A brief introduction to multichannel noise reduction with deep neural networks

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A brief introduction to multichannel noise reduction with deep neural network.

Romain Serizel

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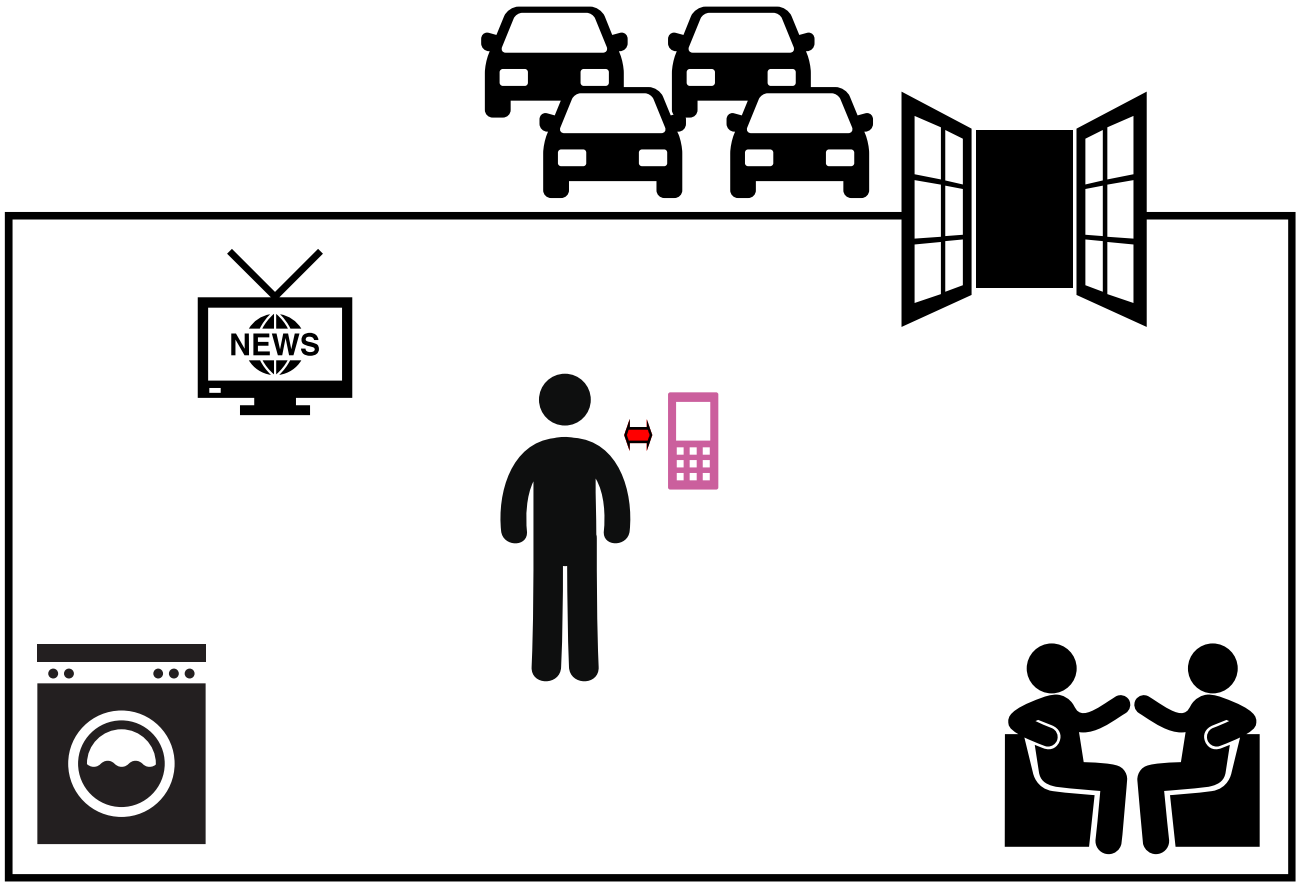
Outline

Speech in real conditions

Problem “solved”

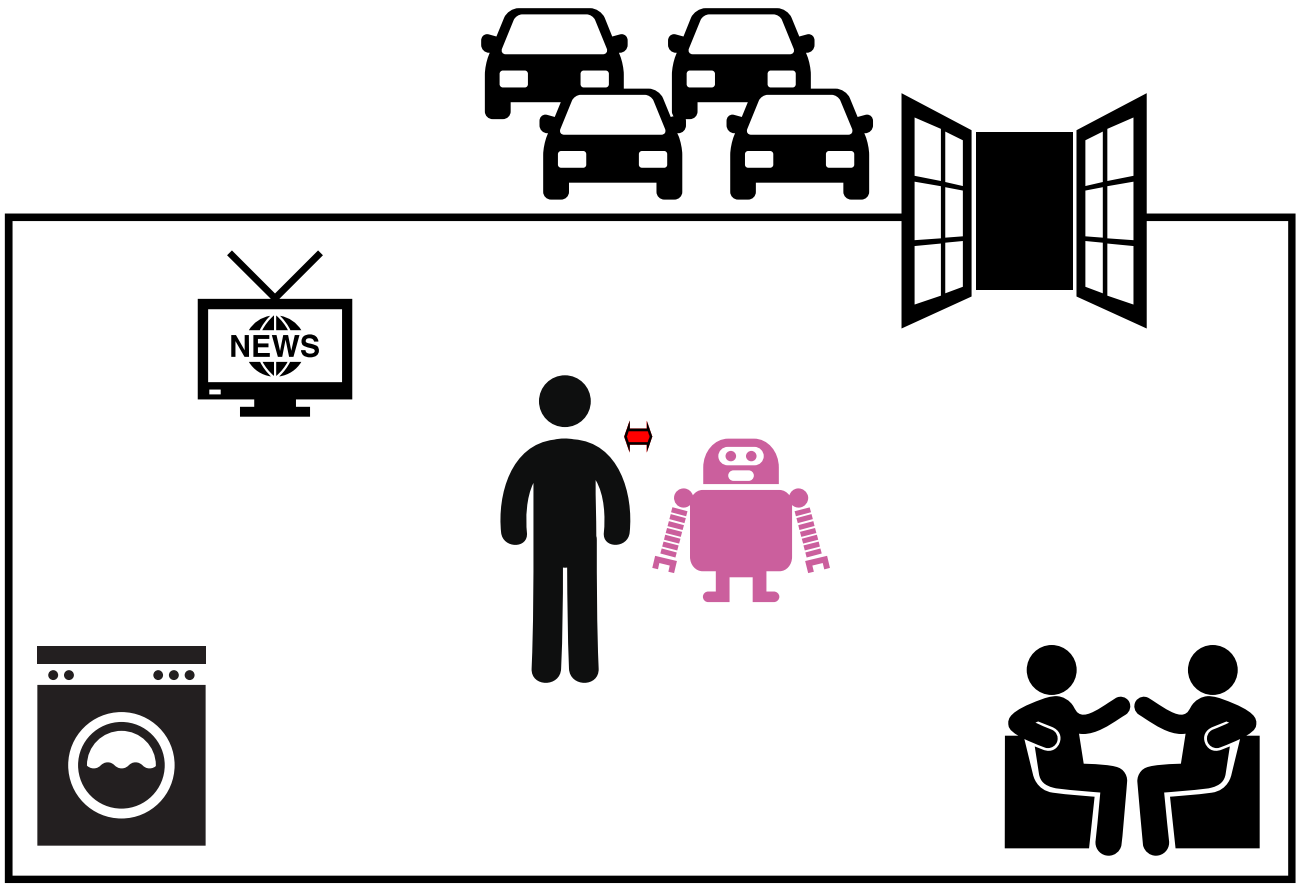
Close-up microphones, clean speech



Speech in real conditions

There is is some work to do :

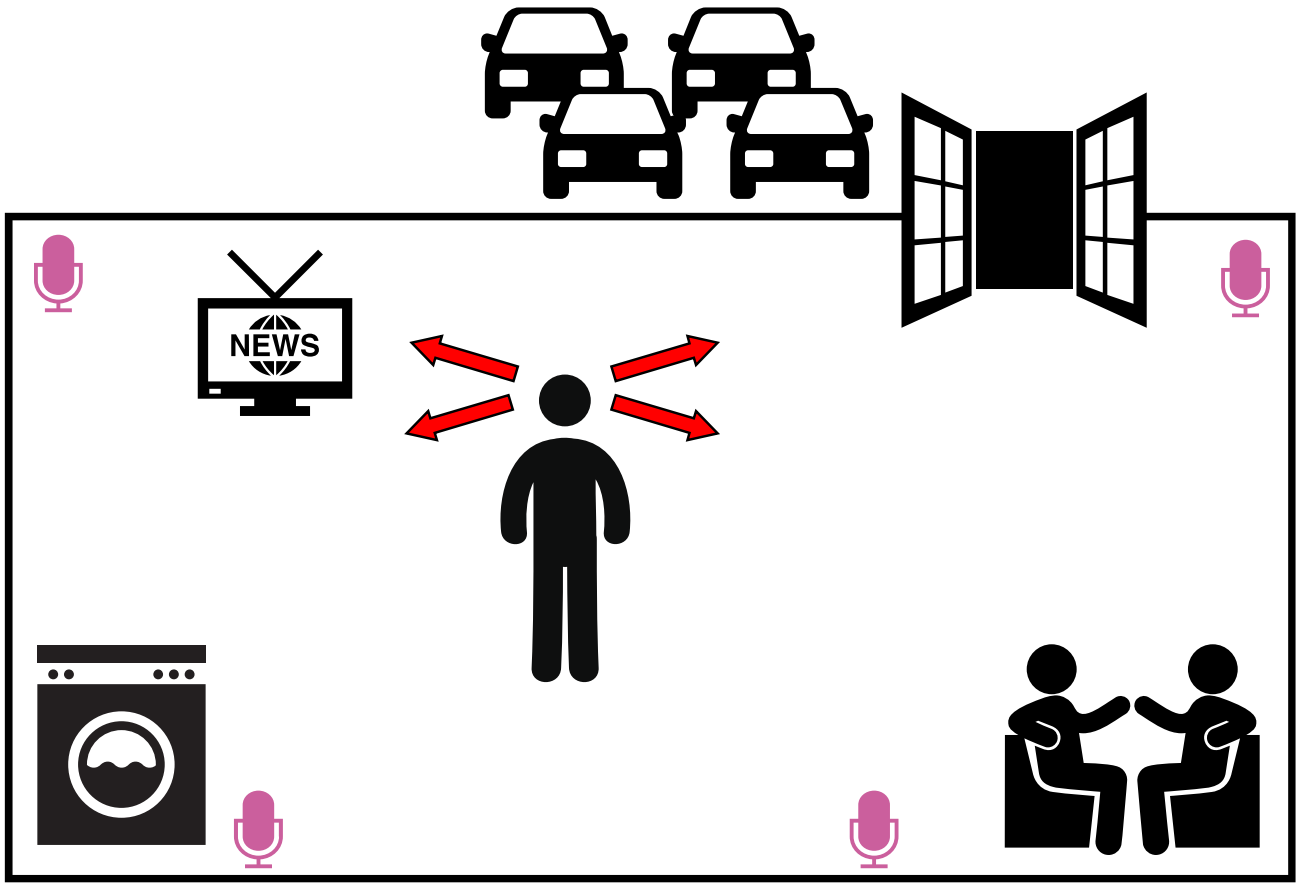
Moving microphones



Speech in real conditions

There is is some work to do :

