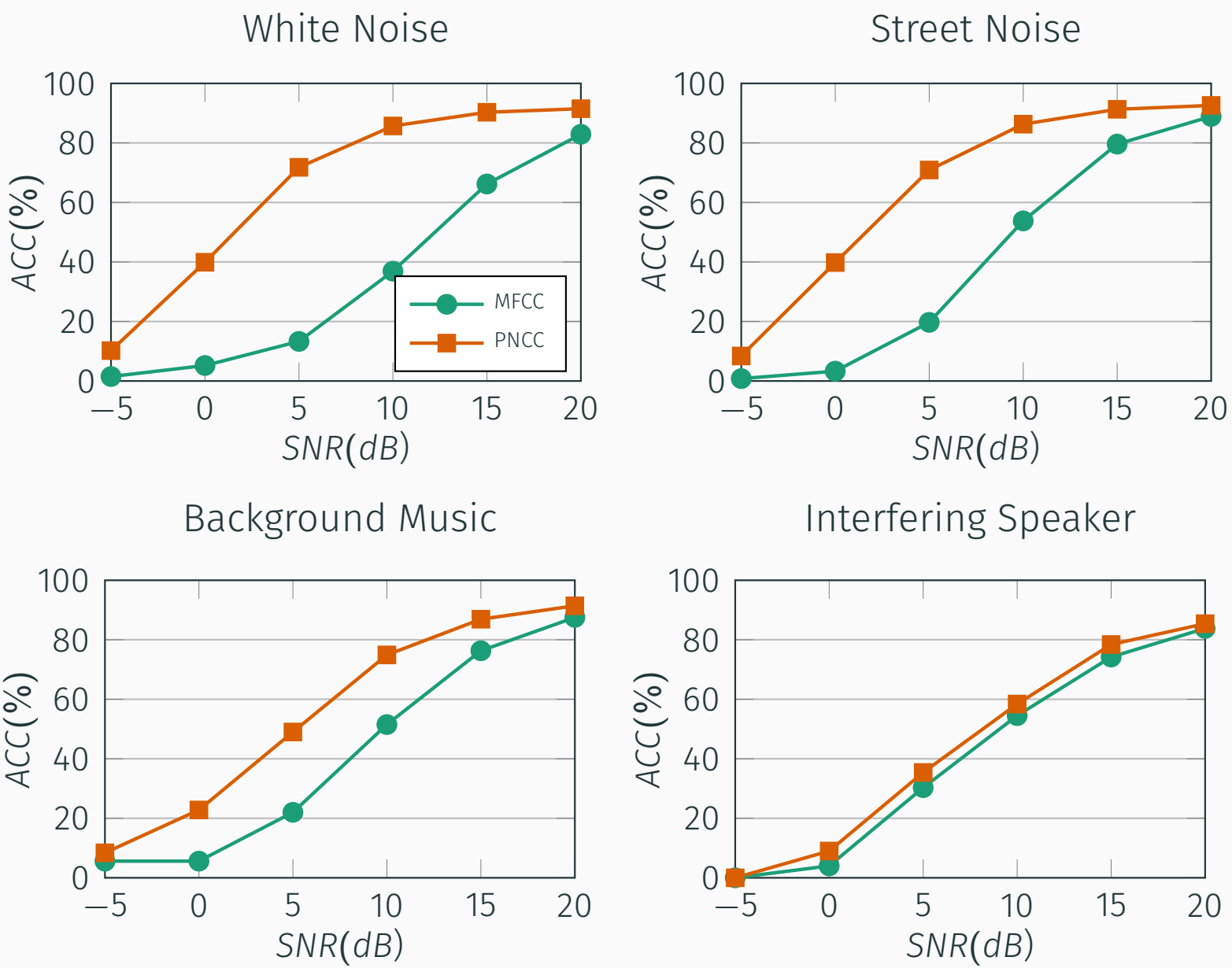

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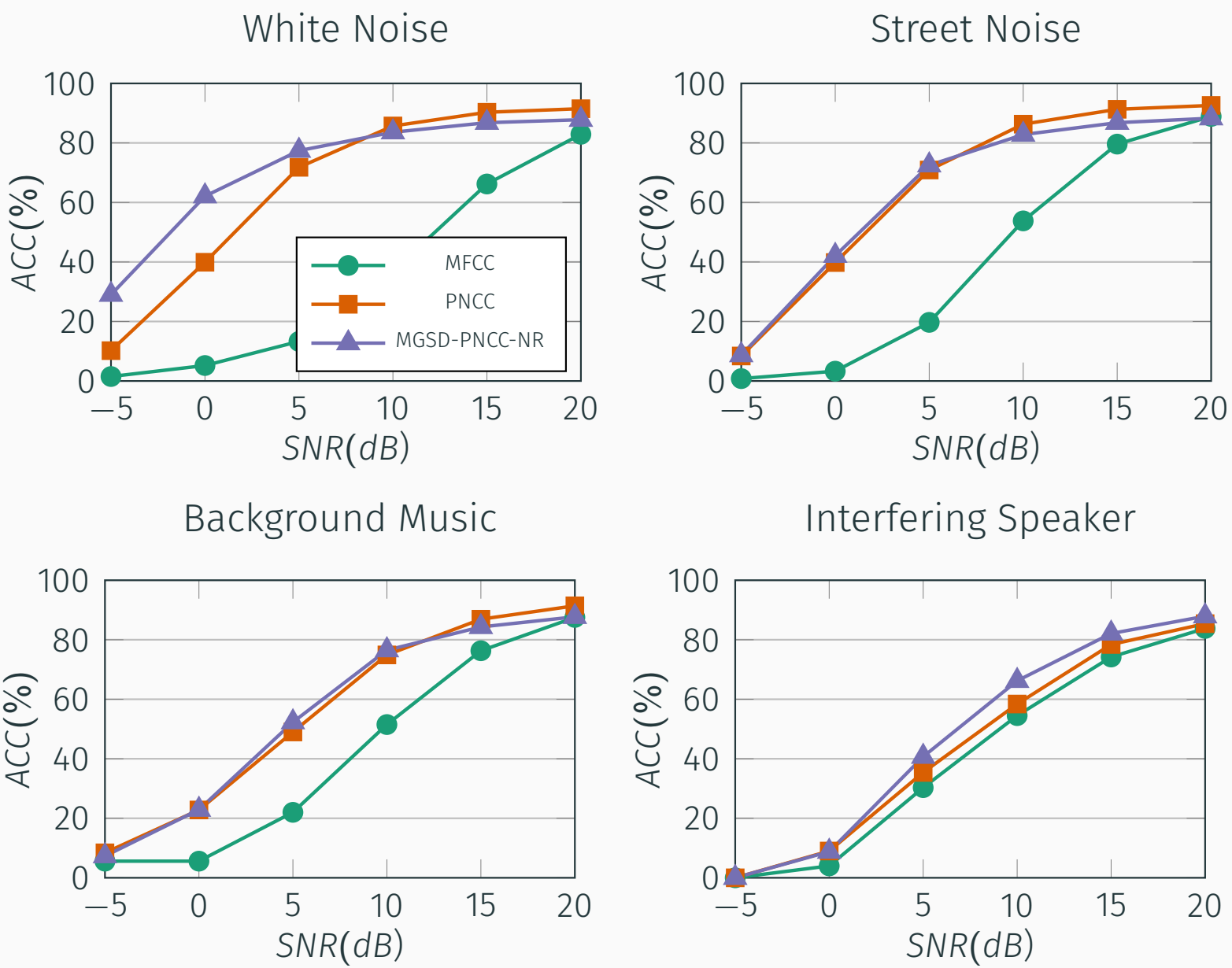
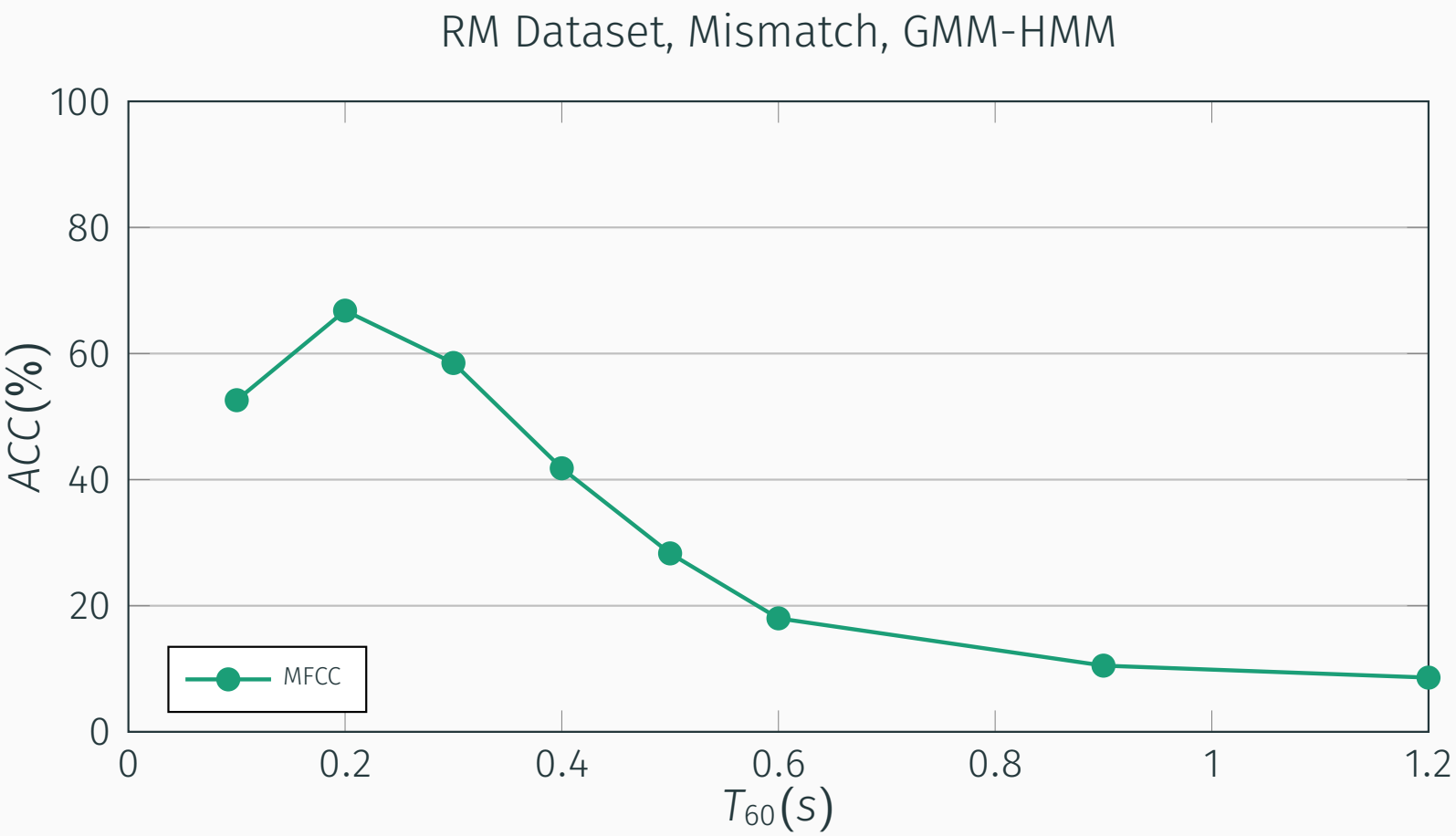


