

MOTIVATION

New ASR upswing

The use of ASR applications has notably increased due to the latest smartphones:

- Great amount of apps (search-by-voice, IPA, dictation, etc.).

Noise-robust ASR in smartphones

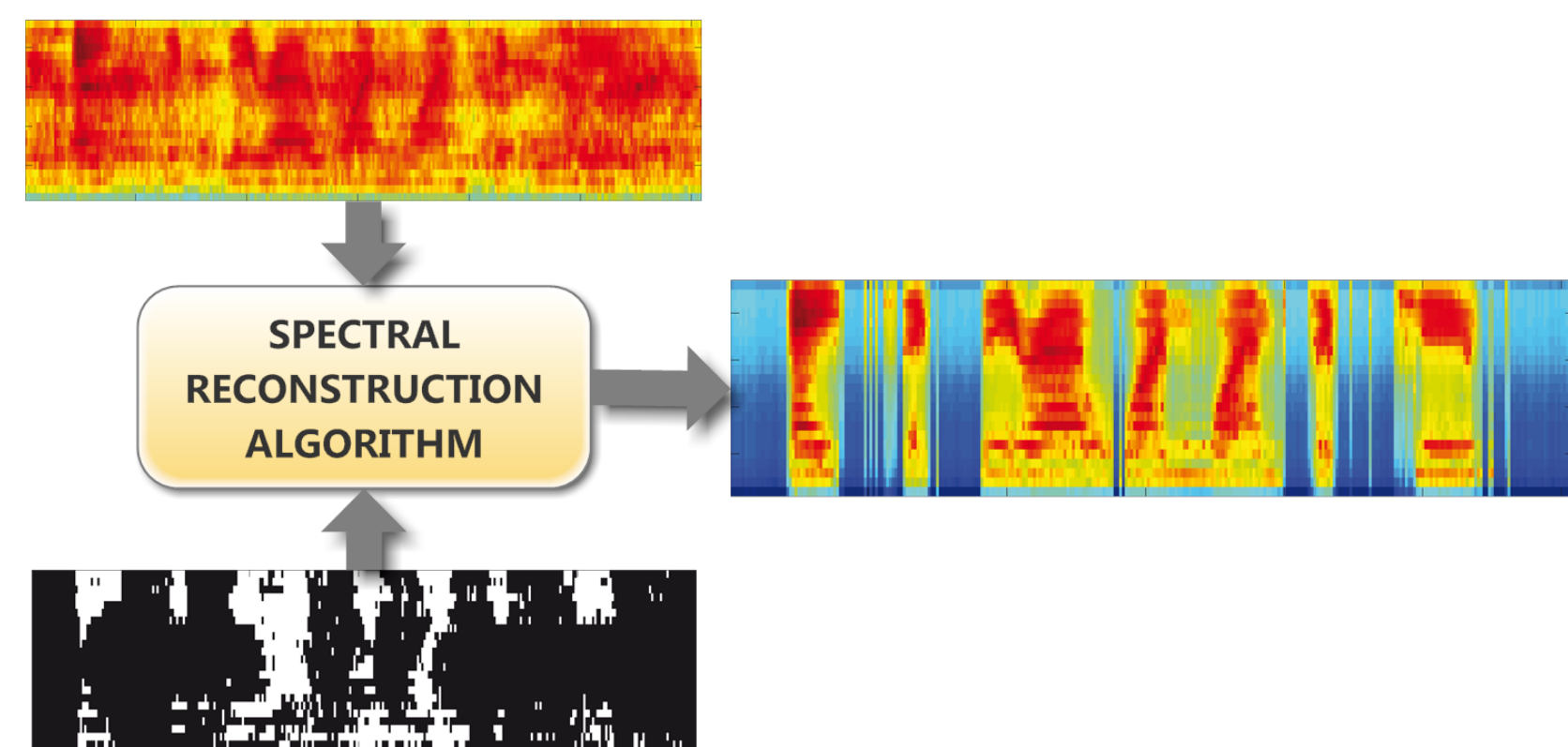
- It is crucial to tackle with **noisy environments**.
- We can benefit from the novel dual-microphone feature.