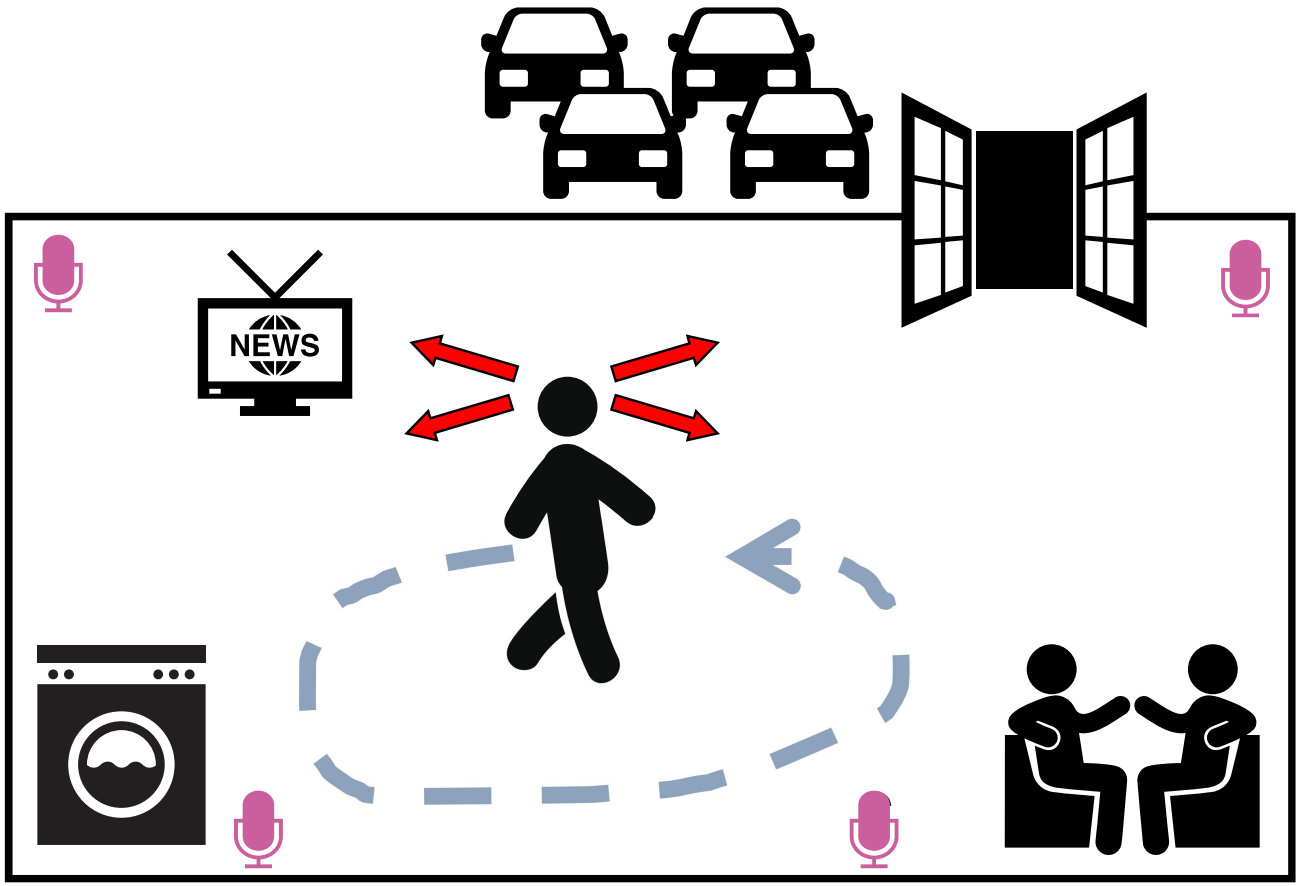
Distant microphones



Speech in real conditions

There is is some work to do :

Distant microphones, mobile sources. . .



Multichannel speech enhancement ?

Context

- Reduce the impact of the acoustic perturbations :
  - Cleaning the signal

In this talk

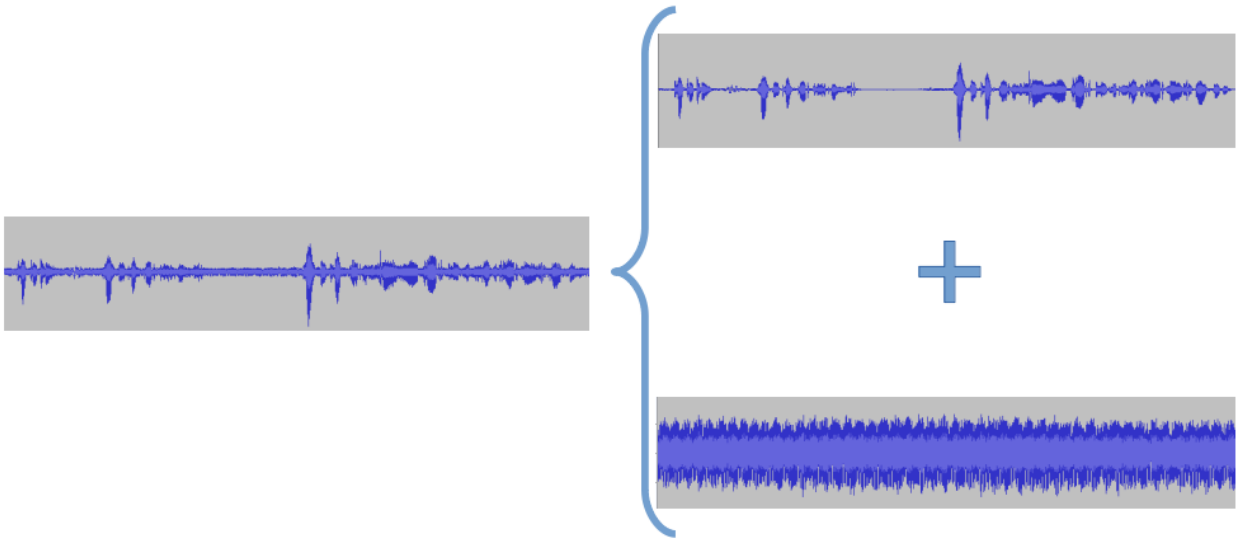
- Focus on noise removal/attenuation
  - Noise reduction
  - Noise suppression
  - De-noising
  - ...