Results: Reverberant condition



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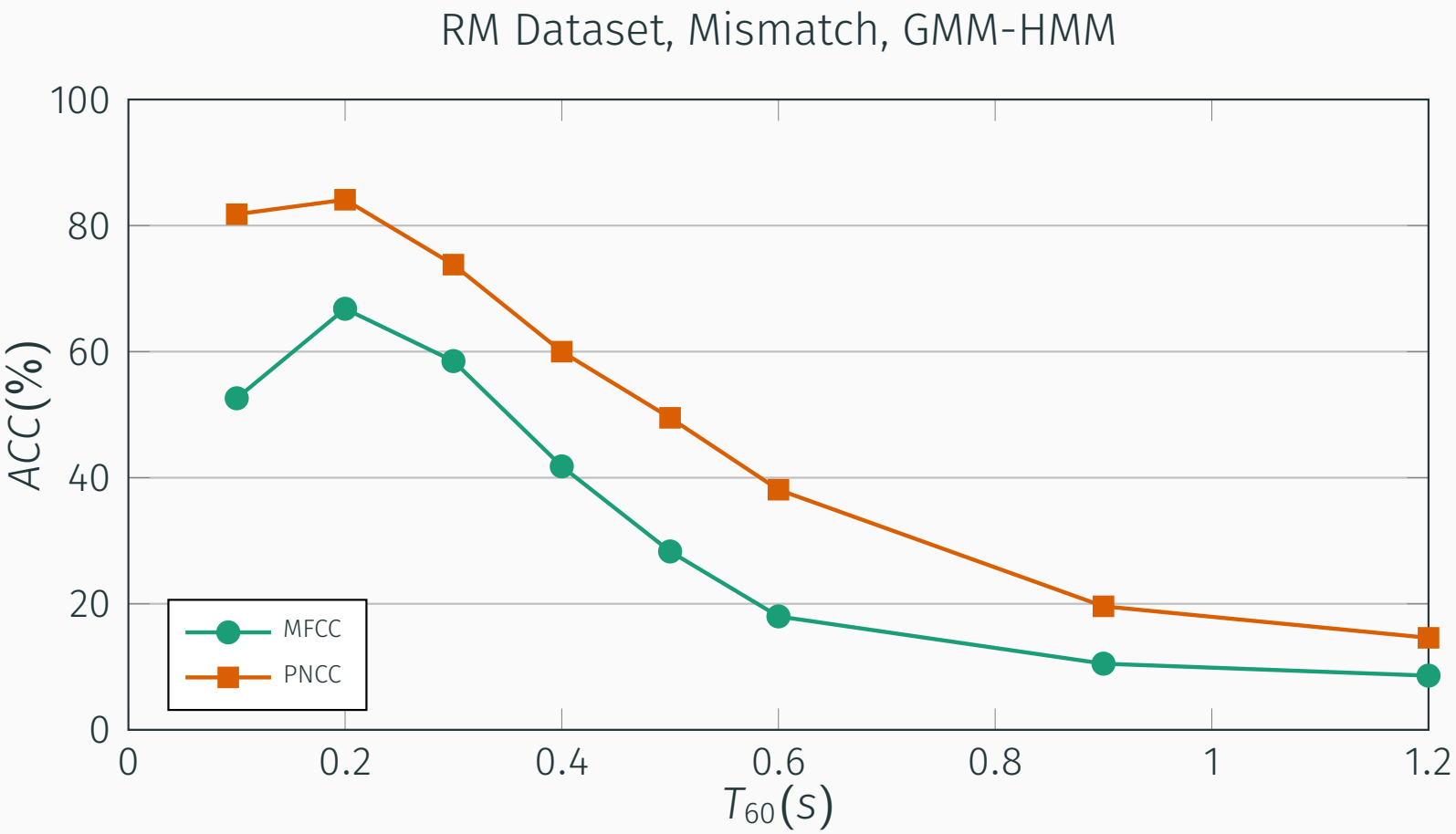

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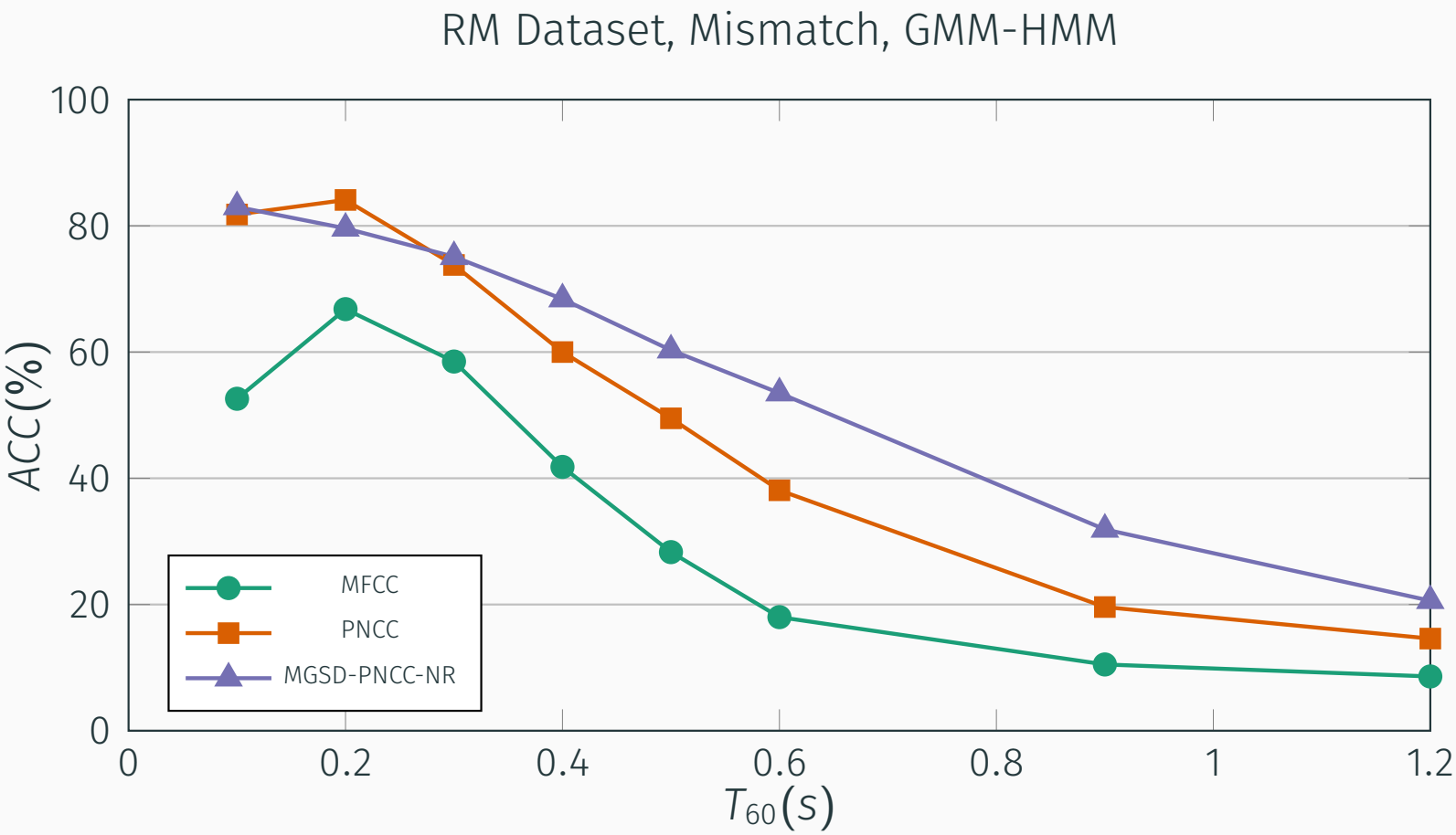