OBJECTIVES

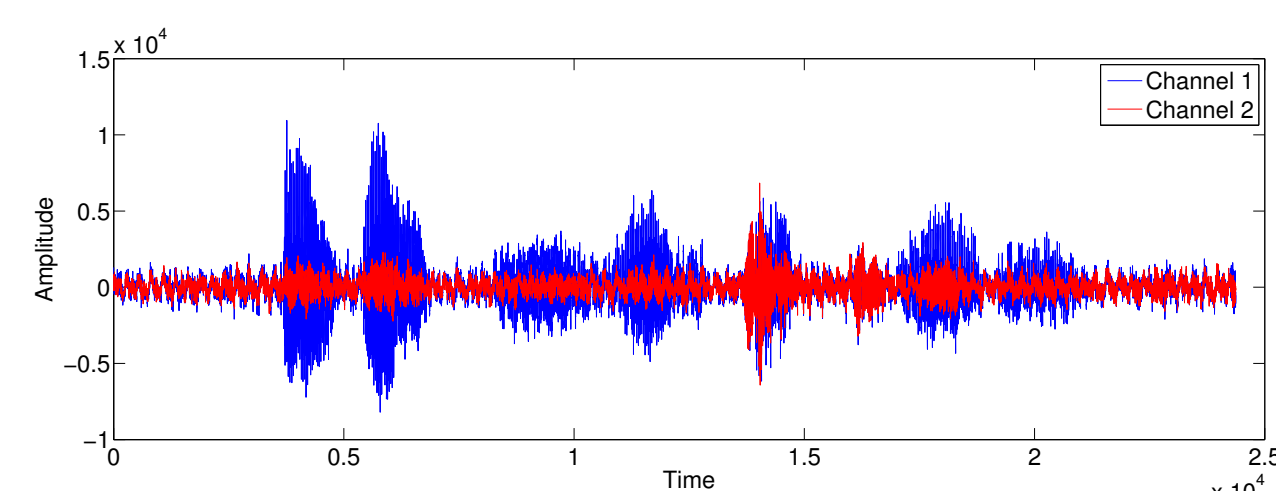
Our goals

- To **improve ASR performance** in noisy conditions by exploiting dual-mic configurations **on smartphones**.
- To use **spectral reconstruction** by means of TGI (truncated-Gaussian based imputation).
- To **estimate missing-data masks by using DNNs**.