Outline

Signal model

Signal observed

$$\mathbf{X} = \mathbf{X}_s - \mathbf{X}_n$$



Filtering

Single-channel filter

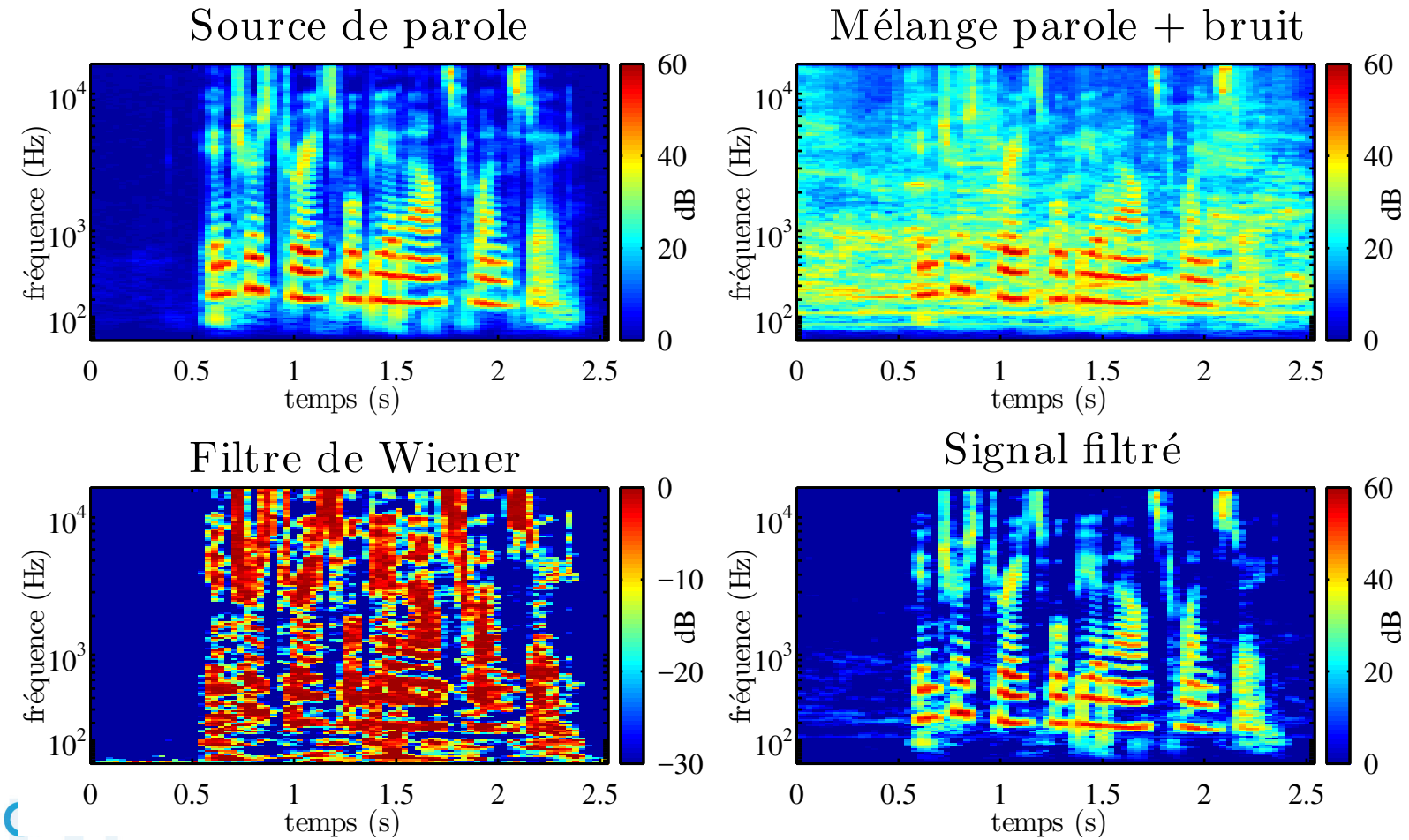
Filtering

Single-channel filter

Multichannel filter

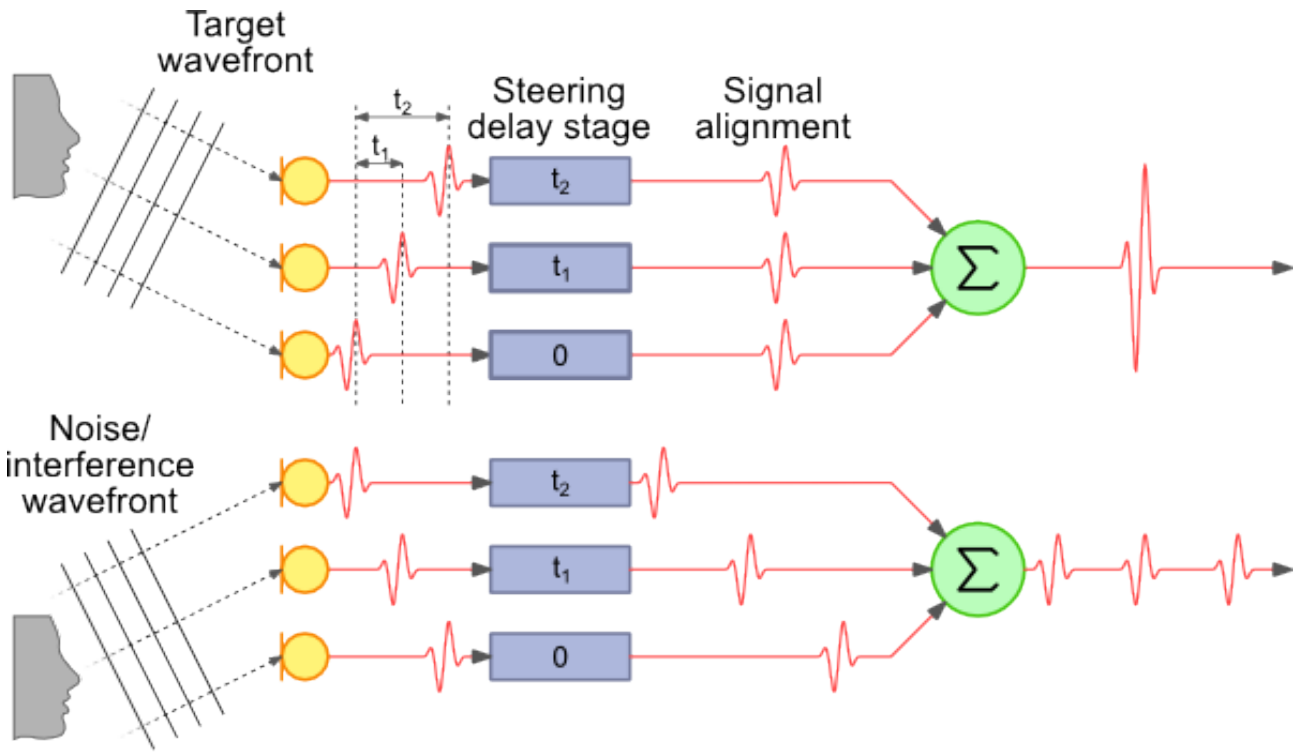
Single-channel enhacement

On single-mic data, perform spectral filtering/masking.



Multichannel enhancement (1)

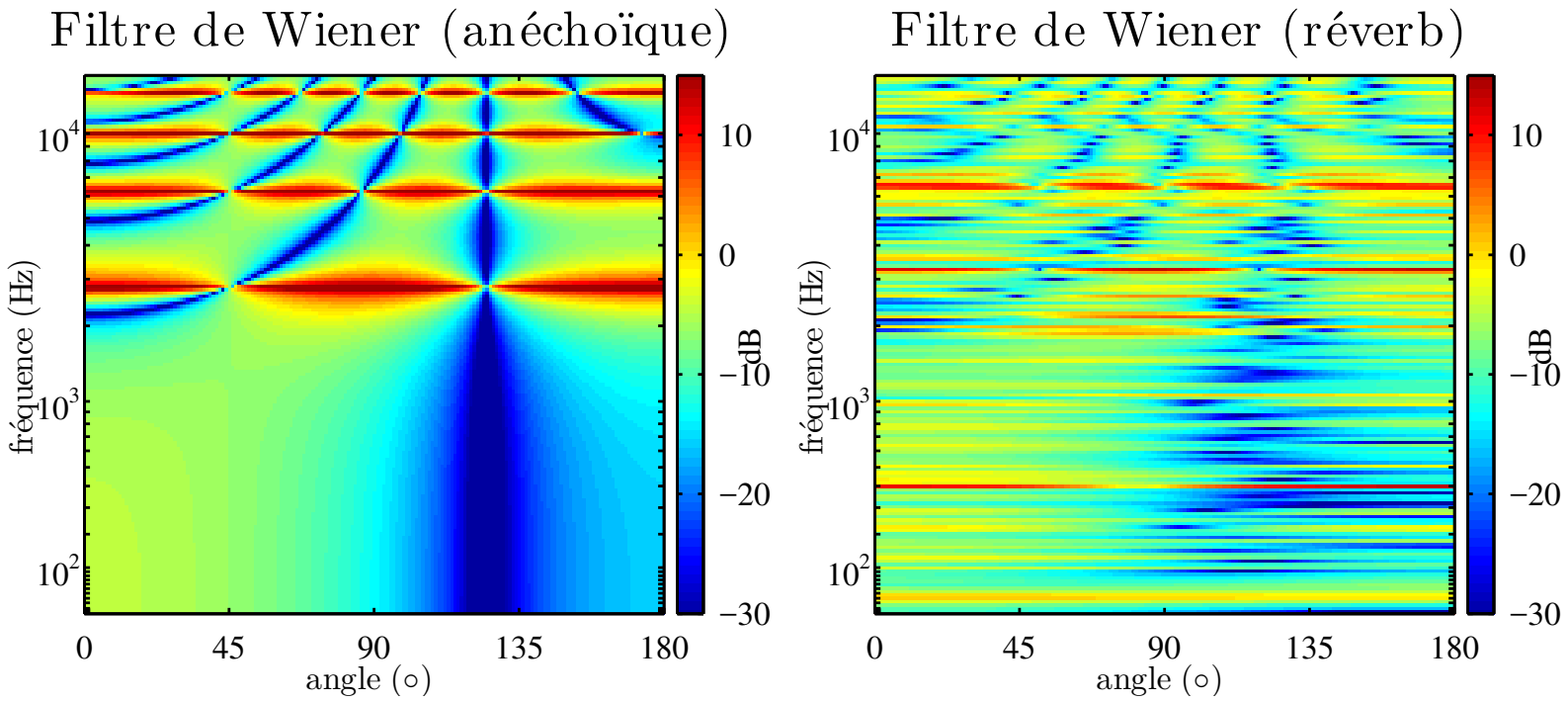
On multi-mic data, exploit spatial localization.



. Image source : the lab book page

Multichannel enhancement (2)

On multi-mic data, perform joint spatial and spectral masking.



MWF-based speech enhancement (1)

Speech distortion weighted MWF (MMSE criterion)

MMSE estimate of the (unknown) speech component :

$$\min_{\mathbf{W}} \; E\{|X_{\text{Ref}} - \mathbf{W}^H \mathbf{X}_s|^2\} + \mu\{\mathbf{W}^H \mathbf{X}_n|^2\}$$

SDW-MWF

$$\mathbf{W} = (\mathbf{R}_s + \mu \mathbf{R}_n)^{-1} \mathbf{R}_s \mathbf{e}_{\text{Ref}}$$

- $\mathbf{X}_s$, $\mathbf{X}_n$: speech, noise components of the microphone signals
- $\mathbf{W}^H\mathbf{X}$: output signal of the filter $\mathbf{W}$
- $\mathbf{R}_s$ and $\mathbf{R}_n$: speech and noise correlation matrices

MWF-based speech enhancement (2)

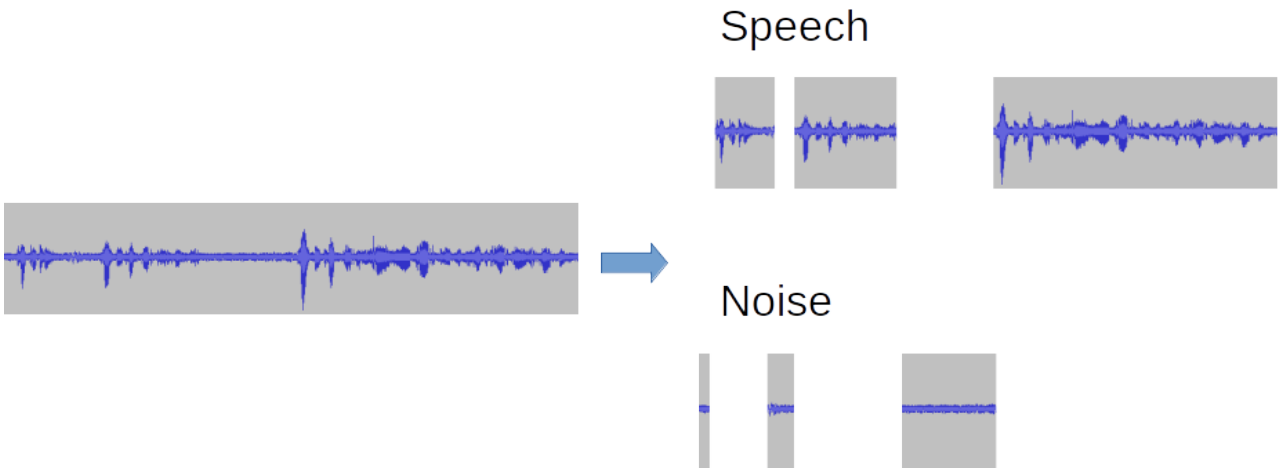
Estimation of the speech correlation matrix

$\mathbf{R}_s$ is estimated from speech+noise correlation matrix $\mathbf{R}_x$
and noise correlation matrix $\mathbf{R}_n$:

$$\mathbf{R}_s = \mathbf{R}_x - \mathbf{R}_n$$

➔ Requires a voice activity detector !