CNNs and Bio-Inspired Features Combination

Motivation

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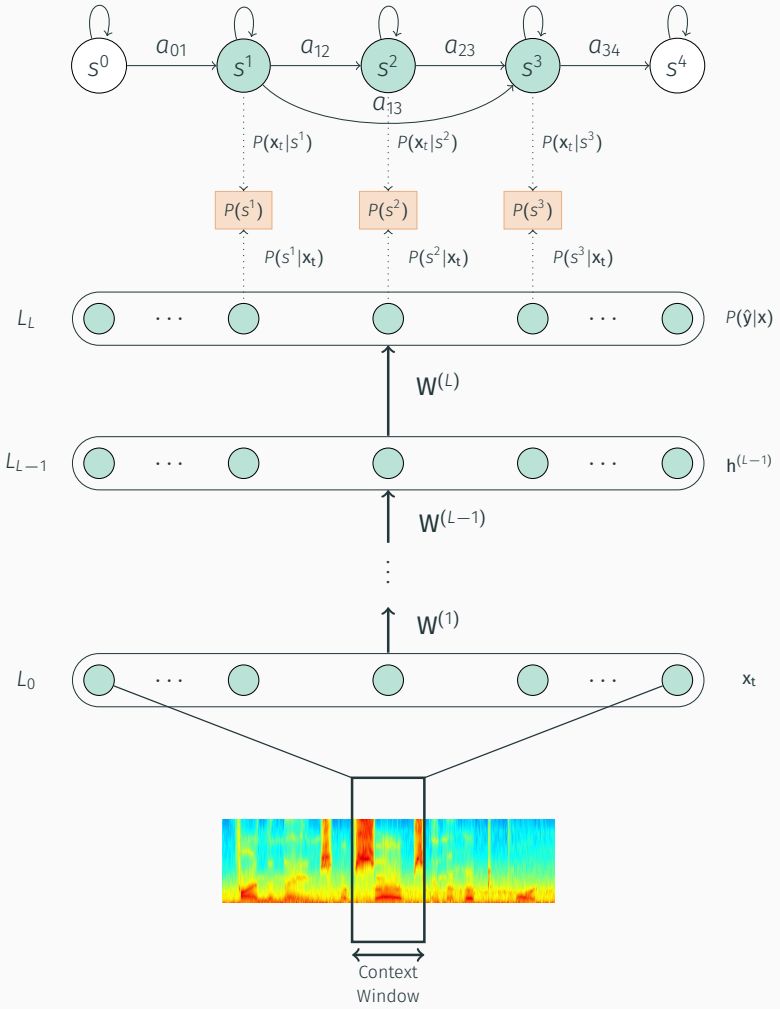
- Not many works have addressed the robustness of these systems under noisy conditions.

Deep Learning in Speech Recognition: CD-DNN-HMM Hybrid model



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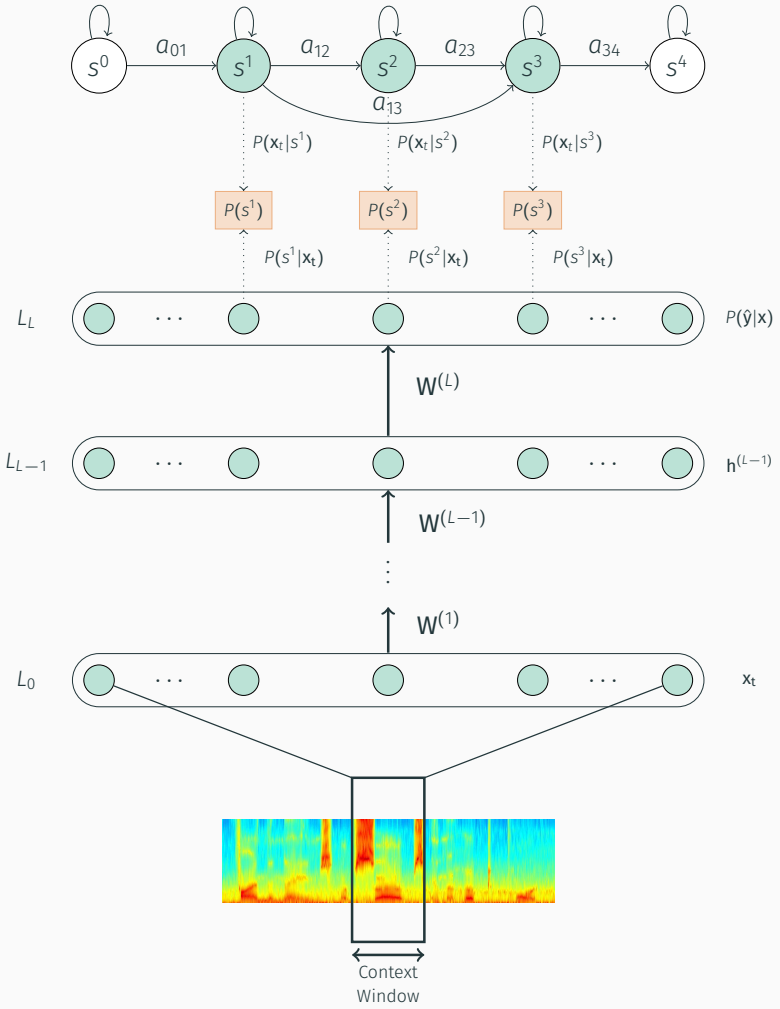

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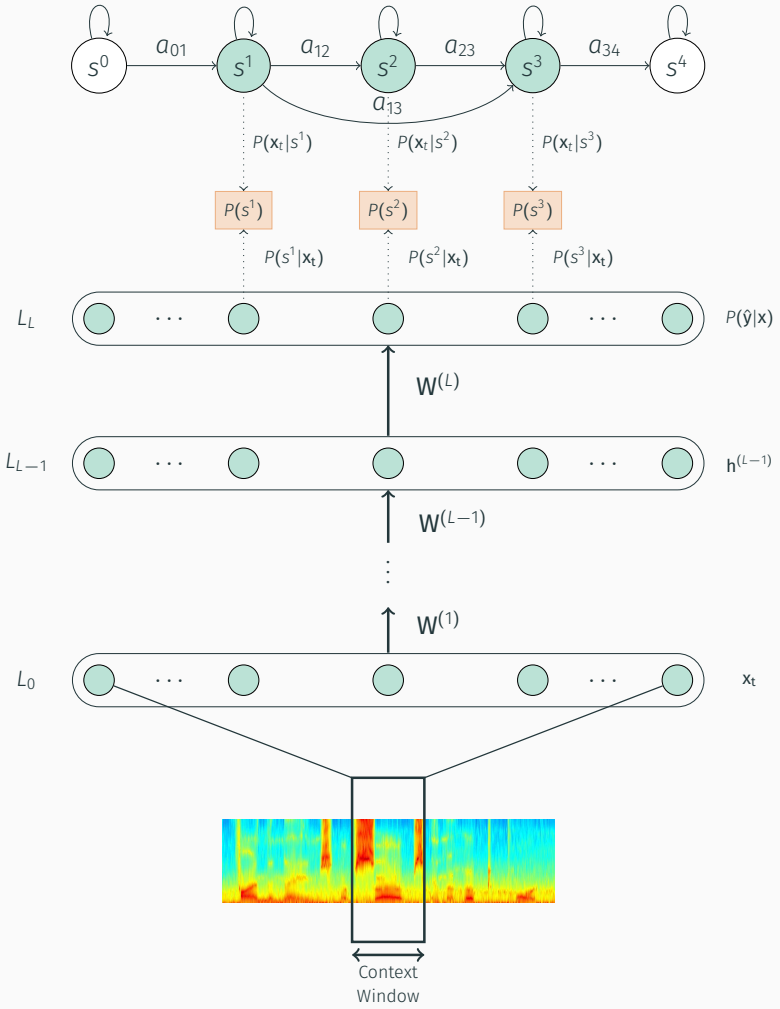

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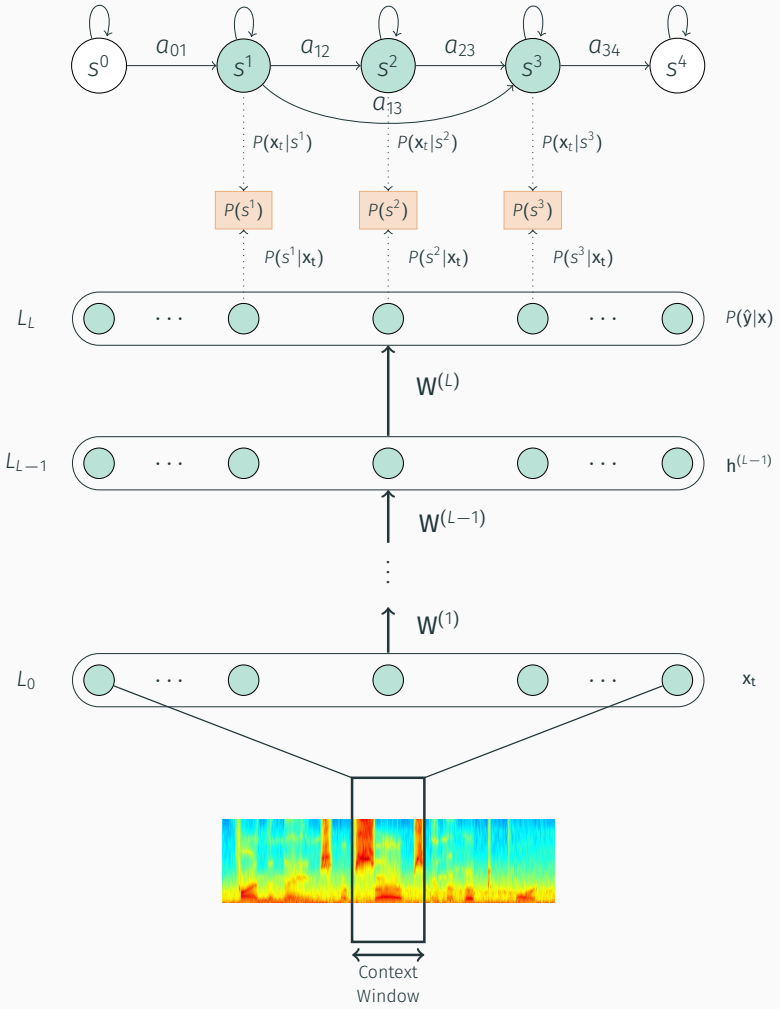

