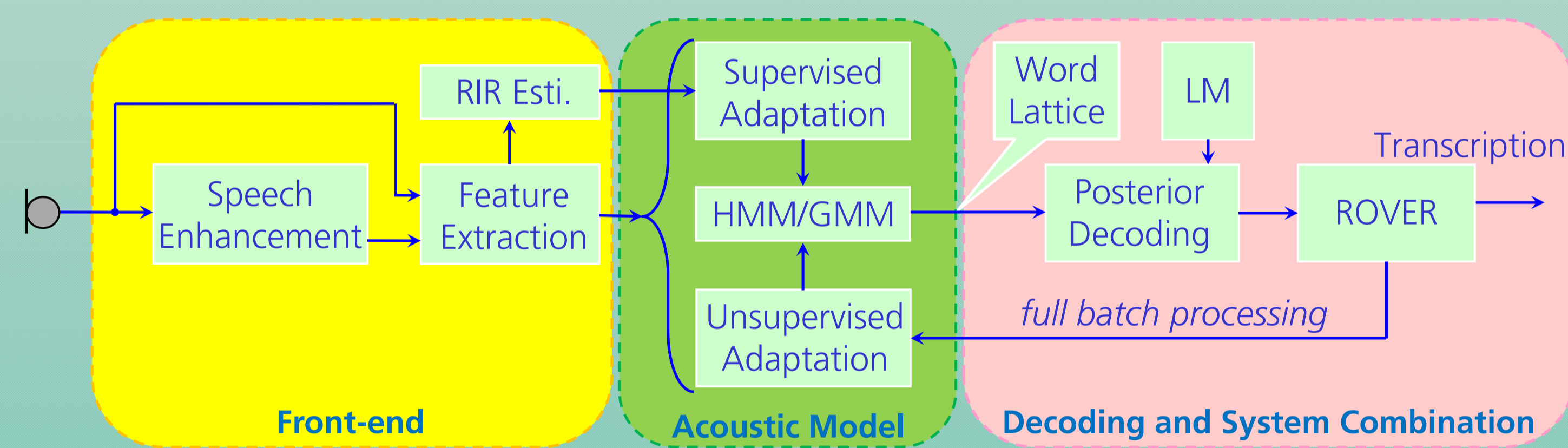


ROBUST ASR IN REVERBERANT ENVIRONMENTS USING TEMPORAL CEPSTRUM SMOOTHING FOR SPEECH ENHANCEMENT AND AN AMPLITUDE MODULATION FILTERBANK FOR FEATURE EXTRACTION