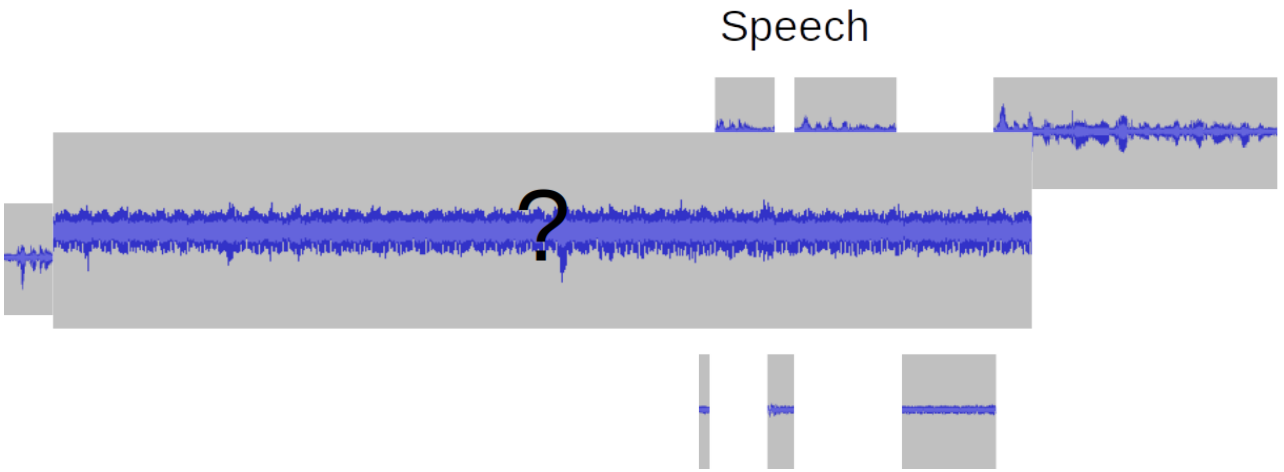
Voice activity detector



Limitations

- Limited to full frequency band
- Energy-based VAD do not work well at low SNR

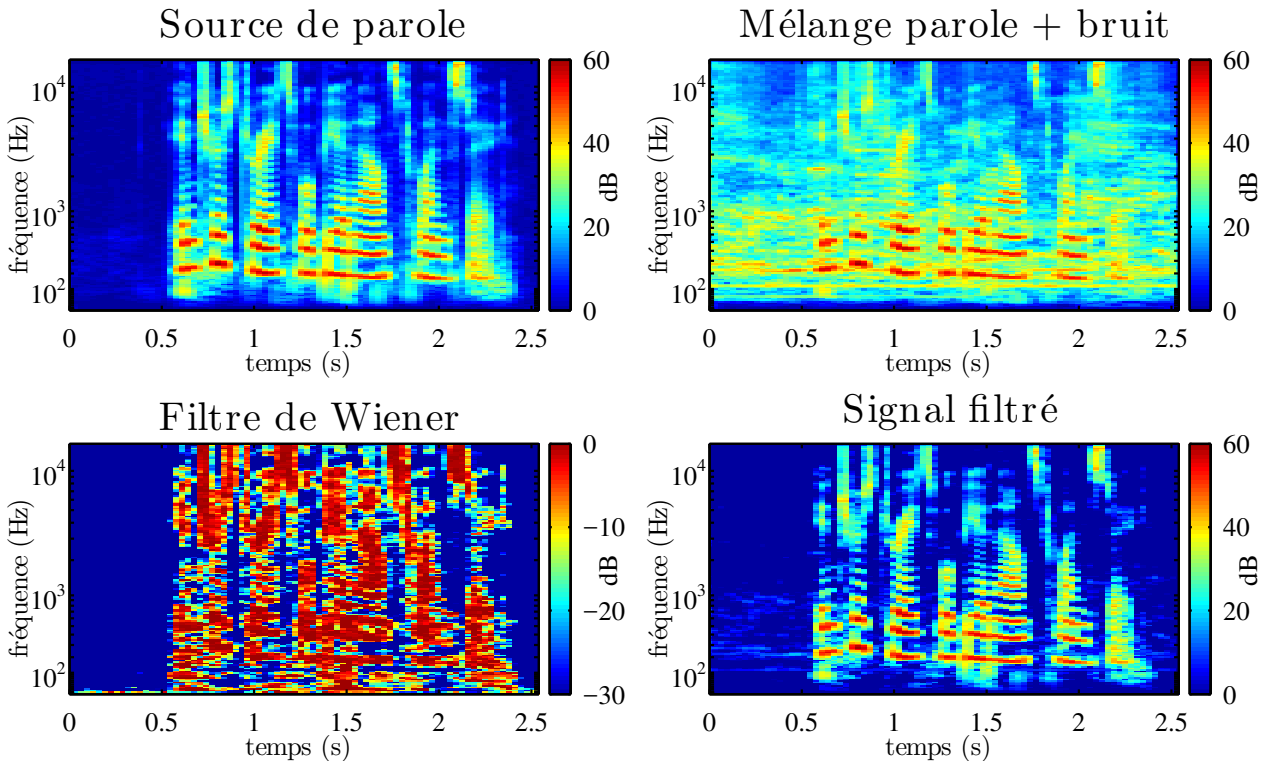
Voice activity detector



Limitations

- Limited to full frequency band
- Energy-based VAD do not work well at low SNR

Time-frequency masks

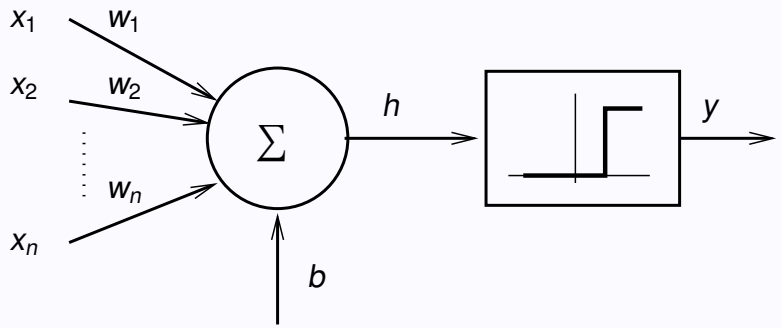


How can we obtain reliable masks ?

Outline

The perceptron 1

Perceptron model



A perceptron is a linear classifier :

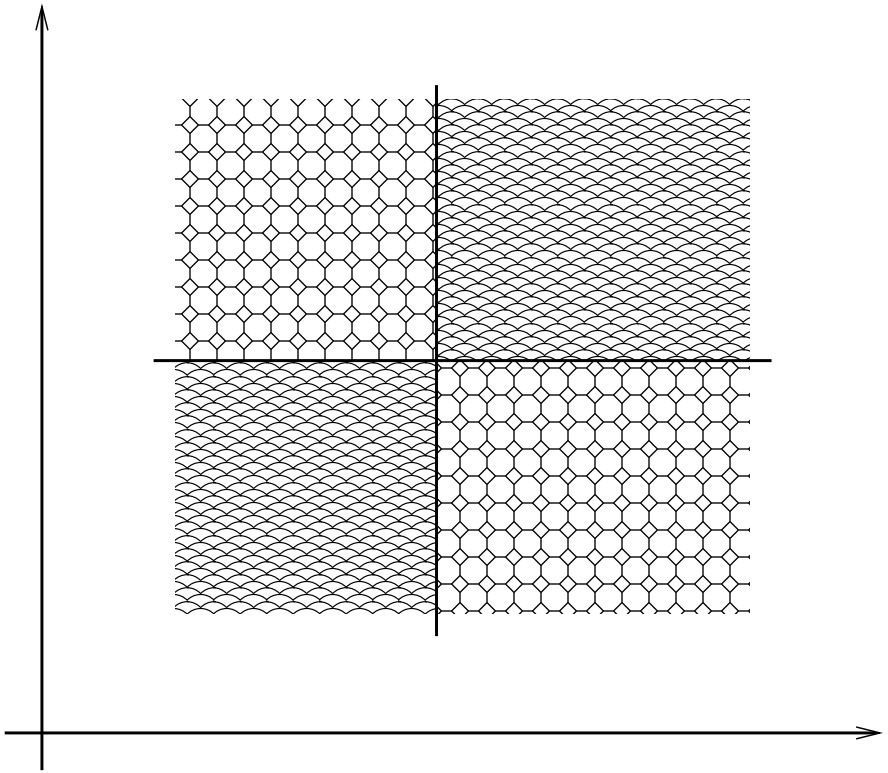
$$h = \mathbf{w}.\mathbf{x} + b$$

$$y = f(h) \; e.g. \begin{cases} 1 & if \quad \mathbf{w}.\mathbf{x} + b > 0 \\ 0 & else \end{cases}$$

The perceptron 2

Perceptron cannot model a XOR [Minsky *et al.*, 1969]

⇒ Work on perceptron stopped



The perceptron 2

Perceptron cannot model a XOR [Minsky *et al.*, 1969]
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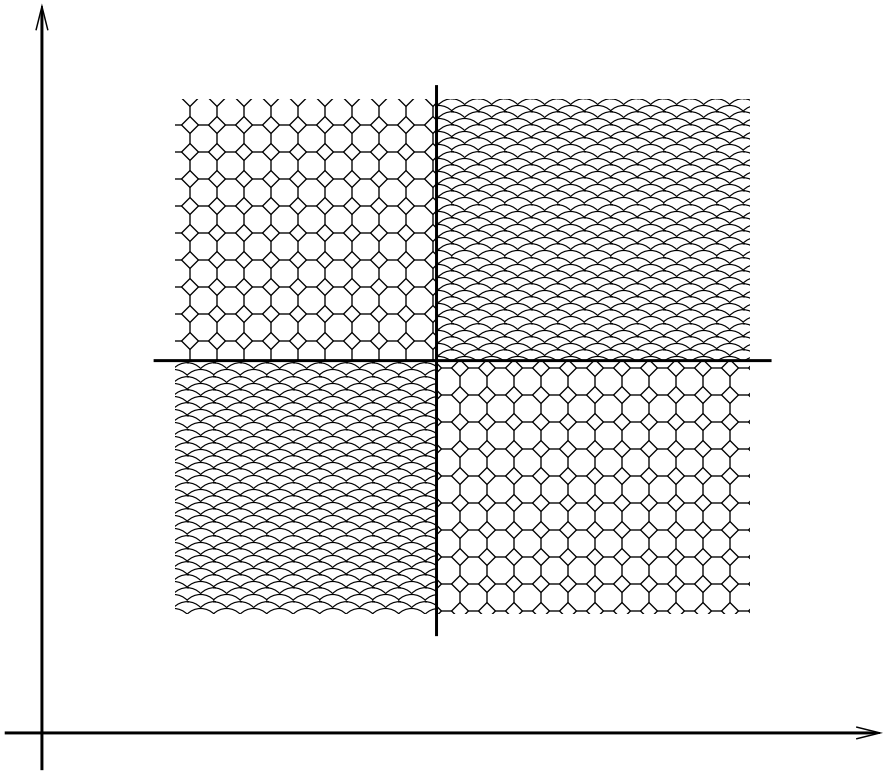
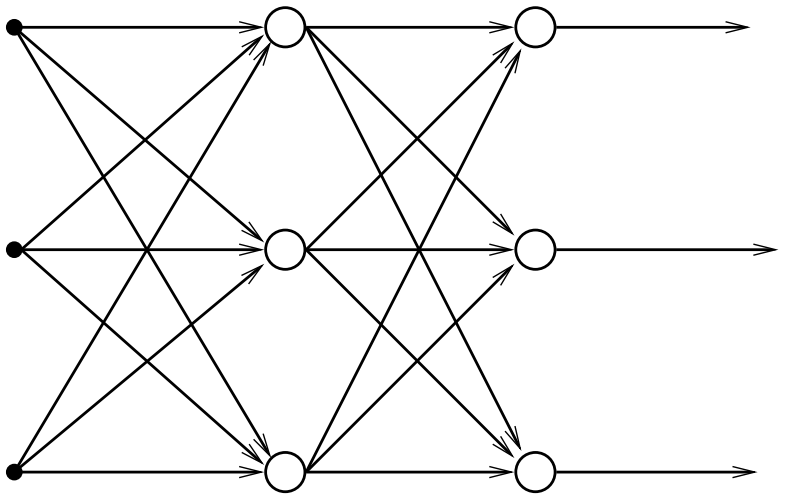


At least single perceptron cannot !

