Towards deep phase recovery for audio source separation

Seminar at Audio Research Group, Tampere University, Finland
August 30, 2023

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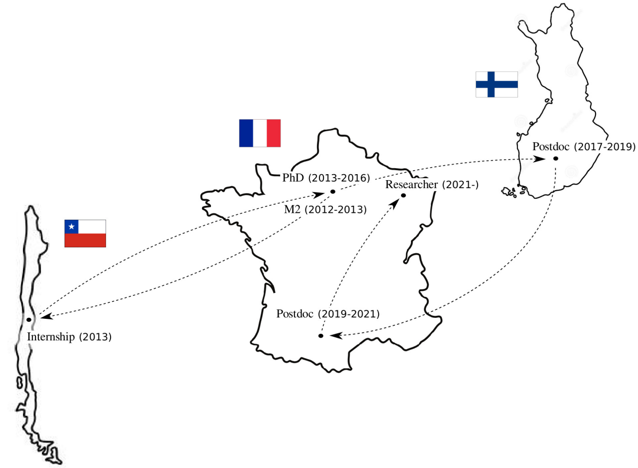
Université de Lorraine, CNRS, Inria, LORIA, Nancy, France

A brief history of me



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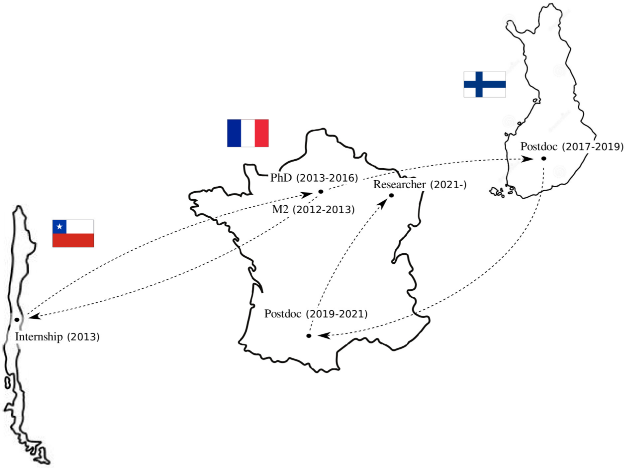

MULTISPEECH

Speech Modeling for Facilitating Oral-Based Communication

Research themes

- Speech enhancement for auditory neuropathy (with N. Monir, R. Serizel).
- Audio inpainting / restoration (with L. Bahrman, M. Krémé, A. Deleforge).

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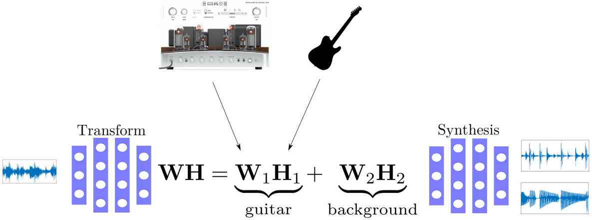
- Joint synthesis / source separation.



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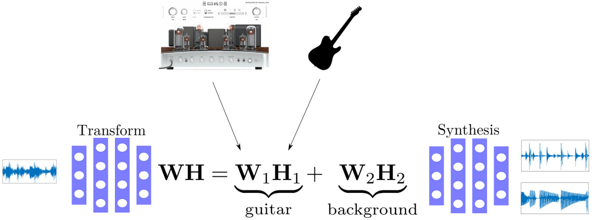

- ▷ **Source separation** (with so many people).