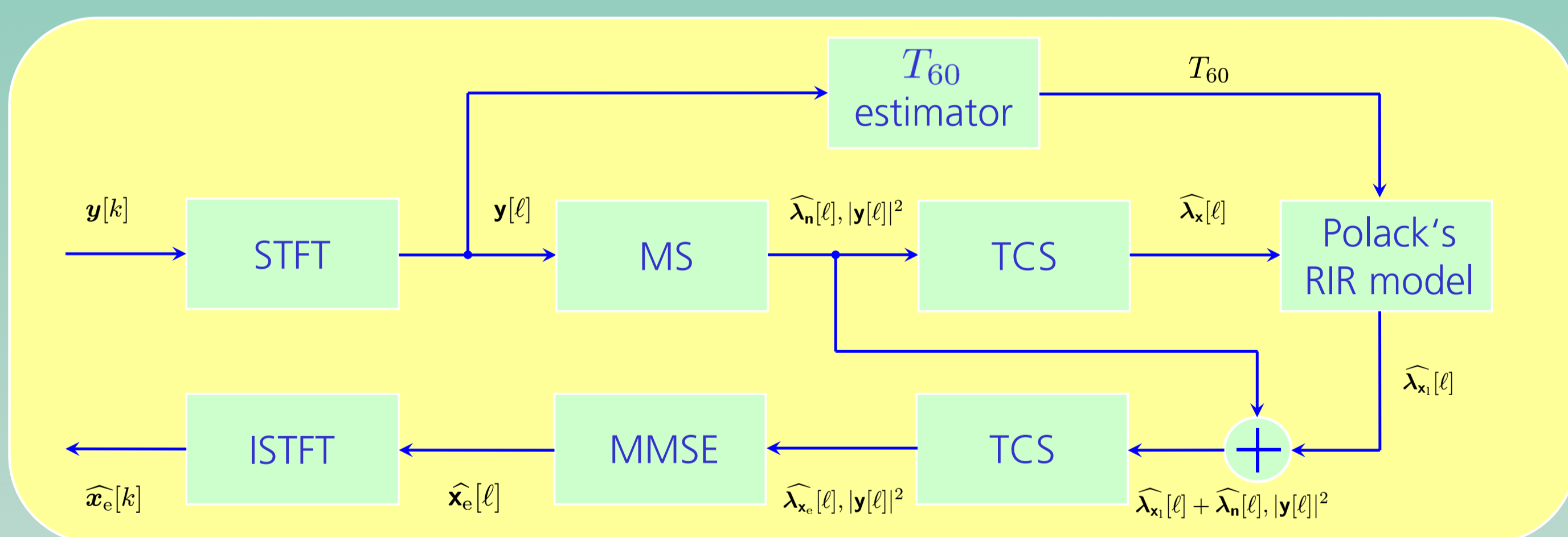
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ABSTRACT

- Improving **ASR** in **1ch** scenario of the REVERB Challenge
- Temporal cepstrum smoothing (TCS) noise reduction technique is applied to enhance the reverberant speech signal at moderate noise levels
- Robust feature extraction is performed by amplitude modulation filtering of the cepstrogram to extract temporal modulation information
- The acoustic models are adopted using different RIRs and a RIR selection scheme based on a multi-layer perceptron (MLP) and Gabor features
- ROVER-based system combination is employed to obtain a jointly optimal recognized transcription
- An overall average absolute improvement of **11%** is obtained
 - utterance-based batch processing (12.43%)**
 - full batch processing (9.41%)**



SPEECH ENHANCEMENT (SE)



- Minimum statistics (MS) → estimate noise PSD (3 s window)
- Temporal cepstrum smoothing (TCS) → estimate speech signal PSD
- Parameterized MMSE spectral magnitude estimator → weighting function
 - minimal gain chosen to -10dB
- For ASR, preserving the fundamental frequency is not crucial
 - smoothing coefficients in TCS