Multilayer perceptrons

Multilayer perceptrons (MLP) :

- Feedforward network
- Perceptrons arranged in fully-connected layers
- Well suited for pattern classification



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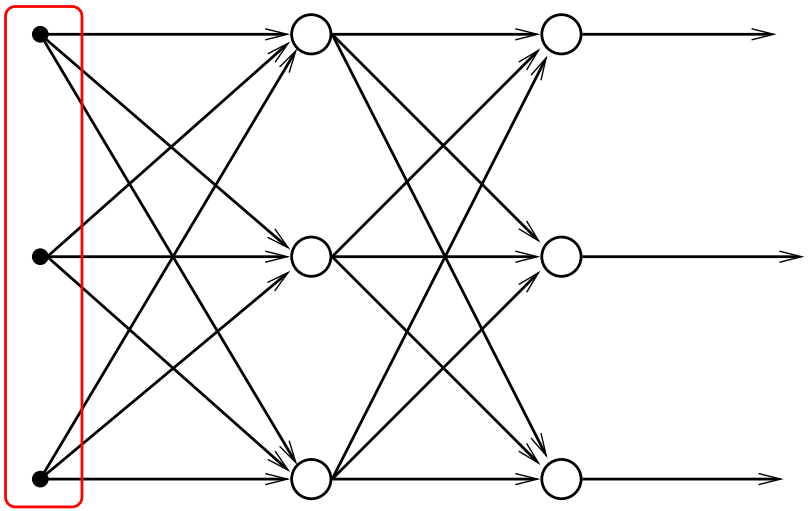

Input layer

Multilayer perceptrons

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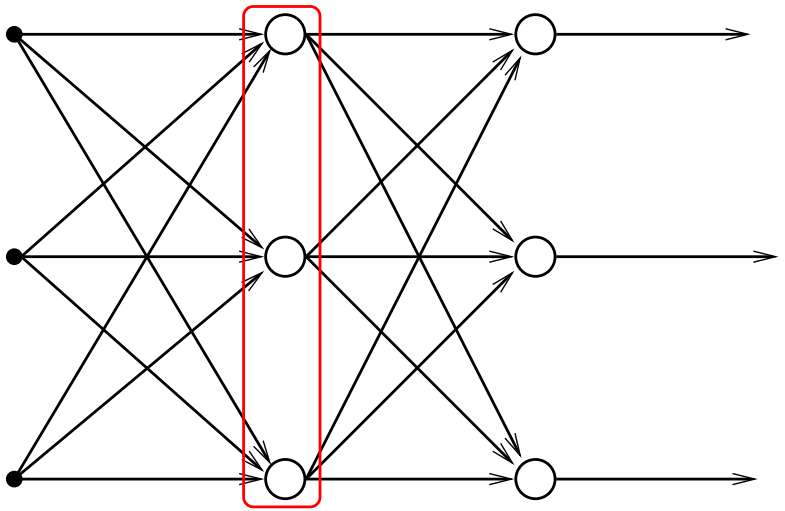

Hidden layer(s)

Multilayer perceptrons

Multilayer perceptrons (MLP) :

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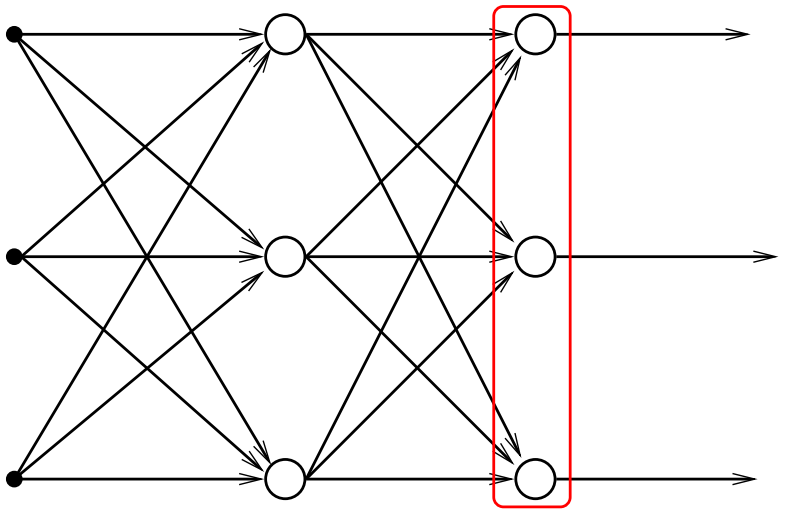

Output layer

Multilayer perceptrons

Multilayer perceptrons (MLP) :

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- Perceptrons arranged in fully-connected layers
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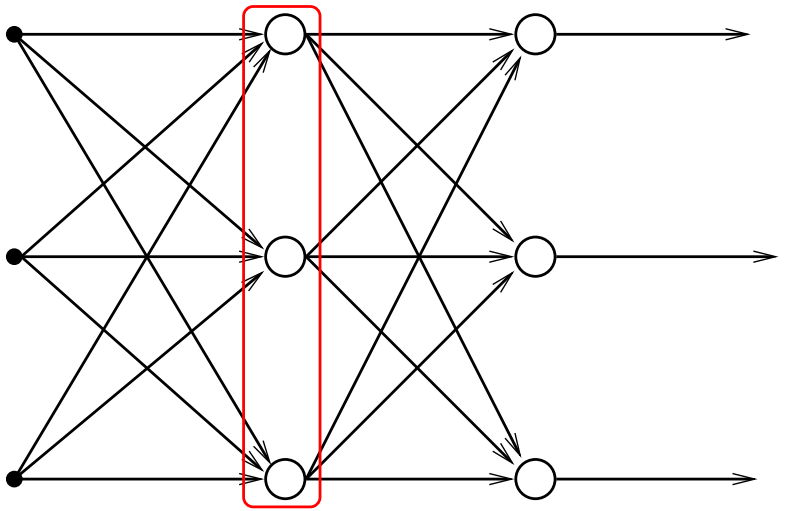
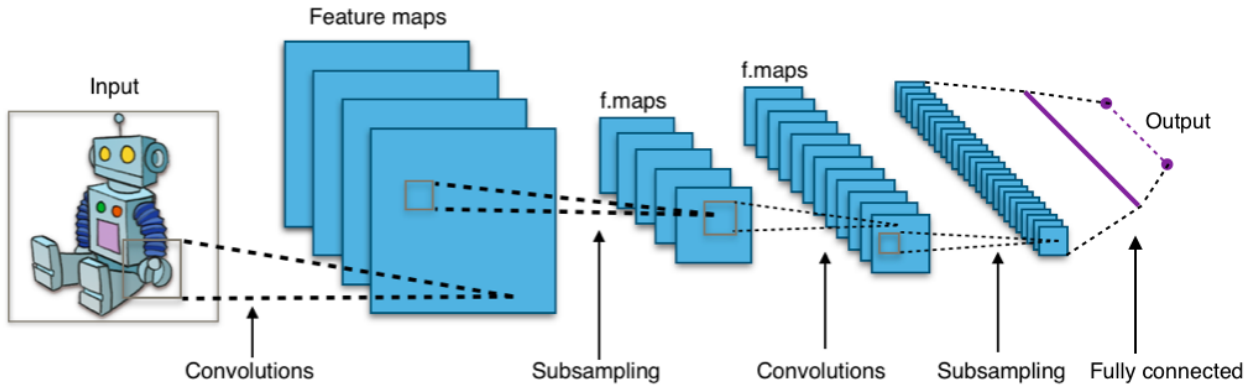


Deep neural networks have more than 1 hidden layers

Convolutional neural networks (CNN)

Keys ideas

- Detect patterns in images/spectrograms
- Apply sets of filters to obtain feature maps
- Subsample to control dimensionality

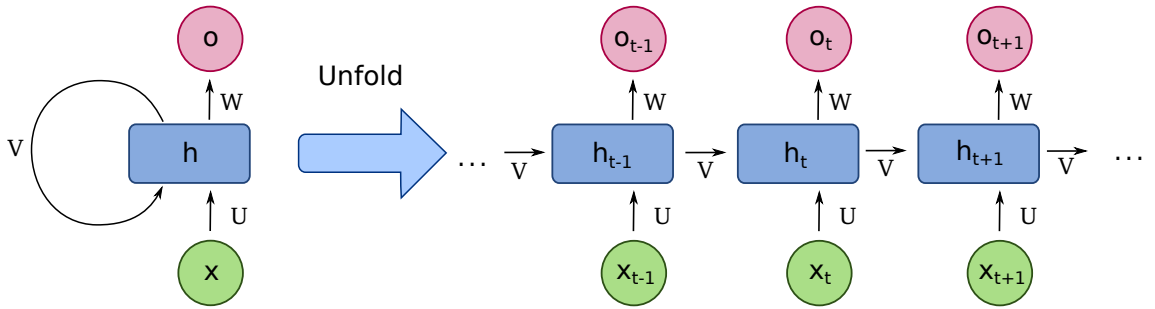


. Image source : wikimedia

Recurrent neural networks (RNN)

Keys idea

- Model context

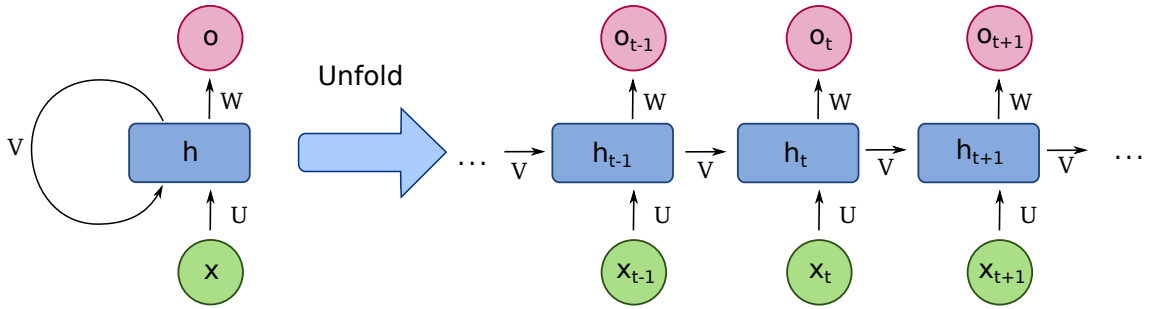


. Image source : wikimedia

Recurrent neural networks (RNN)

Keys idea

- Model context



Problems

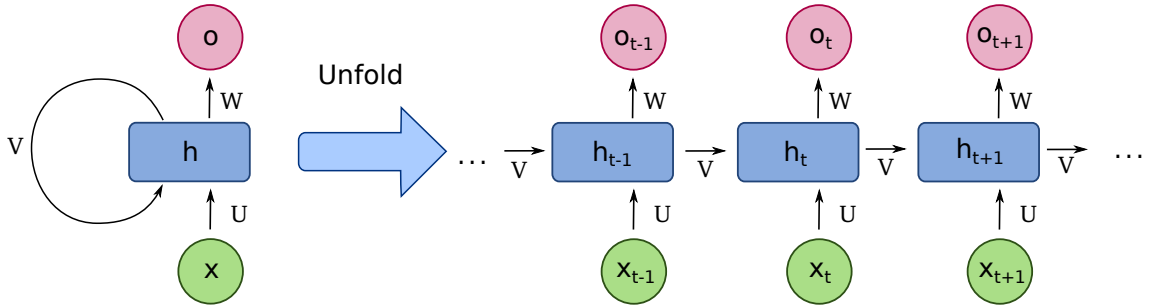
- Hard to train
- Exploding/vanishing gradient