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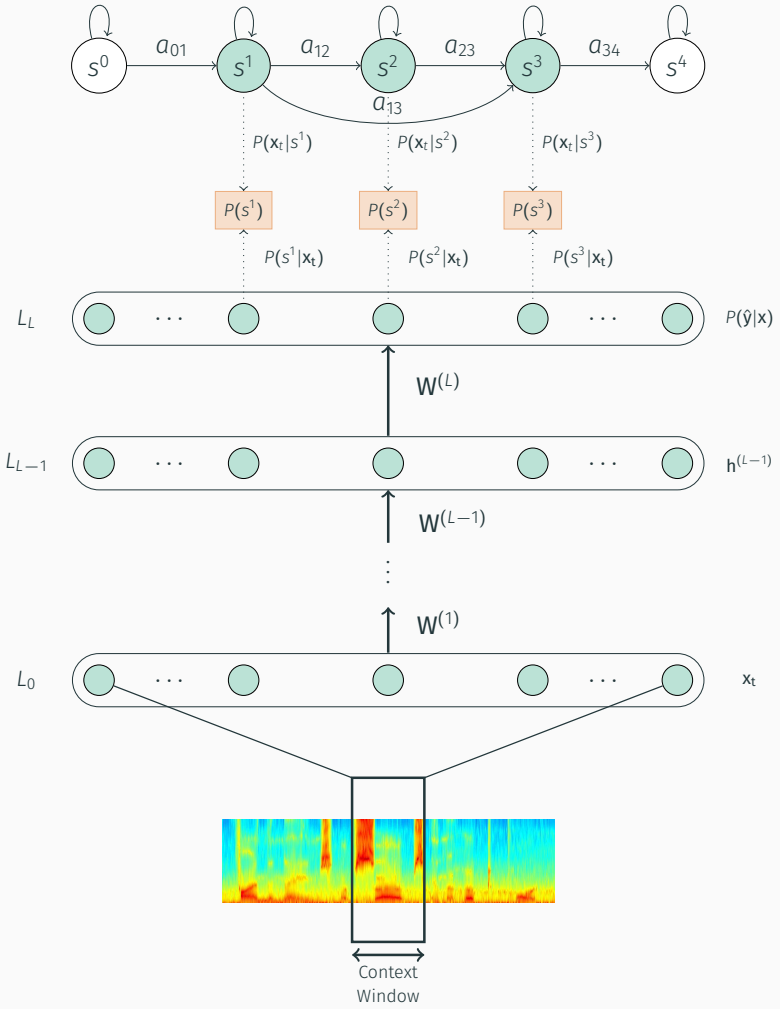

- Bourlard and Morgan (1994)
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- Long context windows (10 to 20 frames)

DNN for Robust Speech Recognition

- Alternatives:

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- Convolution replaces the general matrix multiplication.

Redrawn Dumoulin and Visin (2016).

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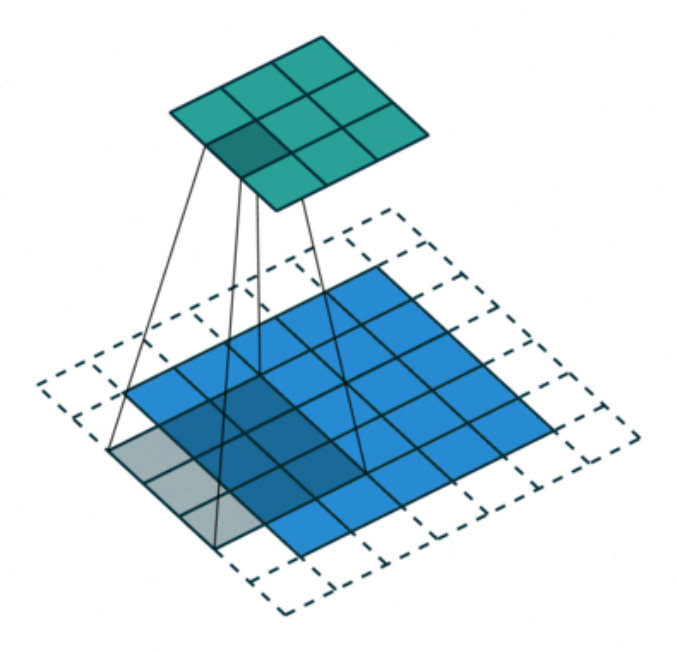

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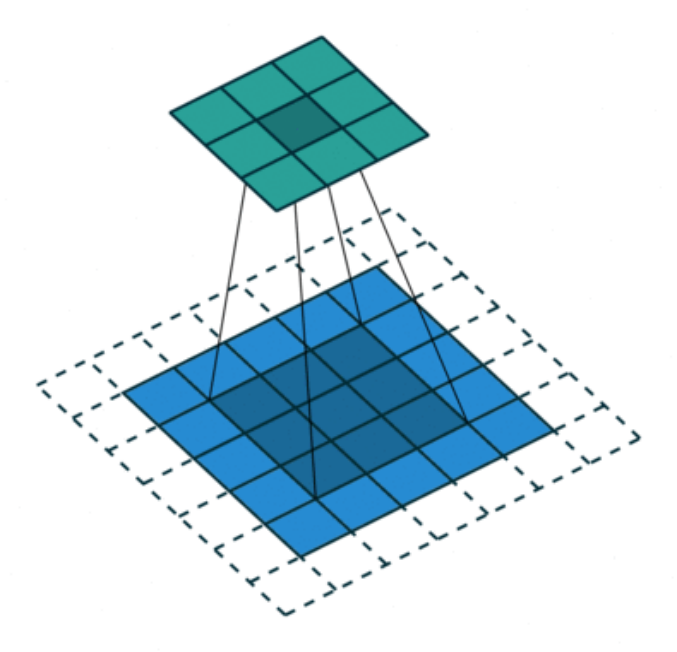

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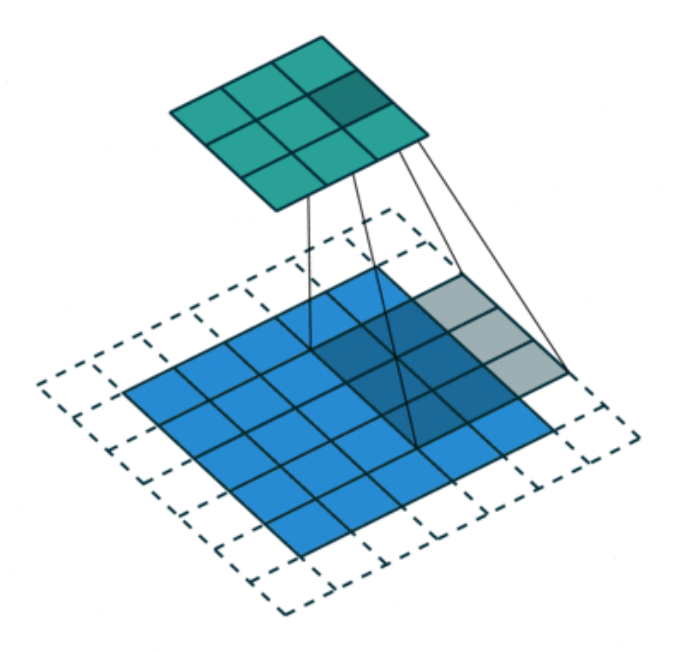

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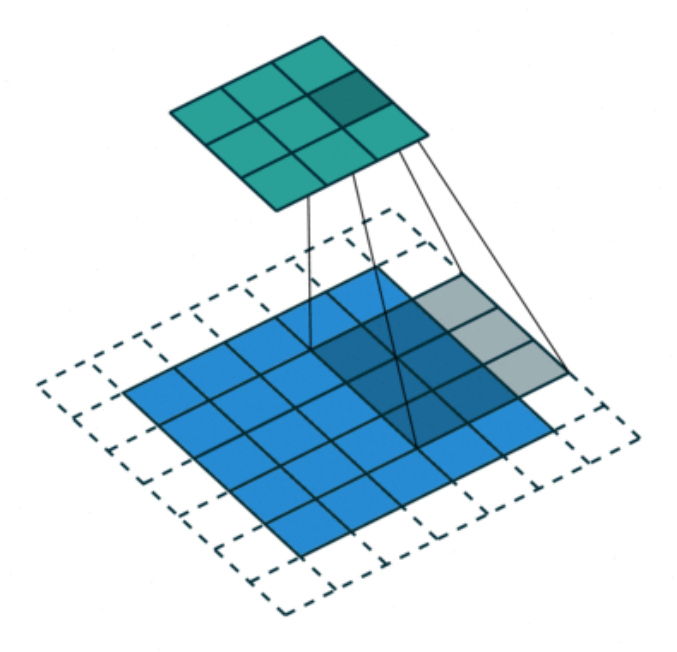

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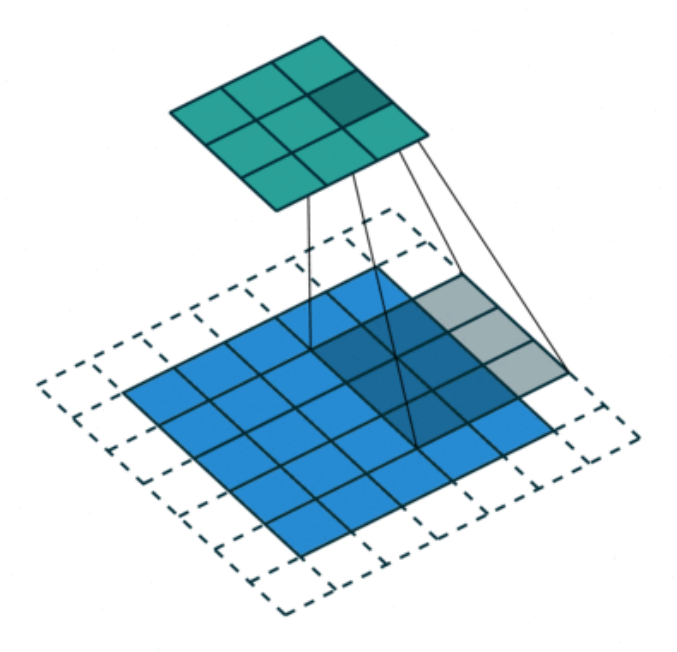