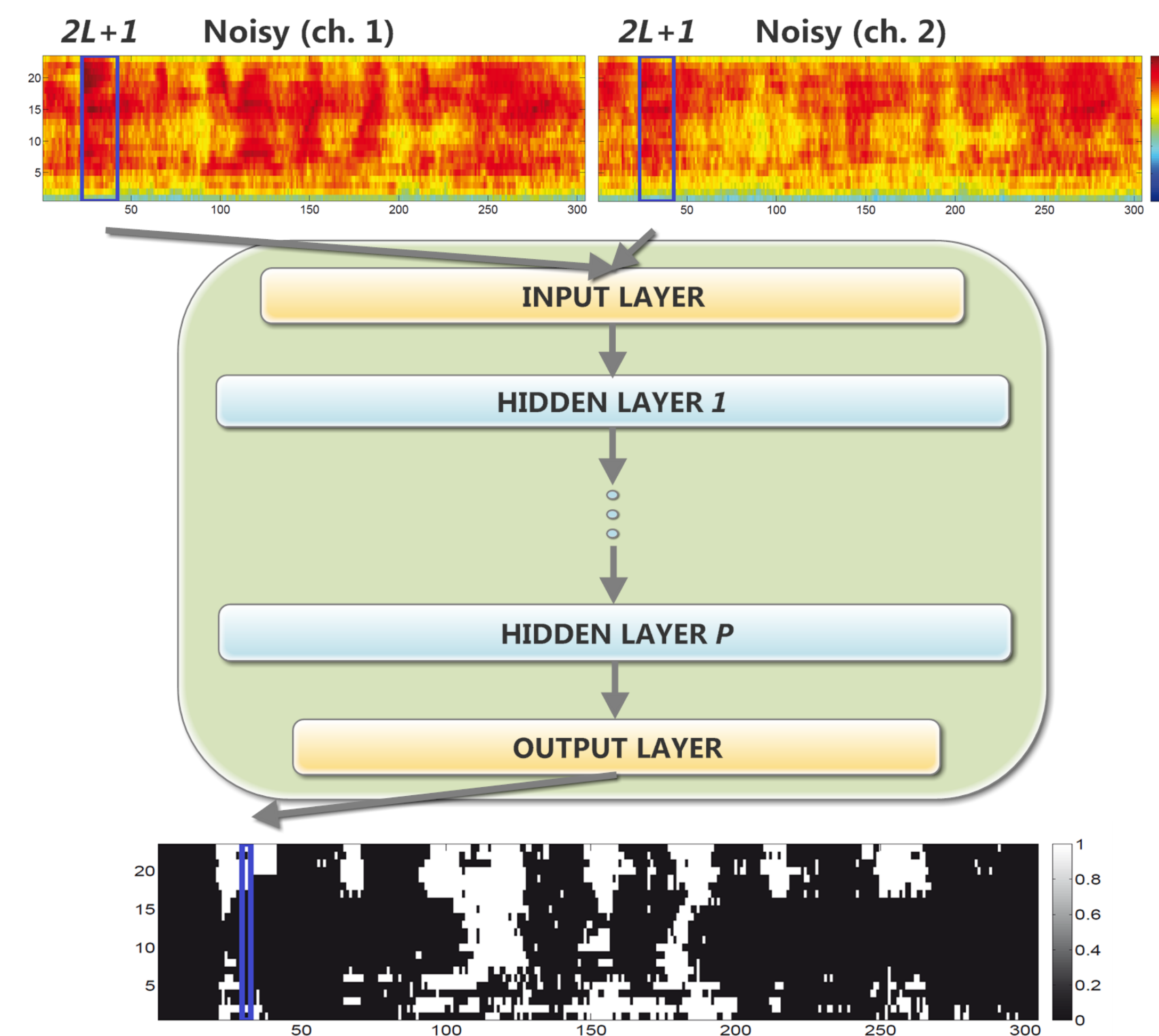
What we want the DNN exploits

- The dual-channel information provided by the smartphone.
- The power level difference (PLD) between the 2 mics in close-talk conditions.



Speech power is greater at the 1st ch. than at the 2nd one.
Noise power is similar at both channels.

DNN-BASED PROPOSED SYSTEM



Features

$$\mathcal{Y} = \begin{pmatrix} \mathbf{y}(t-L) \\ \vdots \\ \mathbf{y}(t+L) \end{pmatrix}, \text{ where } \mathbf{y}(t) = \begin{pmatrix} \mathbf{y}_1(t) \\ \mathbf{y}_2(t) \end{pmatrix}$$