. Image source : wikimedia

Recurrent neural networks (RNN)

Keys idea

- Model context



Solutions

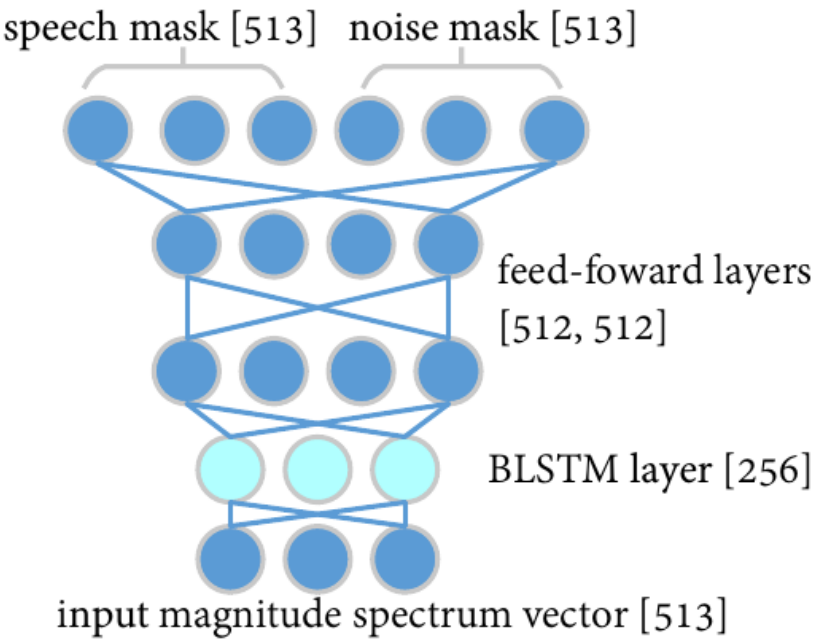
- LSTM, GRU. . .

. Image source : wikimedia

Outline

DNN-base mask estimation for multichannel filtering

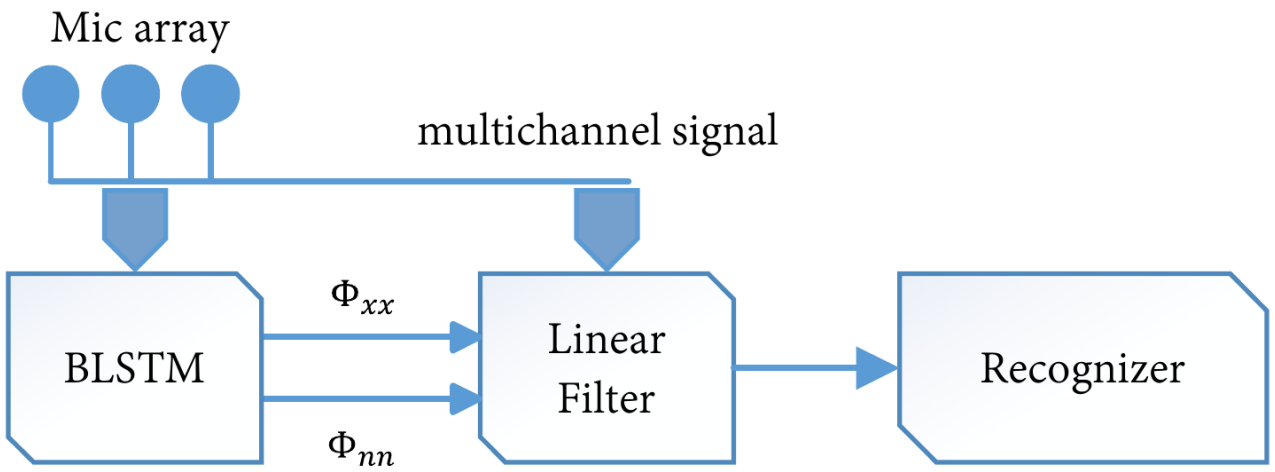
Use LSTM to estimate speech/noise masks [Heymann et al.].



. J. Heymann, L. Drude, R. Haeb-Umbach. *Neural network based spectral mask estimation for acoustic beamforming*. Proc ICASSP 2016

DNN-base mask estimation for MWF [Z. Wang]

Use the masks to estime the correlation matrices and MWF filters.



. Z. Wang, E. Vincent, R. Serizel, Y. Yan. *Rank-1 Constrained Multichannel Wiener Filter for Speech Recognition in Noisy Environments*. Computer Speech and Language

Exemple performance

Evaluation in terms of word error rate (WER).

Noisy		WER baseline
Single-channel DNN		no WER reduc.
Delay-and-sum		21% rel. WER reduc.
DNN post-filter		20% rel. WER reduc.
Multichannel DNN		39% rel. WER reduc.

Greatly outperforms multichannel NMF (25% rel. WER reduc.) and DNN used to directly predict multichannel filters.

CHiME-3 : speech recorded in a bus/café. Single DNN iteration, no post-processing.

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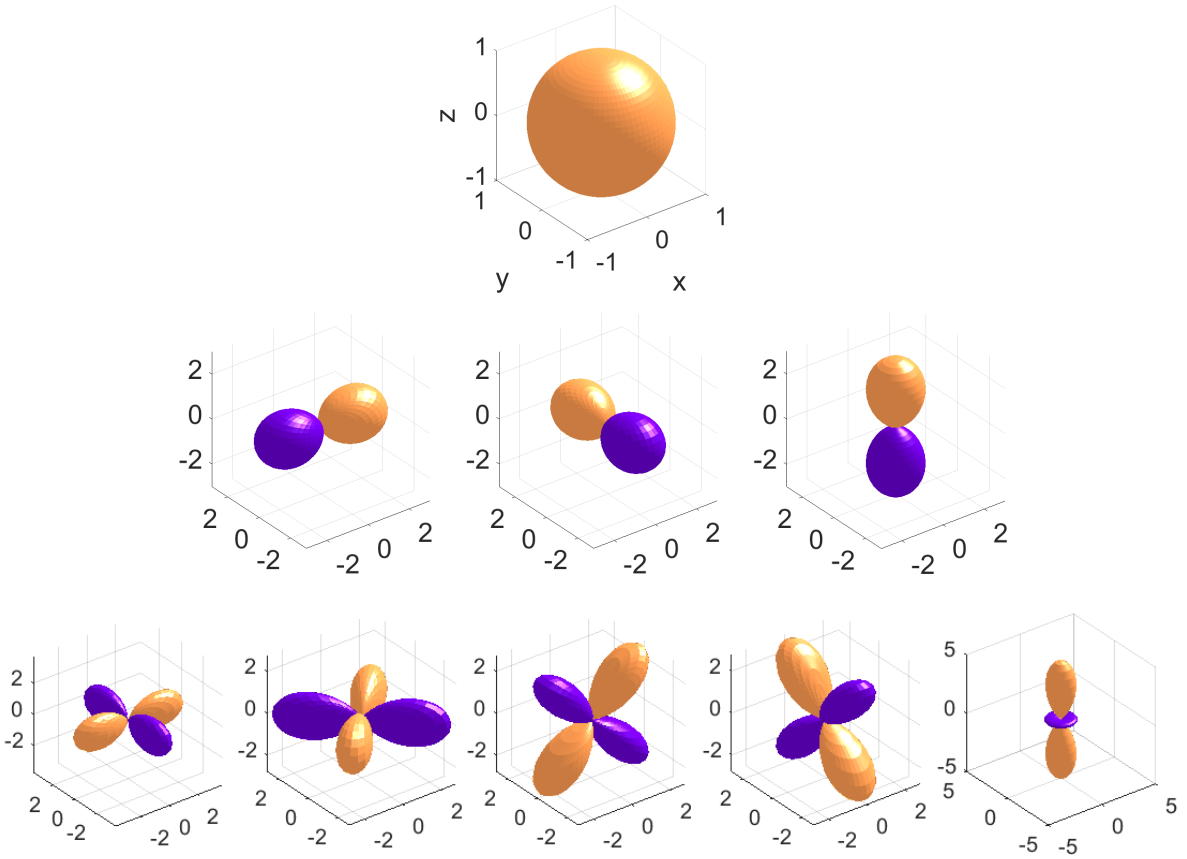
. A. A. Nugraha, A. Liutkus, E. Vincent. *Multichannel audio source separation with deep neural networks*. IEEE/ACM TASLP, 24 (9), pp. 1652 - 1664, 2016.

What input should we give to the network ?
(Part of Phd work from L. Perotin)

[With E. Vincent and A. Guérin]