Audio source separation

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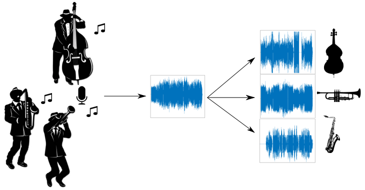

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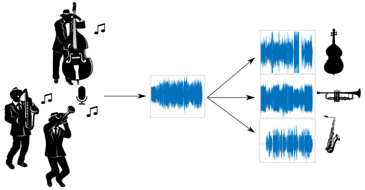
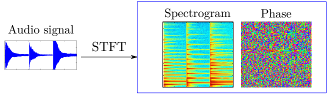


Framework

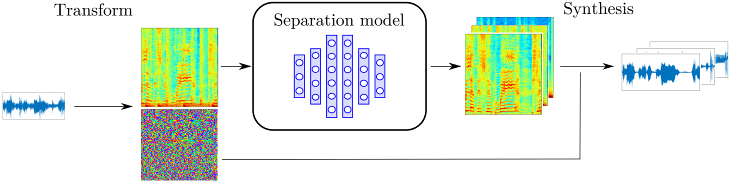
- ▷ Monaural signals.
- ▷ Short-time Fourier transform (STFT)-domain separation.
- ▷ Mixture model: $\mathbf{X} = \sum_{j=1}^{J} \mathbf{S}_j$.



$$\mathbf{x} \in \mathbb{R}^N \xrightarrow{\text{STFT}} \mathbf{X} \in \mathbb{C}^{F \times T}$$

Typical separation pipeline

Nonnegative time-frequency (TF) masking:



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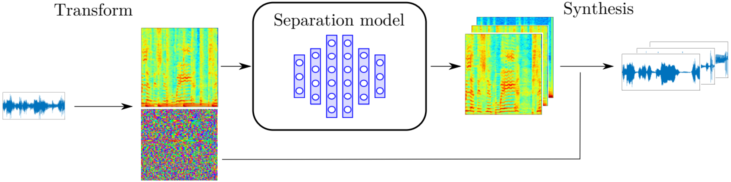

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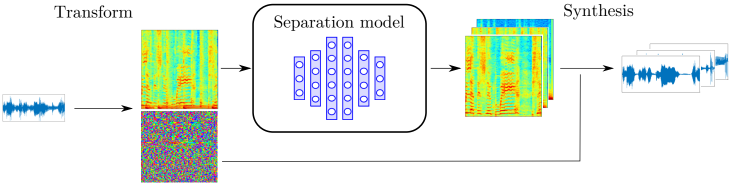

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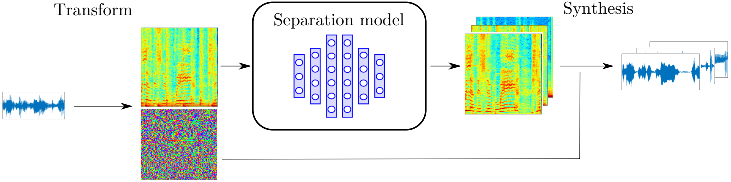


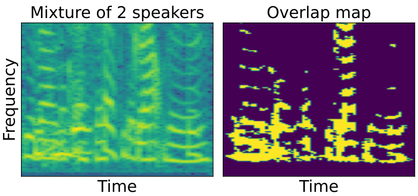
- A nonnegative representation is processed (e.g., magnitude or power spectrogram).
- The separator is a deep neural network, trained using a (large) dataset with isolated sources.
- The mixture's phase is assigned to each source using a Wiener-like filter or masking process.

The phase problem

✗ Nonnegative masking: Issues in sound quality when sources *overlap* in the TF domain.

$$|X| \neq |S_1| + |S_2|$$

$$\angle X \neq \angle S_1 \text{ or } \angle S_2$$



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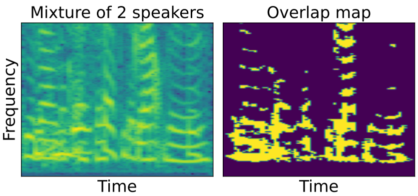
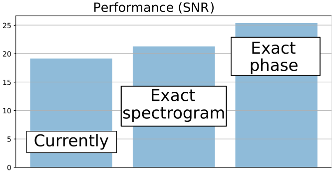
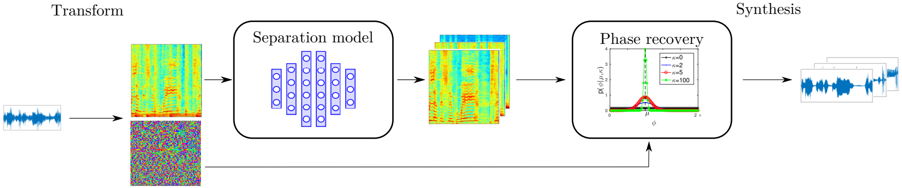