- Input dim.: $d_F = 2 \cdot \mathcal{M} \cdot (2L + 1) \times 1$

Target

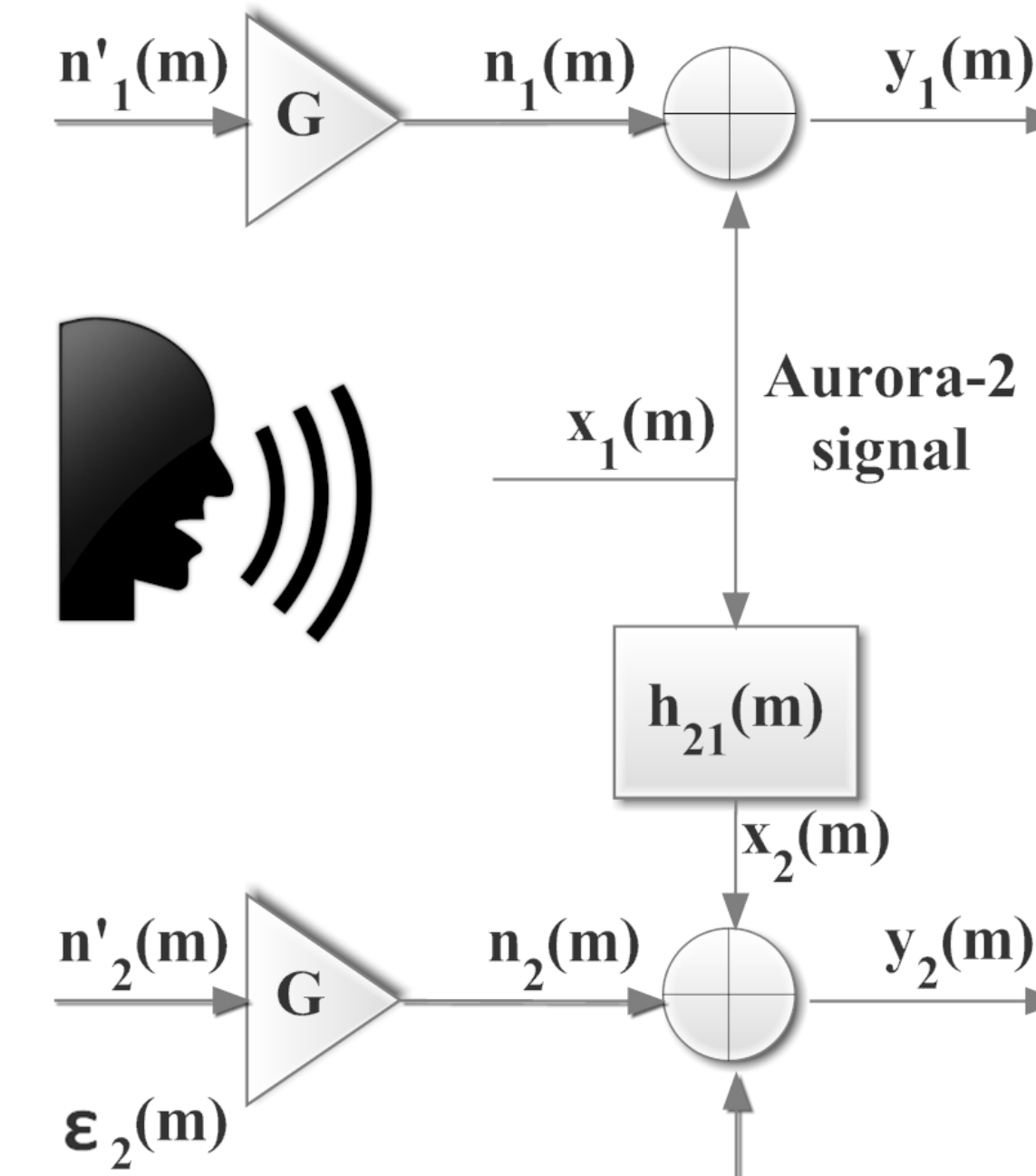
- Oracle binary mask vector for $\mathbf{y}_1(t)$
- 7 dB SNR threshold
- Output dim.: $d_T = \mathcal{M} \times 1$

Training issues

- The DNN is pre-trained by considering each pair of layers as RBMs.
- The DNN is trained by using the backpropagation algorithm (**cross-entropy criterion**).
- Since $\mathcal{M} = 23$ and $L = 2$, $d_F = 230$ and $d_T = 23$.
- We use 2 hidden layers with $2d_F = 460$ nodes in each one.