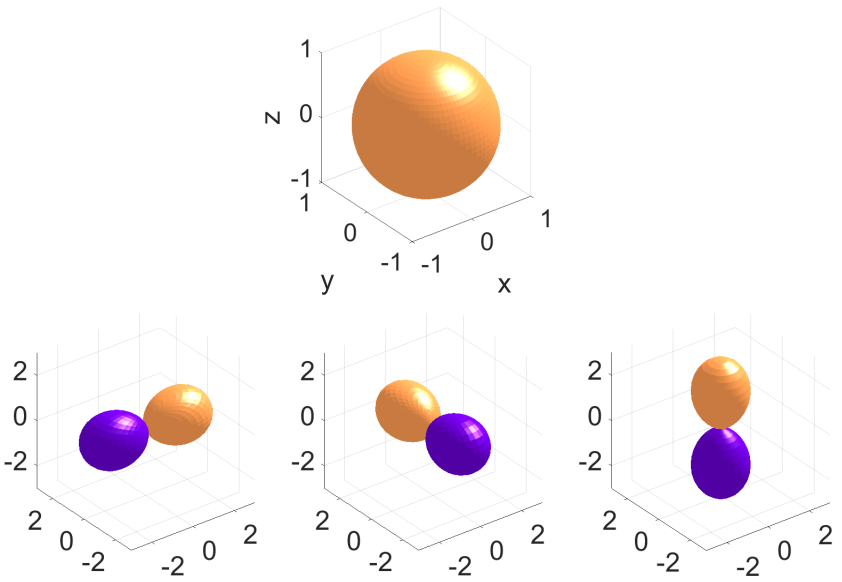
Multichannel speech enhancement for HOA

Represent the sound field in a basis of spherical harmonics



Multichannel speech enhancement for HOA

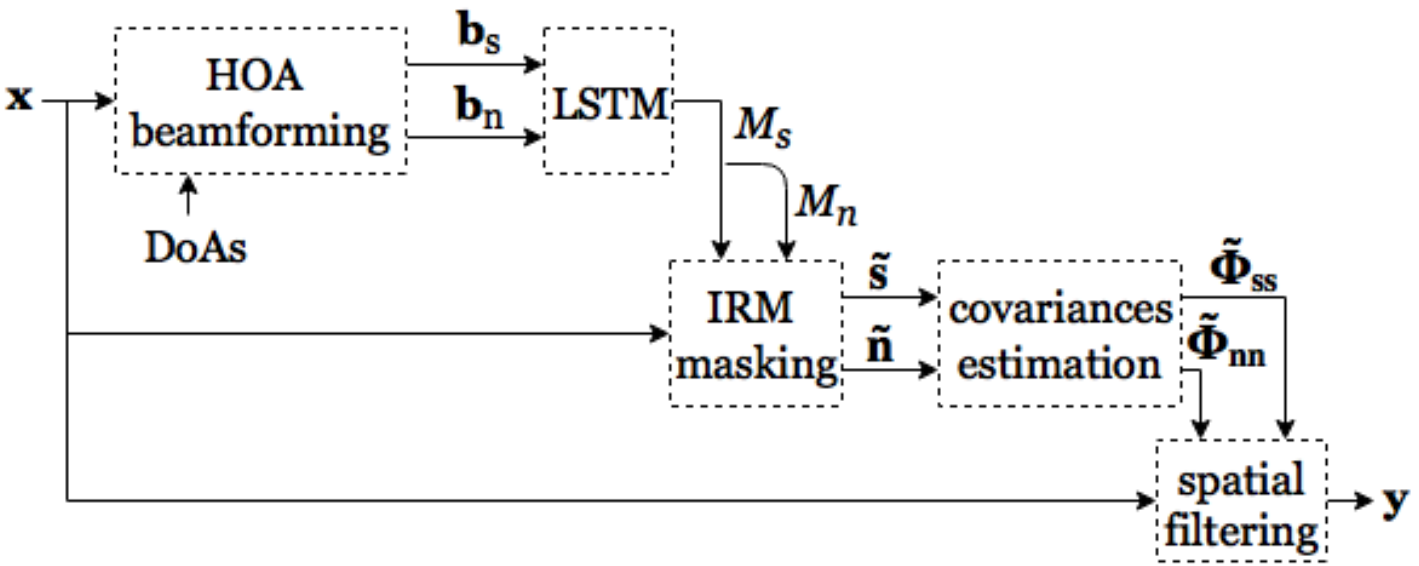
Use only the 4 channels from the first 2 orders



. L. Perotin, R. Serizel, E. Vincent, A. Guérin. *Multichannel speech separation with recurrent neural networks from high-order ambisonics recordings*. In proc. of ICASSP, 2018,

Multichannel speech enhancement for HOA [L. Perotin]

- HOA beamformer
- LSTM to estimate speech/noise masks
- GEVD-MWF filter



. L. Perotin, R. Serizel, E. Vincent, A. Guérin. *Multichannel speech separation with recurrent neural networks from high-order ambisonics recordings*. In proc. of ICASSP, 2018,

Results

Setup

- Tested on a subset of ESTER
- 20 sentences (4043 words)
- Acoustic conditions : TR_{60}=350ms, room-mic = 1.65m

Results

Interference	**noise**	**speaker**		
		25°	**45°**	**90°**
Reverberant source	9.80	10.80	10.82	10.76
Mixture	68.25	91.96	88.56	89.00
Simple beamformer	40.80	75.42	39.06	20.54
GEVD (w/o noise est.)	21.69	78.43	18.55	12.02
GEVD (w noise est.)	21.72	23.1	16.05	12.47

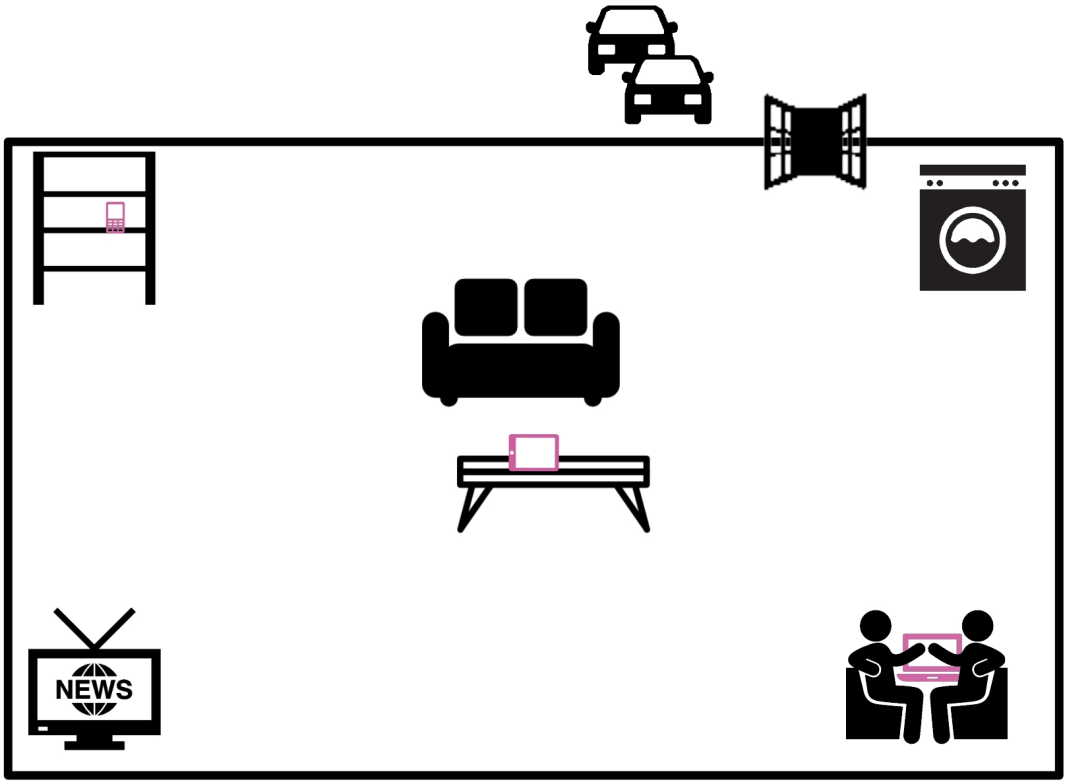
How can we deal with ad-hoc microphone arrays ? (Part of Phd work from N. Furnon)

[With I. Illina and S. Essid]

Heterogeneous unconstrained microphone arrays

Target :

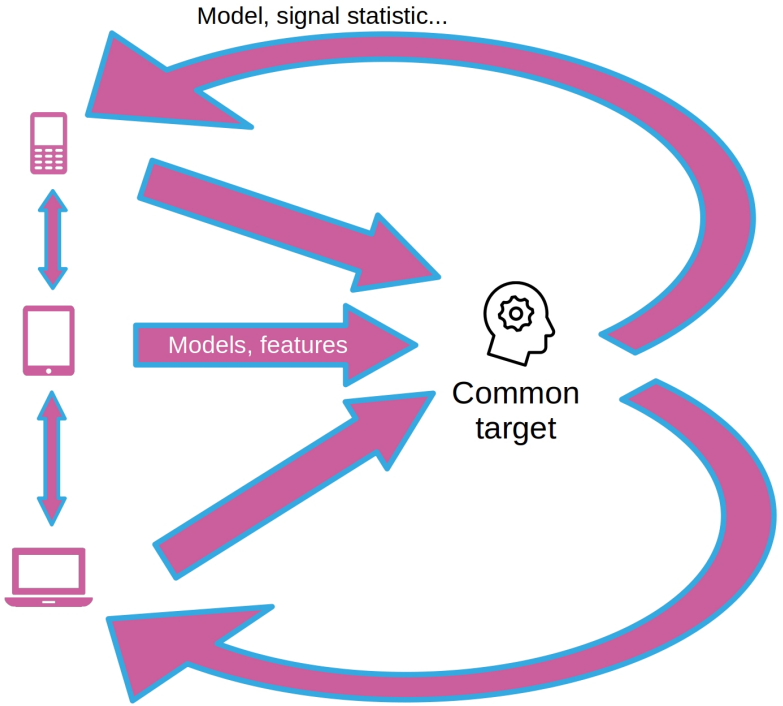
- Use the microphones already available



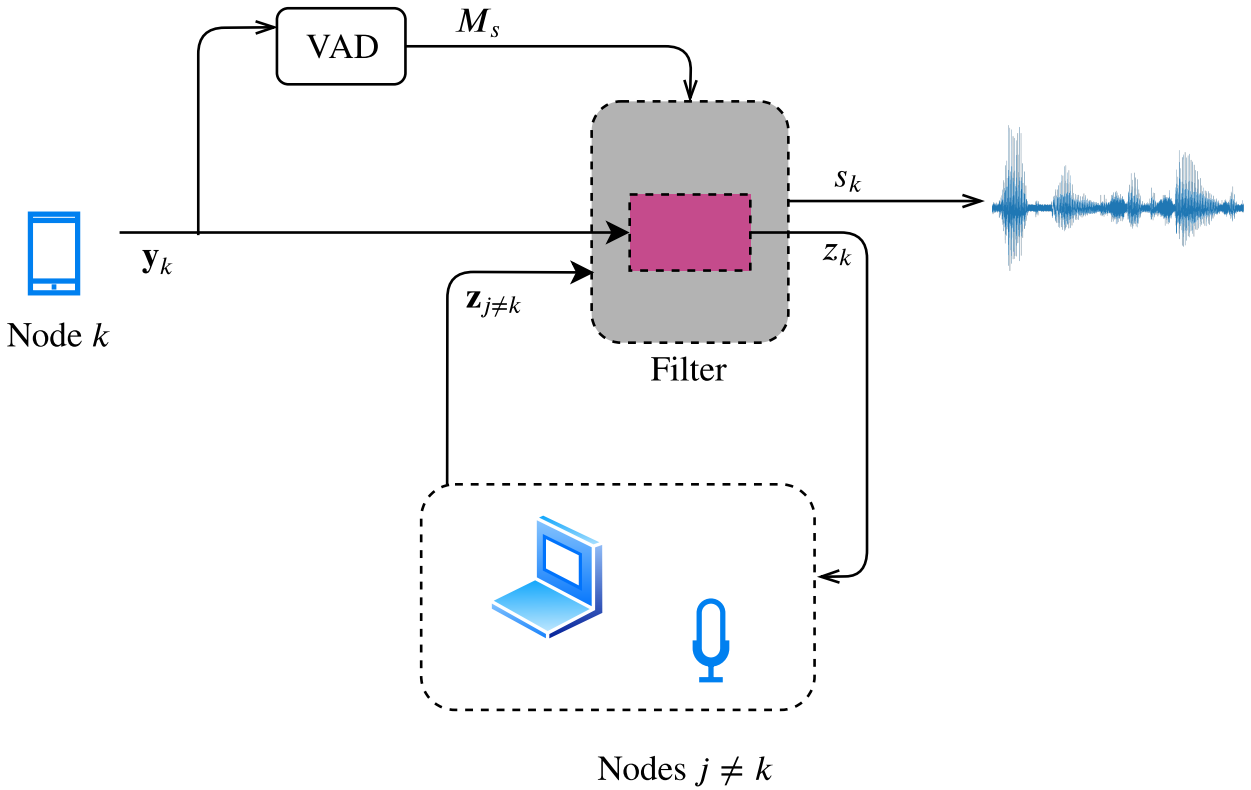
Collaborative approach

Targets :

- Collaboration between the nodes (common target)
- Feedback from the common target to the node level