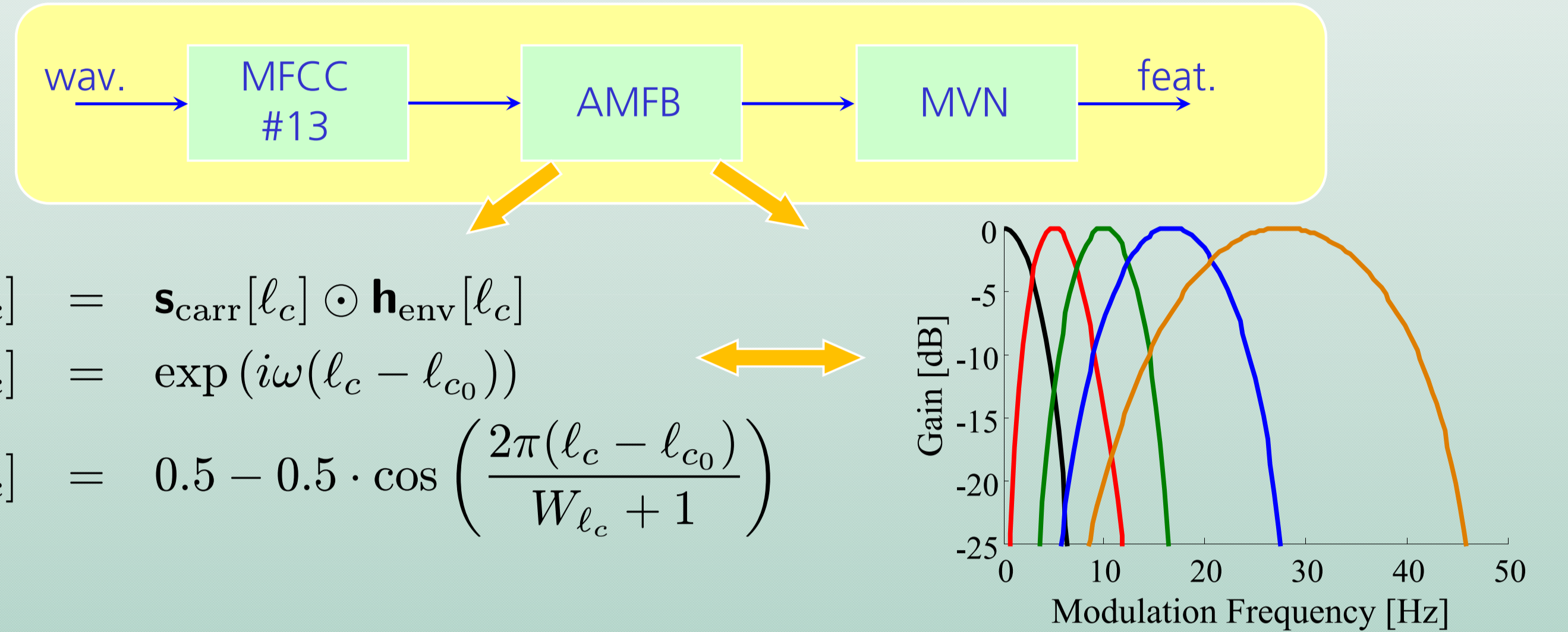
$$\alpha^c[l_c] = \begin{cases} 0.0 & l_c = 0, \dots, [f_s \cdot 0.5 \text{ ms}] - 1 \\ 0.5 & l_c = [f_s \cdot 0.5 \text{ ms}], \dots, [f_s \cdot 1 \text{ ms}] - 1 \\ 0.9 & \text{otherwise} \end{cases}$$