THE AURORA2-2C-CT

The AURORA2 - 2 Channels - Close-Talk database



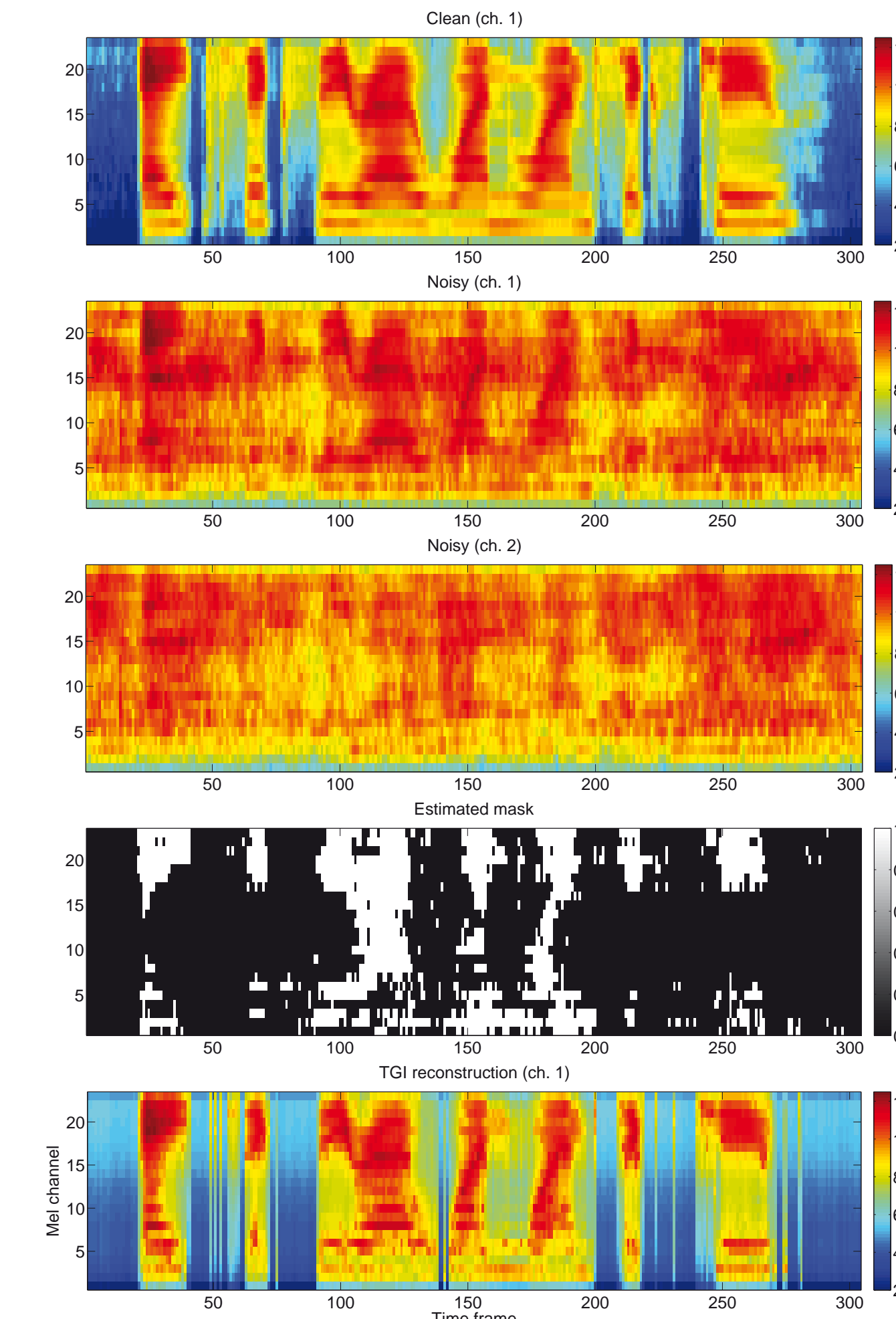
- The AURORA2-2C-CT emulates the acquisition of noisy speech data with a dual-microphone smartphone used in close-talk conditions.
- It is based on the well-known Aurora-2 database.
- It is used for speech recognition experiments in this work.

Design

- $h_{21}(m)$ is modeled as a time-invariant FIR filter trained from speech recorded with a smartphone.
- $\{n'_i; i = 1, 2\}$ were recorded with a smartphone and scaled by G to get a certain SNR for $y_1(m)$.
- The AURORA2-2C-CT is structured as Aurora-2.

EXAMPLE OF APPLICATION

- Example of the TGI reconstruction of an utterance (all the spectrograms are in the log-Mel domain):



- From top to bottom: clean utterance at the 1st ch., corrupted by bus noise at 0 dB at the 1st ch., corrupted by bus noise at 0 dB at the 2nd ch., mask estimated by the proposed DNN-based system and resulting TGI reconstruction (1st ch.).