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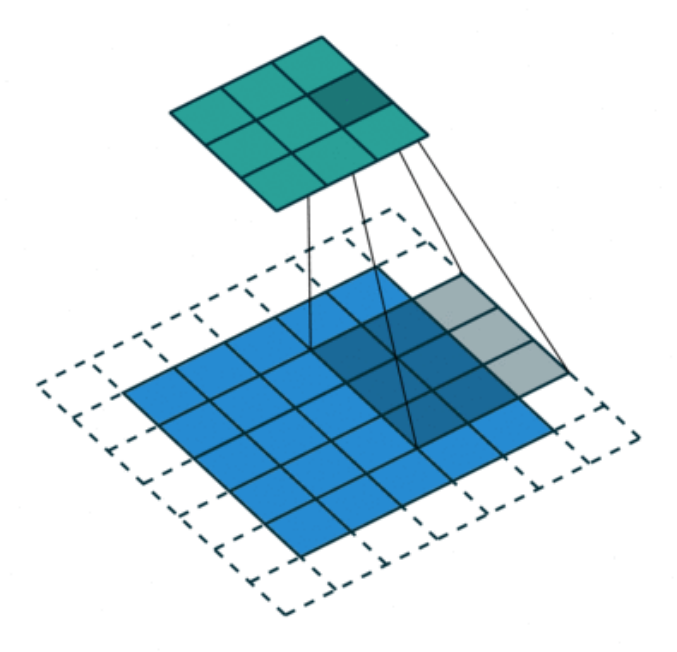

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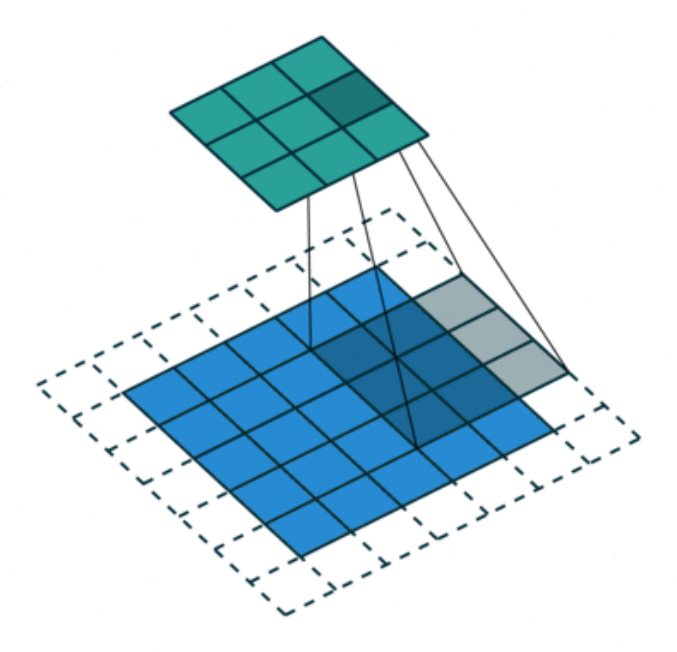

- Robust architecture due to:
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- We propose a new architecture based on RestNets and its combination with our robust features.

Redrawn Dumoulin and Visin (2016).

ResNets

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- Approximate the residual function:

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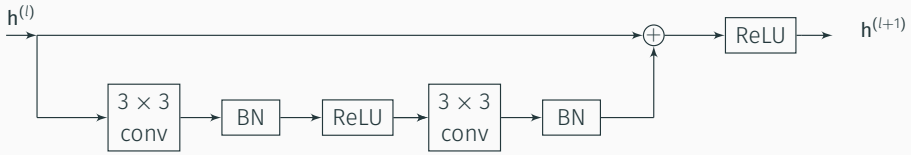

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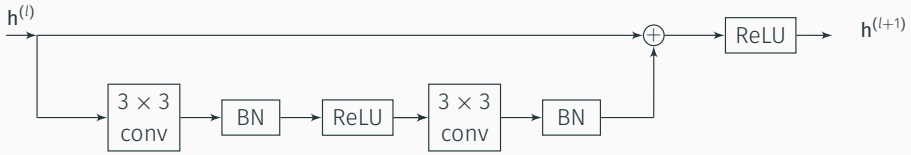
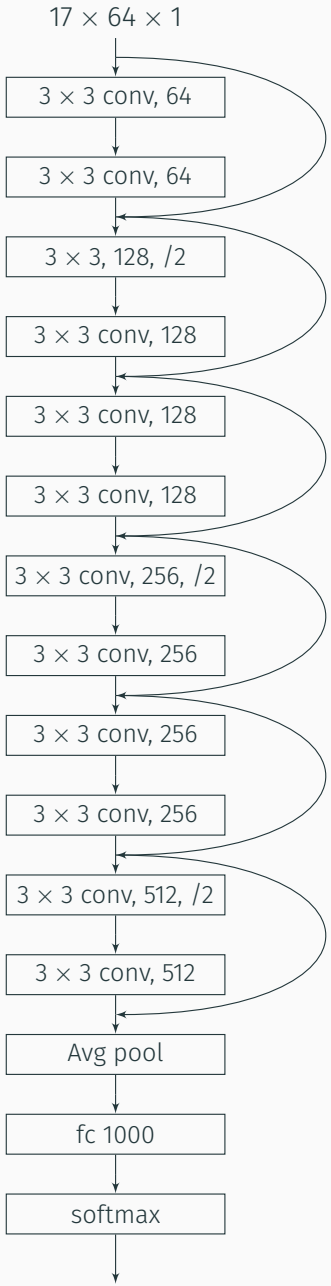


- Easy to optimize and performance gains when networks are deep.

Proposed ResNet architecture



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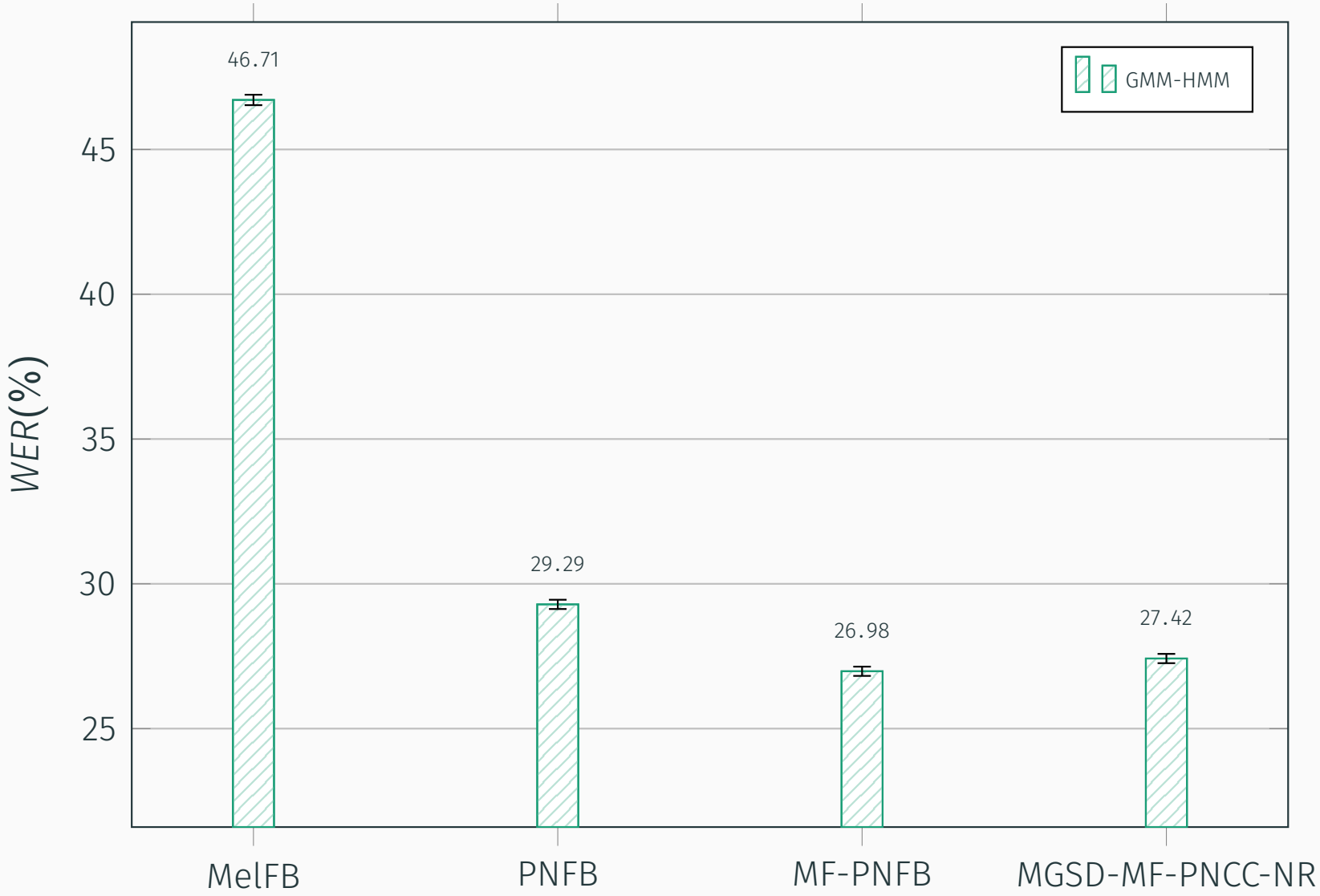