BACK-END

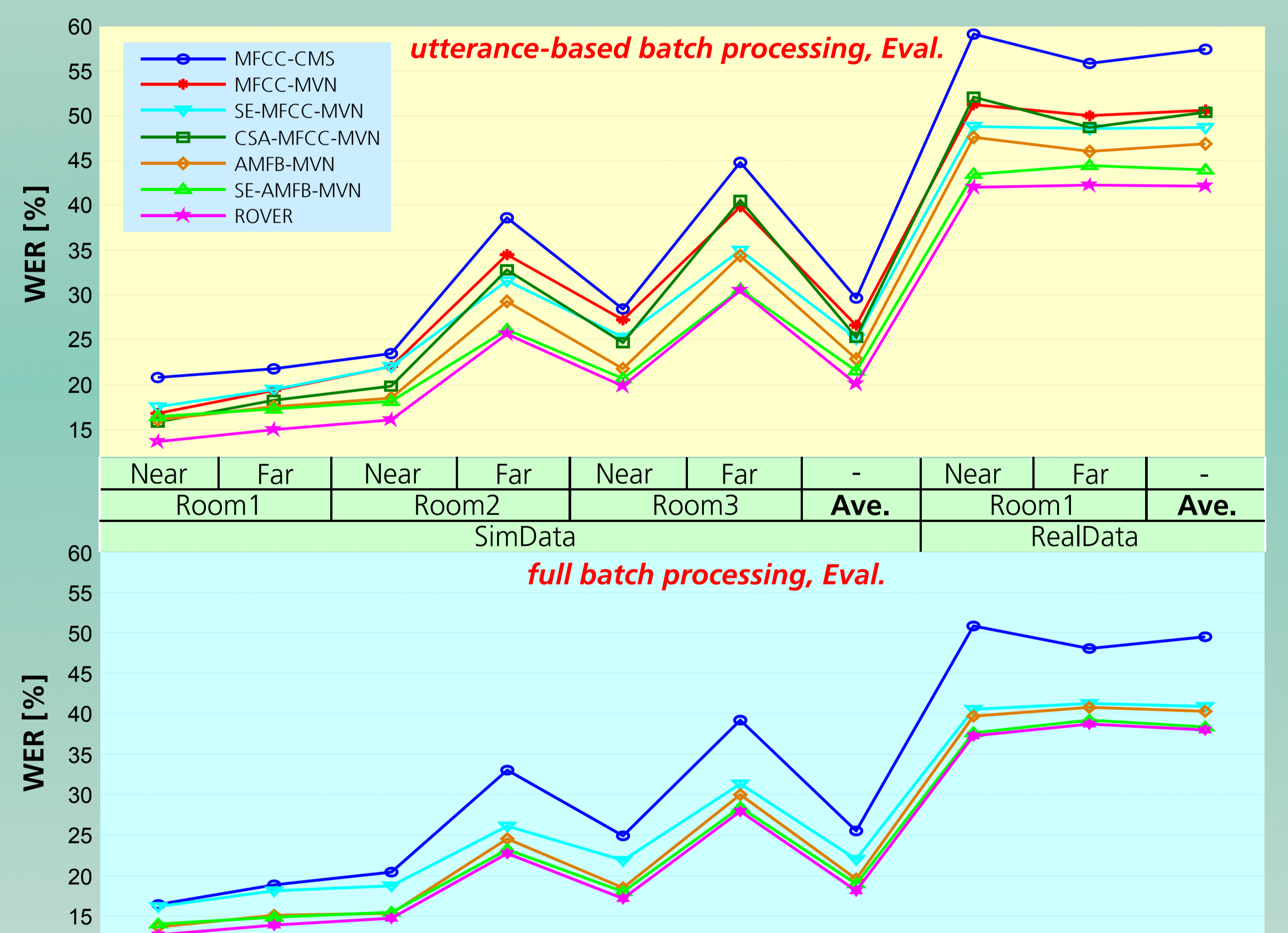
- Baseline HTK framework
- Cluster-based supervised adaptation (CSA) with MLLRMEAN
 - a set of 24 models ↔ 24 different RIRs
 - model selection based on an MLP classifier with 2D Gabor features
- Unsupervised adaptation with MLLRMEAN in the *full batch processing*
 - MLLRMEAN performs better than CMLLR
- Lattice-based posterior decoding (SRILM toolkit)
- ROVER with confidence scores for system combination

AMPLITUDE MODULATION FILTERBANK (AMFB) FEATURES

- To extract the temporal dynamics of cepstral coefficients
- 5 AM filters were selected; @{0, 5, 10, 16.67, 27.78} Hz



RESULTS



- Similar trend of the WERs reduction for the Dev. and Eval. test sets
- Constant 1~1.5% absolute WER reduction can be observed by the proposed SE algorithm
- AMFB features achieve an average absolute WER reduction of more than 4% compared to MFCCs
- Additional average absolute WER reduction of 1~2% is achieved by ROVER with complementary systems ← fine-tuning
- A better recognition transcription assists MLLR to better adapt the model to match more to the test set condition

CONCLUSIONS

- 1ch** combined ASR system consisting of speech enhancement, robust feature extraction, acoustic model adaptation, posterior decoding and ROVER-based system combination
- SE based on TCS is proven to be advantageous to cope with the reverberation effect to ASR systems
- Capturing the temporal modulation information is crucial for feature extraction when facing the reverberant speech for ASR systems