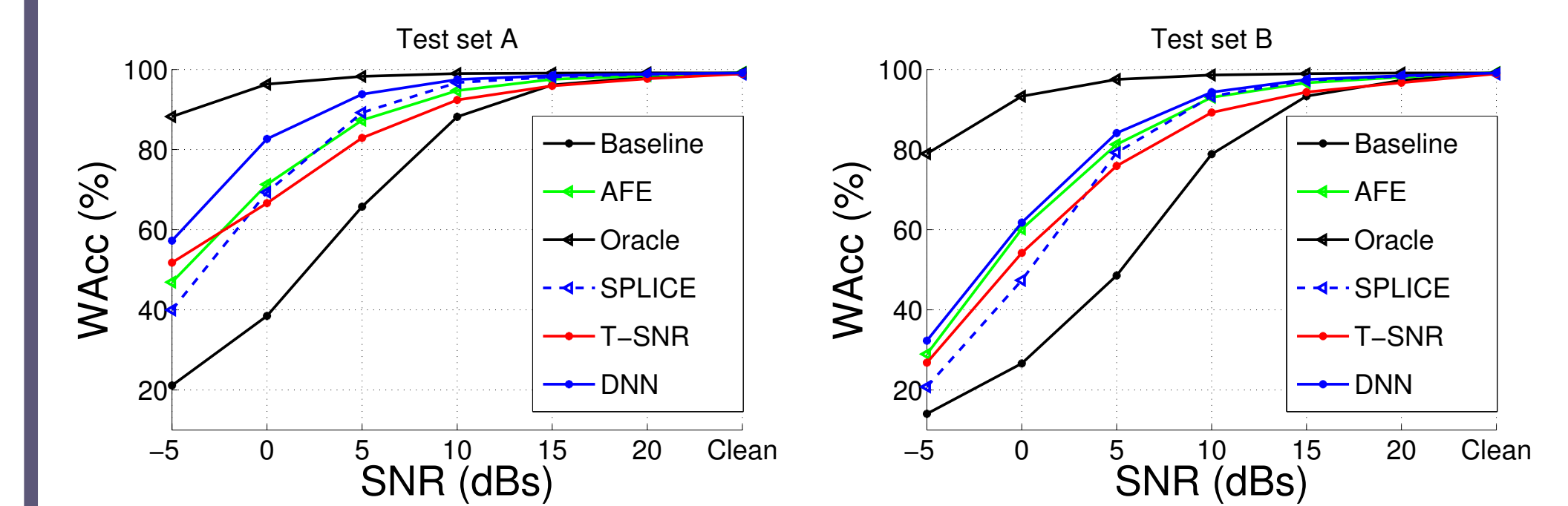
EXPERIMENTAL RESULTS

Experimental framework

- We use the ETSI front-end to extract features.
- A GMM-HMM-based ASR back-end trained on clean speech is employed.
- The DNN is trained with the noises in test set A.
- TGI is combined with our proposal (DNN), with oracle masks and with masks estimated by thresholding an ML-based SNR estimate (T-SNR).
- Baseline, AFE and SPLICE are also included for comparison.

Results

	WAcc (%)			Wrong mask bins (%)		
	Test A	Test B	Avg.	Test A	Test B	Avg.
Baseline	67.96	59.78	63.87	-	-	-
AFE	82.71	76.37	79.54	-	-	-
Oracle	96.67	94.41	95.54	0	0	0
SPLICE	82.03	72.72	77.38	-	-	-
T-SNR	81.21	72.87	77.04	17.97	19.89	18.93
DNN	88.10	78.07	83.08	10.07	16.19	13.13



- The DNN exhibits some generalization ability to unseen noises during the training phase according to the results for test set B.

CONCLUSIONS

Conclusions

- The DNN has been able to take advantage of the dual-channel information.
- The DNN overcomes the analytical modeling capabilities and allows better performance.

Future work

- To extend this method to deal with a far-talk scenario, where the PLD assumptions are not completely valid.

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