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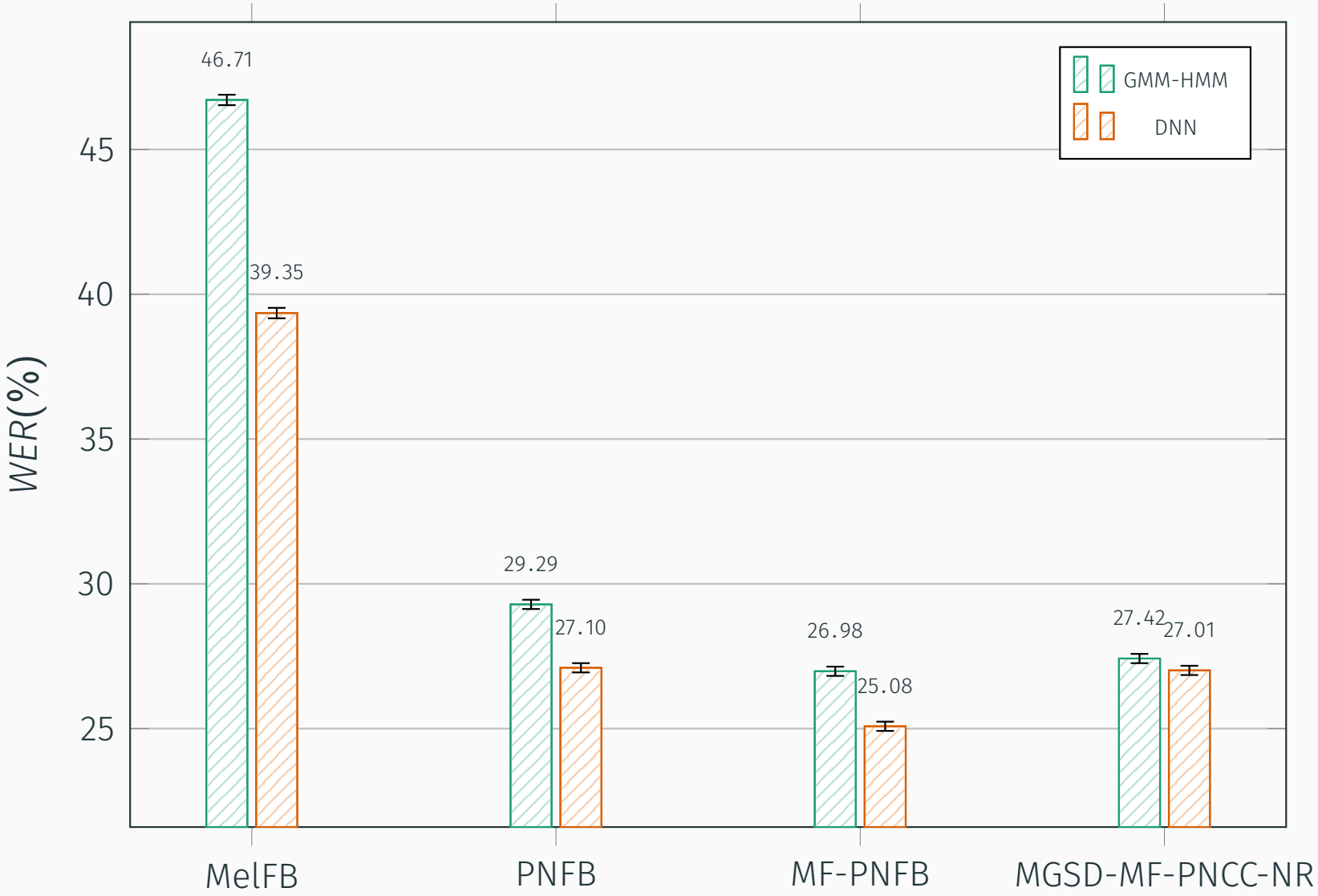

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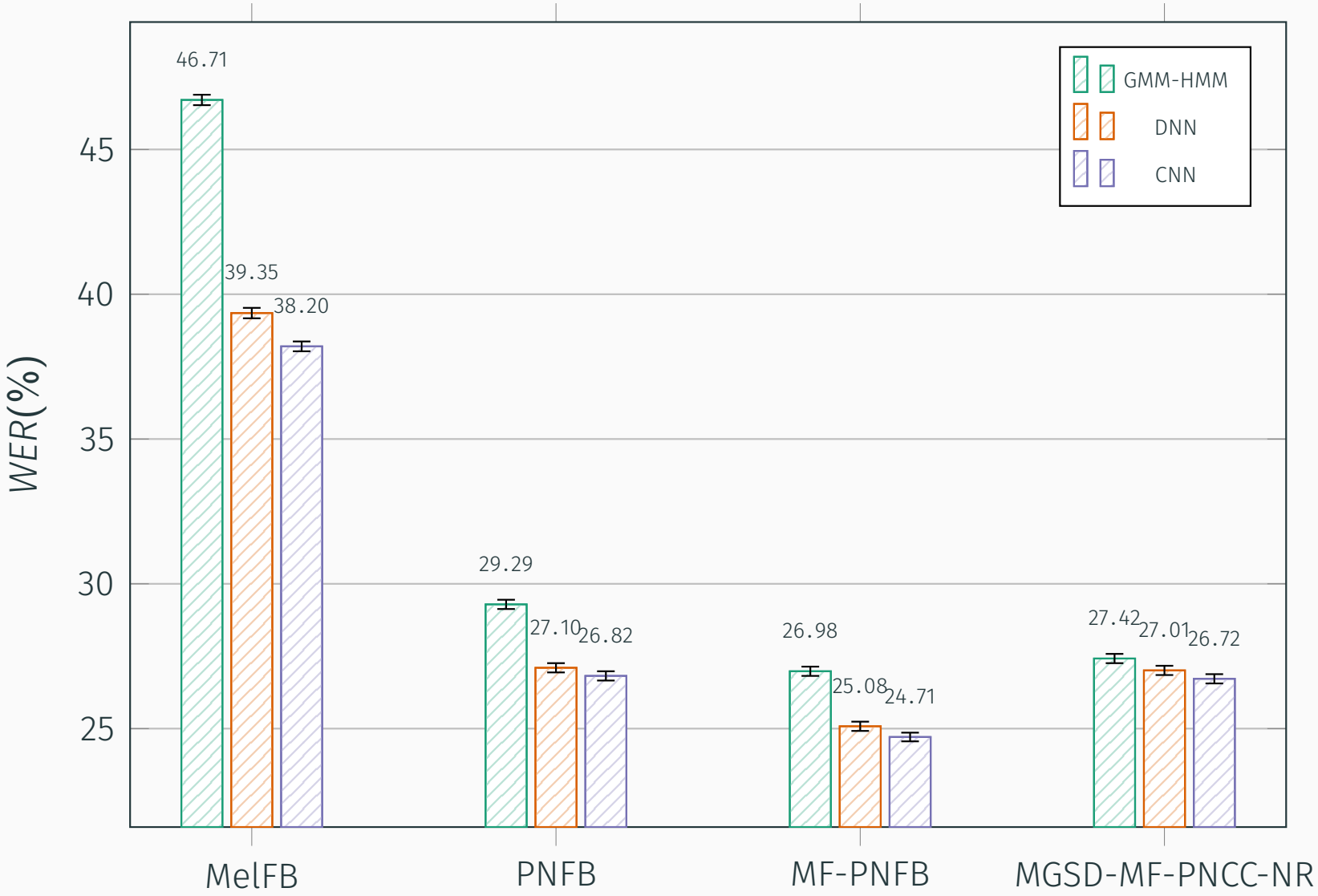

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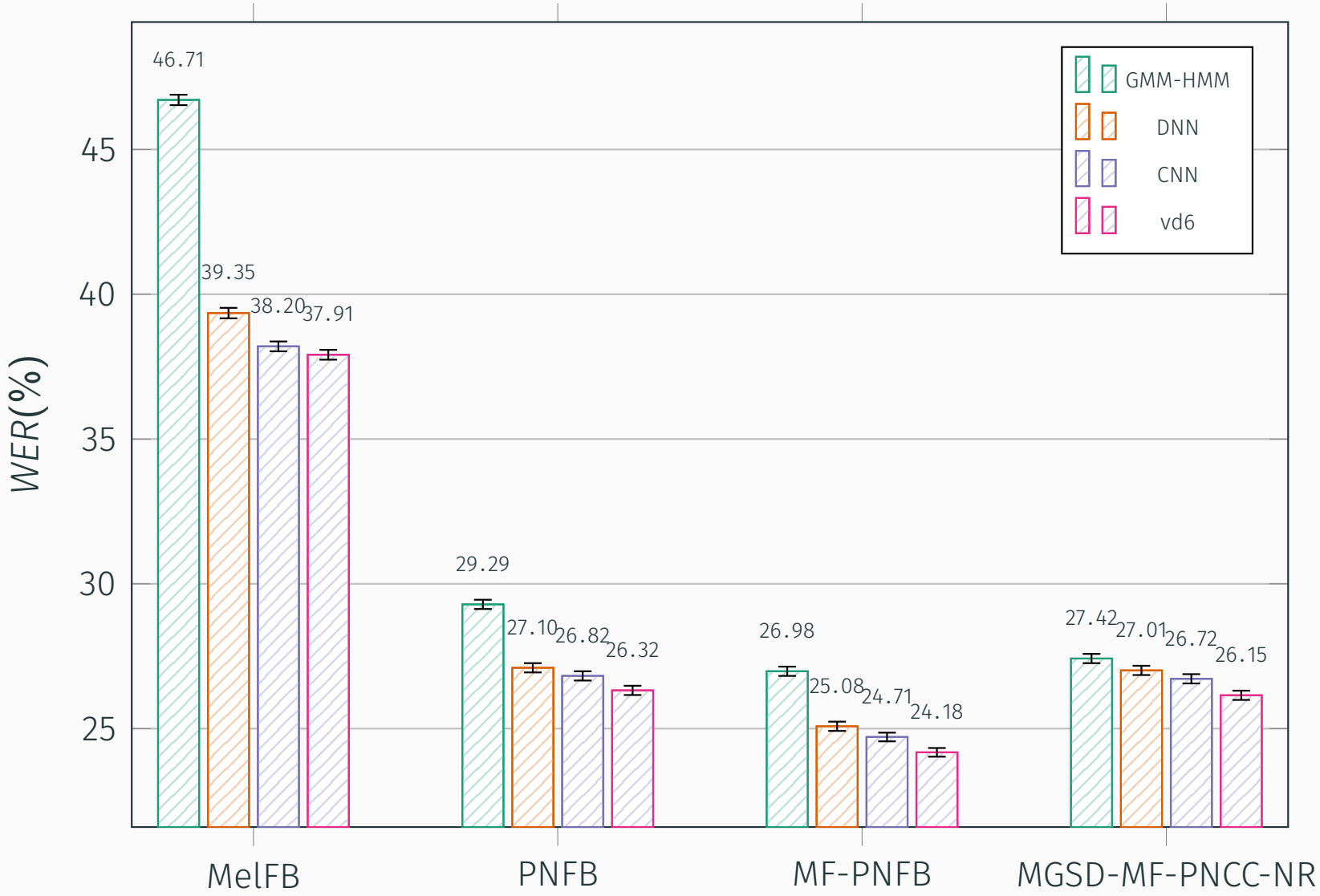