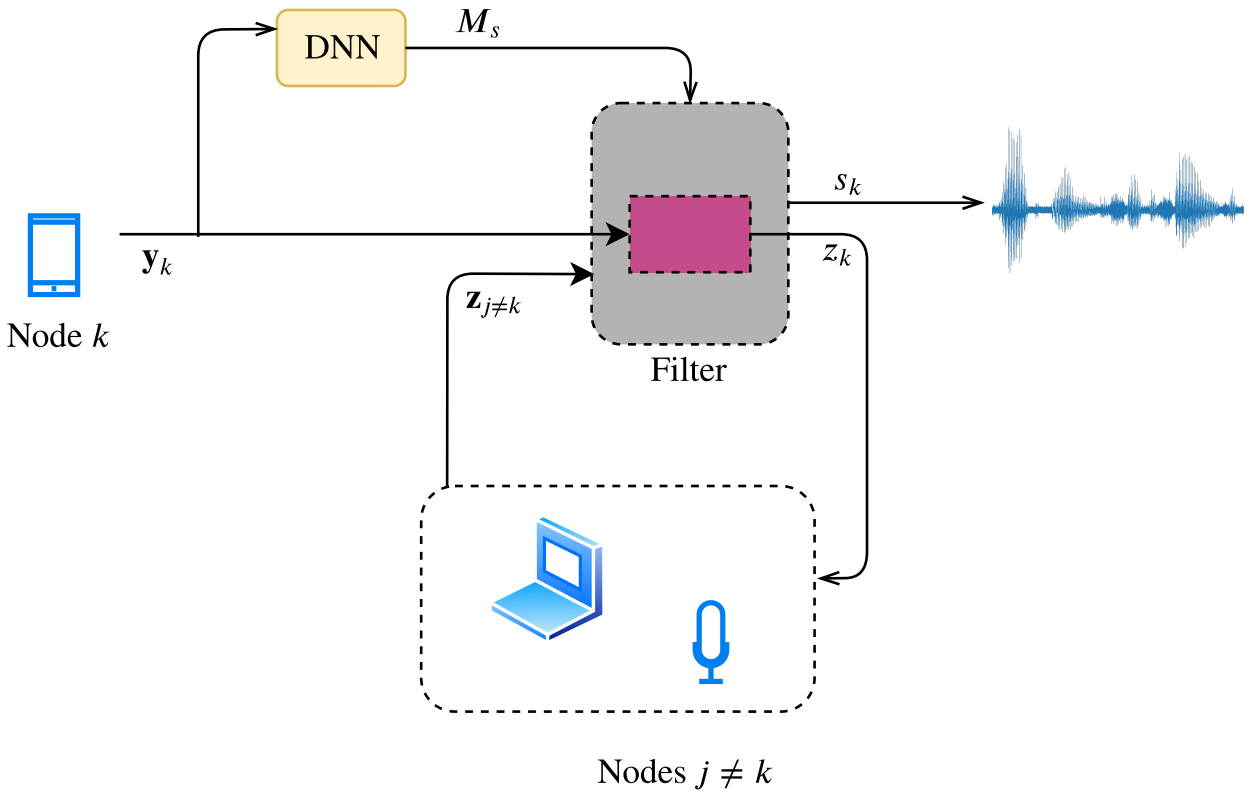


Distributed node specific MWF



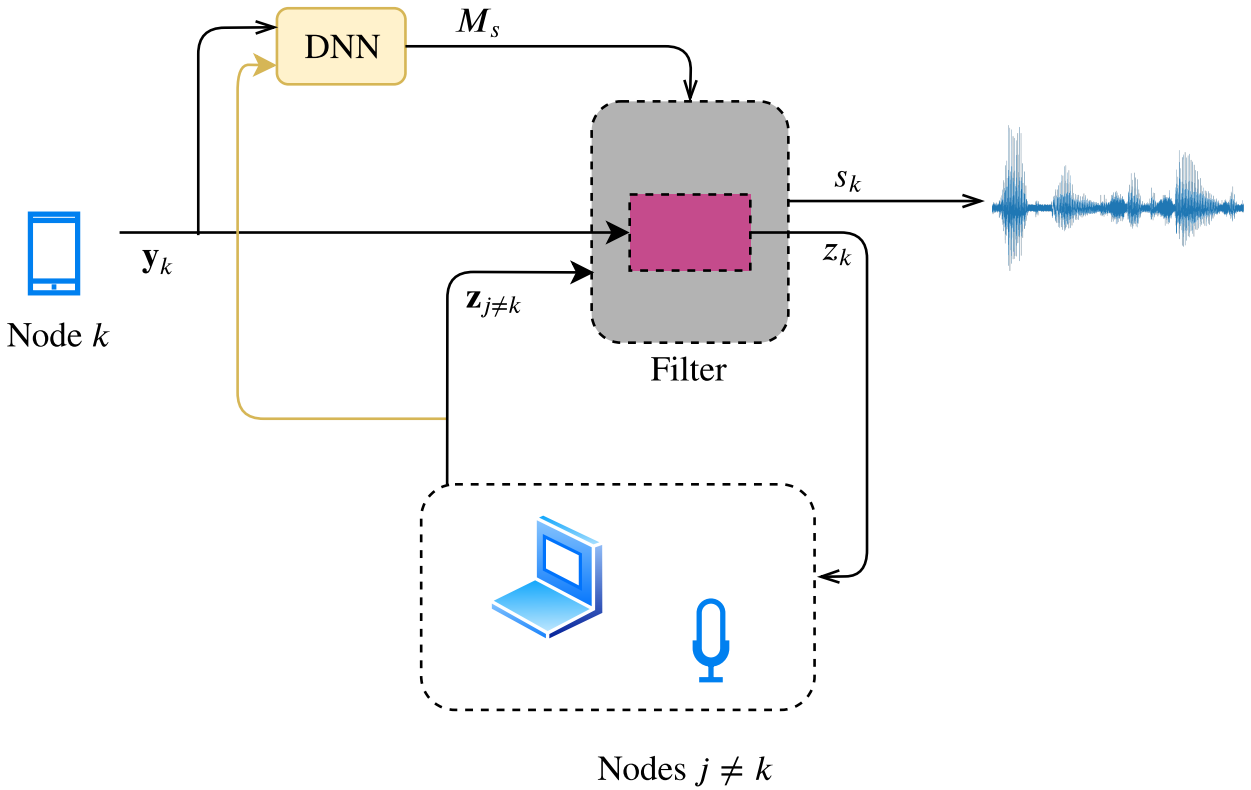
. A. Bertrand, M. Moonen. *Distributed adaptive node-specific signal estimation in fully connected sensor networks—Part I : Sequential node updating*. IEEE Transactions on Signal Processing.

Distributed MWF with DNN [N. Furnon]



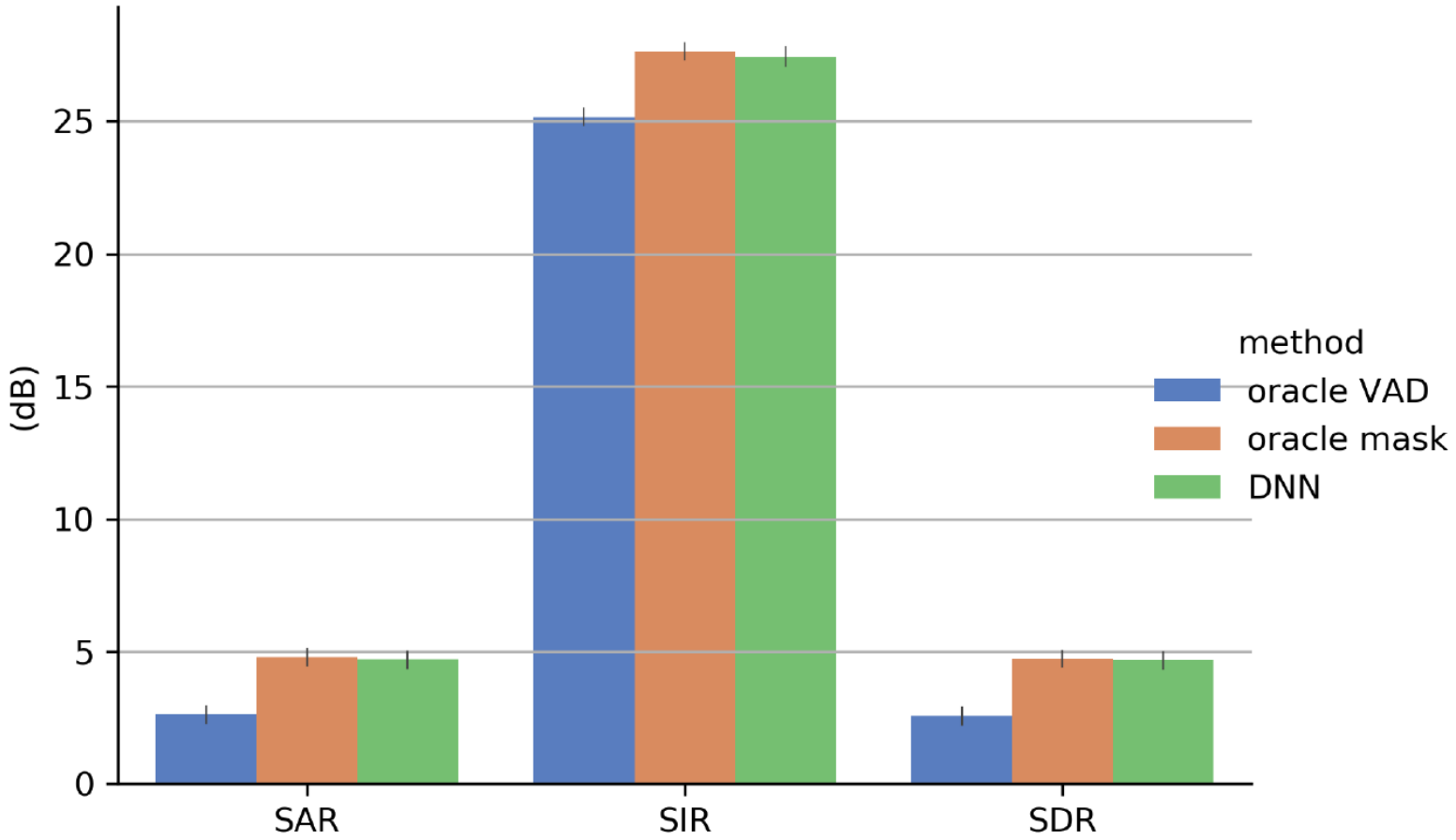
. N. Furnon, R. Serizel, I. Illina, S. Essid. *DNN-Based Distributed Multichannel Mask Estimation for Speech Enhancement in Microphone Arrays.* Submitted to ICASSP 2020.

Distributed MWF with DNN [N. Furnon]



. N. Furnon, R. Serizel, I. Illina, S. Essid. *DNN-Based Distributed Multichannel Mask Estimation for Speech Enhancement in Microphone Arrays.* Submitted to ICASSP 2020.

Distributed MWF with DNN (Results)



. N. Furnon, R. Serizel, I. Illina, S. Essid. *DNN-Based Distributed Multichannel Mask Estimation for Speech Enhancement in Microphone Arrays.* Submitted to ICASSP 2020.

Outline

Conclusions and perspectives

Conclusions

- Deep learning is now the state-of-the-art in multichannel speech enhancement
- Important improvements compared to previous approaches

Perspectives

- Unconstrained microphone array processing,
- Distributed learning,
- Application to real-world conditions,
- Extension to other related domains. . .