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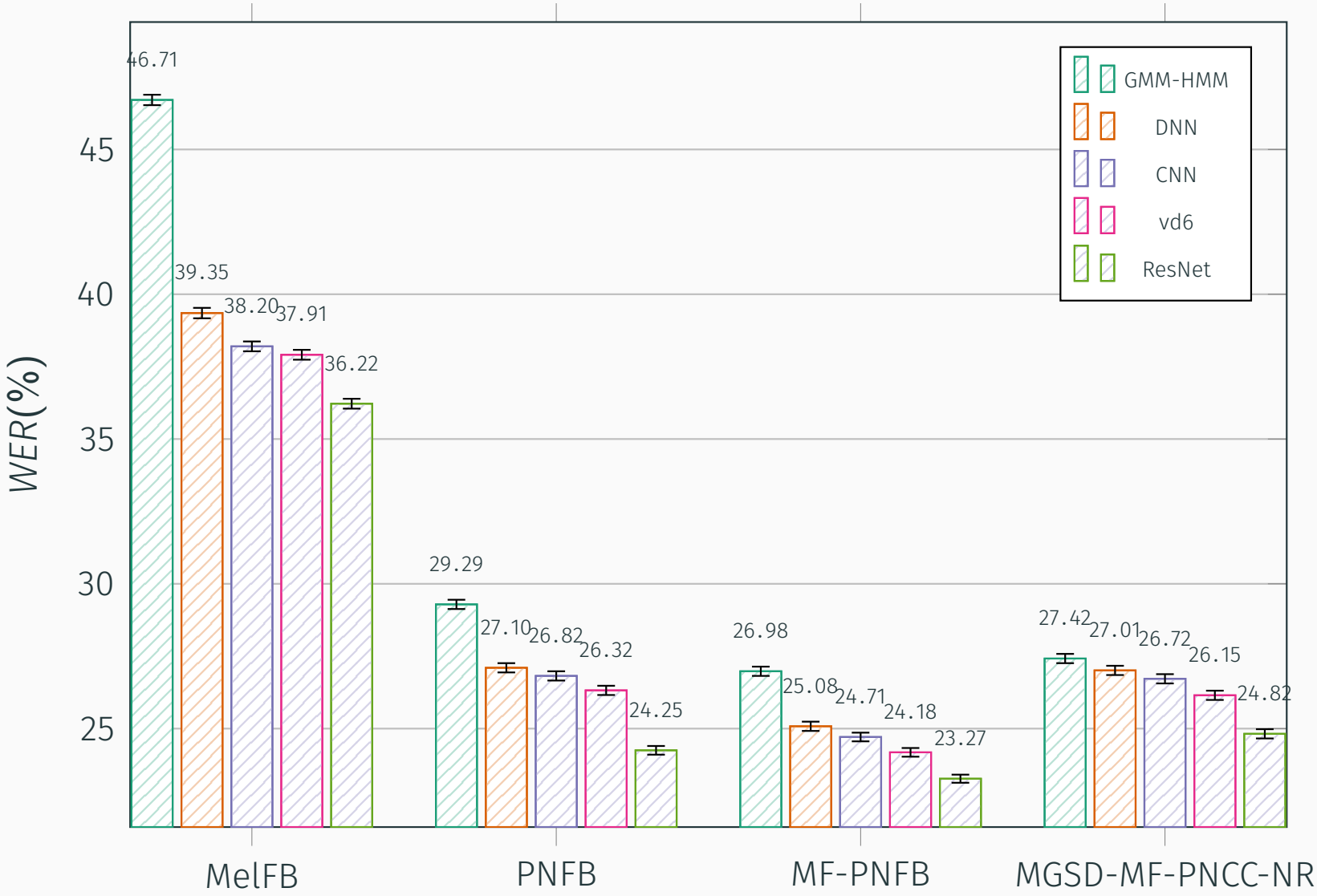

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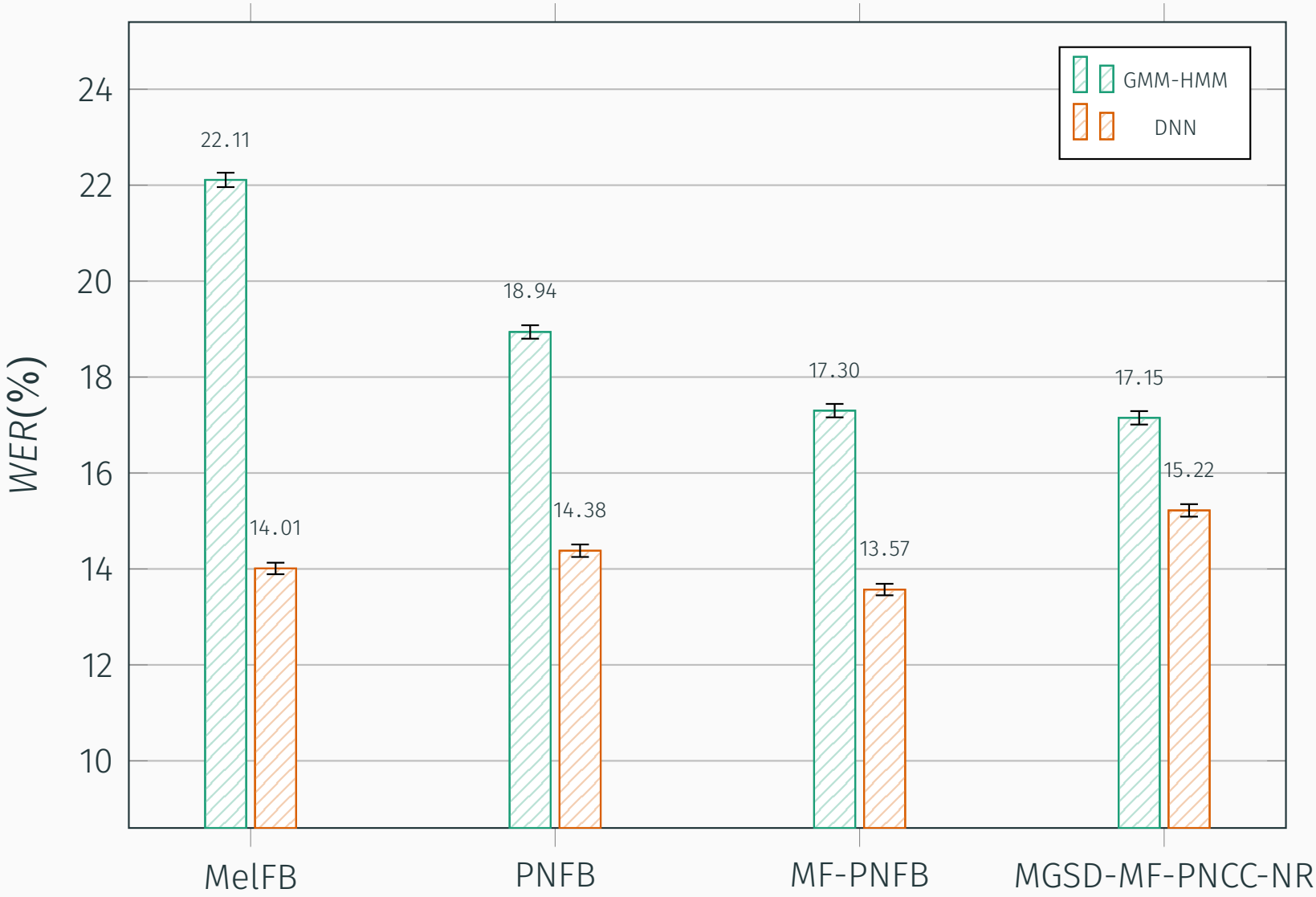

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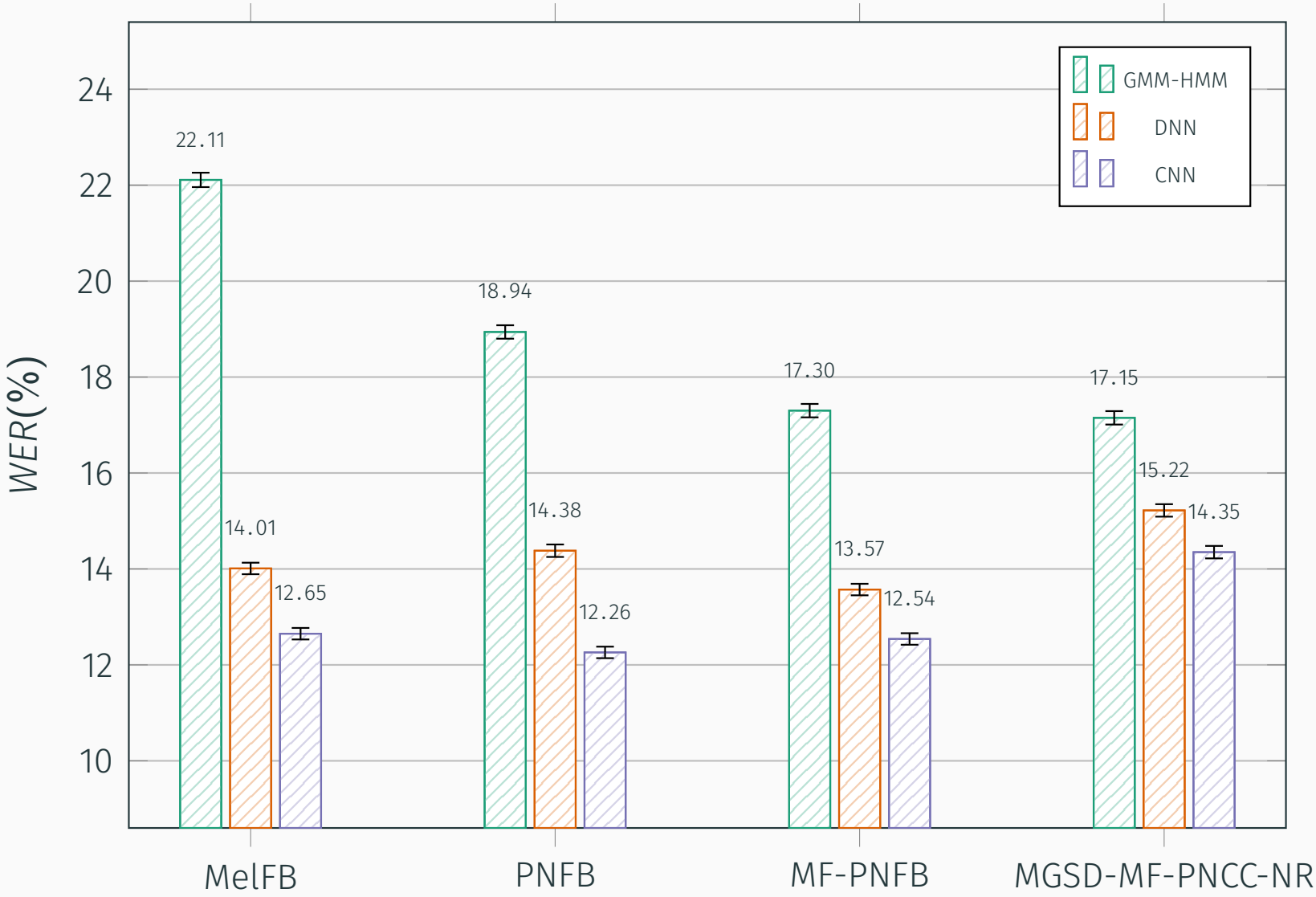

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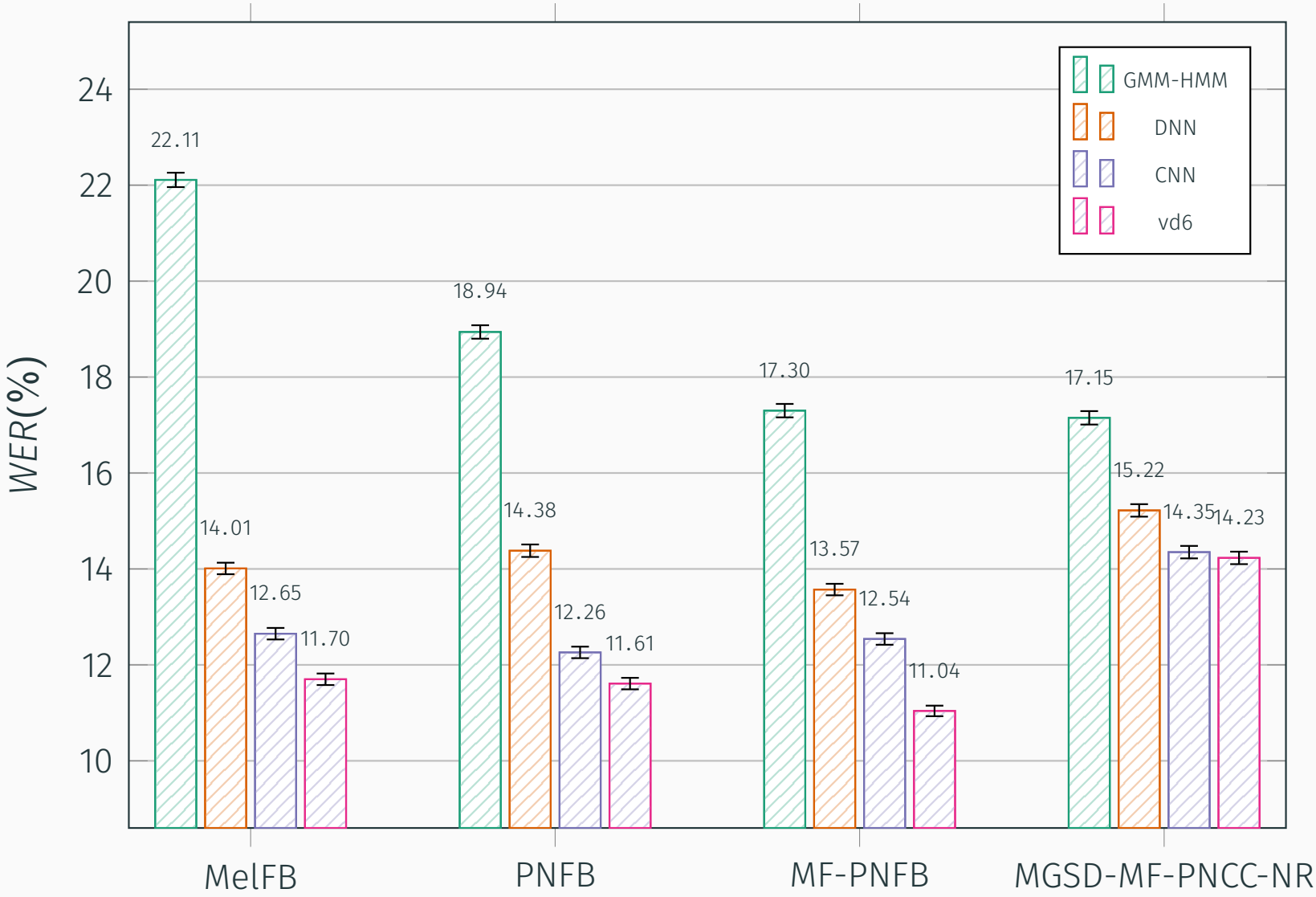

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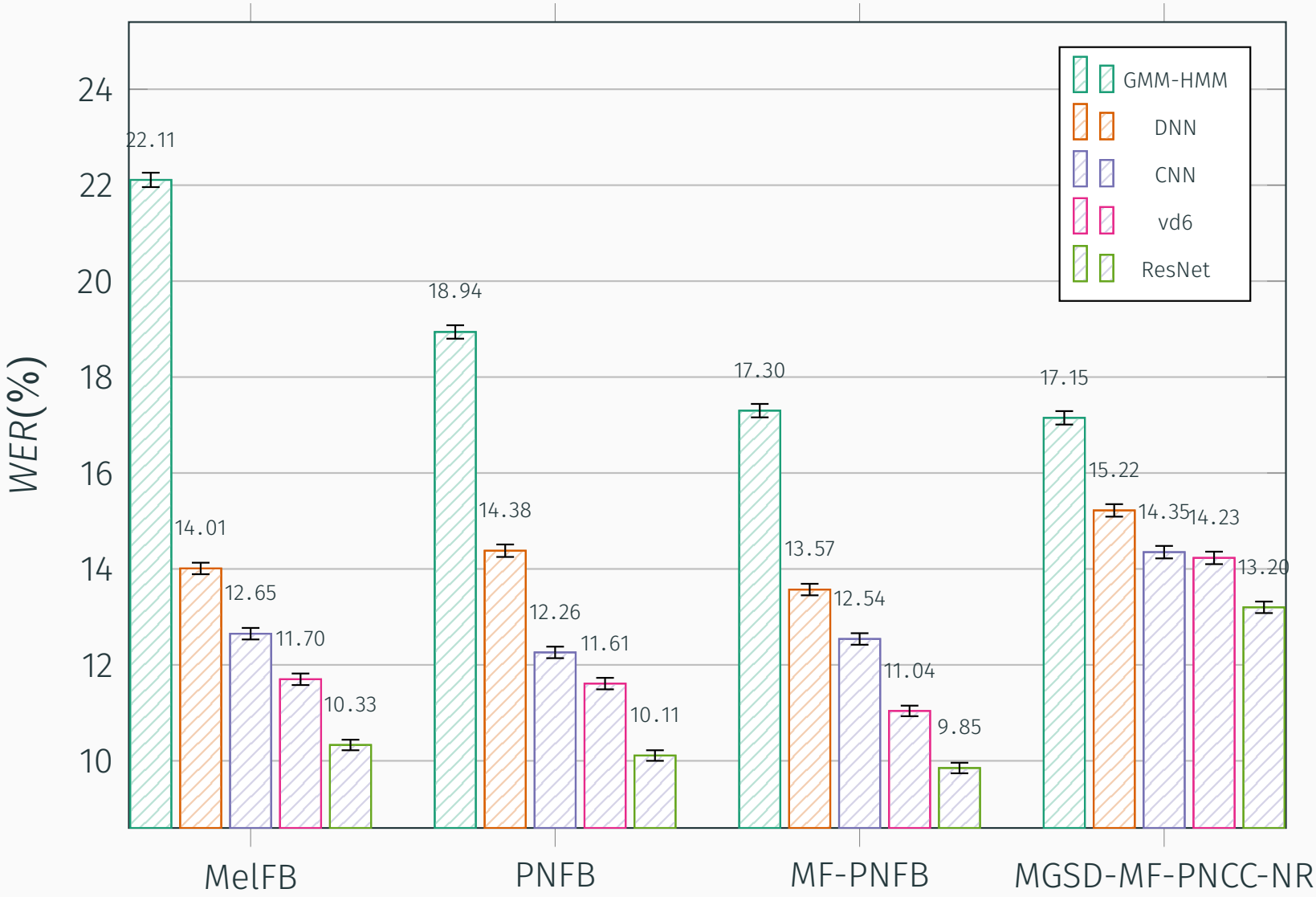

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SPL Journal

F. de-la-Calle-Silos and Richard M. Stern. *'Synchrony-Based Feature Extraction for Robust Automatic Speech Recognition,"* in *IEEE Signal Processing Letters, vol. 24, no. 8, pp. 1158, Aug. 2017*

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