The potential of phase recovery



Given the current state-of-the-art, more potential gain in phase recovery than in magnitude estimation.

Phase recovery for source separation



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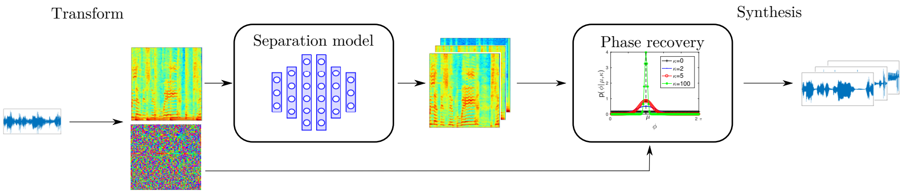
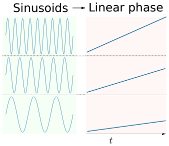
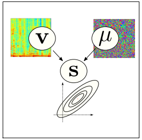


Main contributions

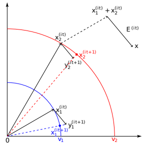
Phase models



Statistical framework



Iterative algorithms



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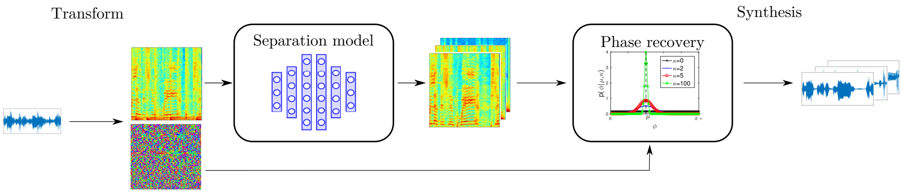

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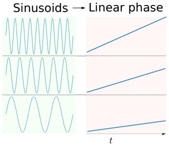

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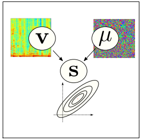

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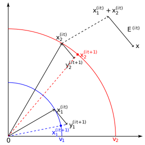

- ▷ So far using “old-school” signal processing.
- ▷ Perspective: leveraging deep learning for phase recovery.

Phase models

Sinusoidal phase model

Consider a mixture of sinusoids: $x(n) = \sum_{p=1}^{P} A_p \sin(2\pi \underbrace{\nu_p}_{\text{normalized frequency}} n + \phi_{0,p})$.

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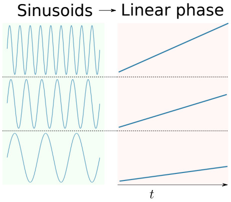

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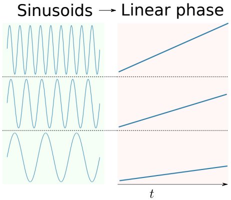

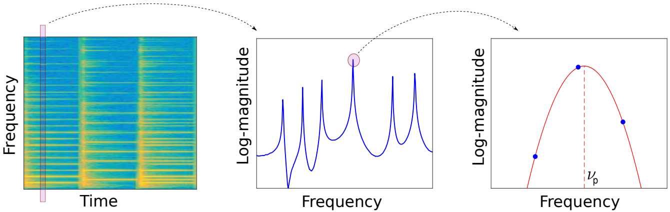

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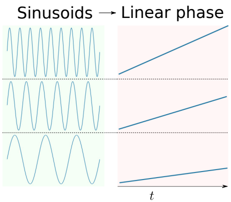

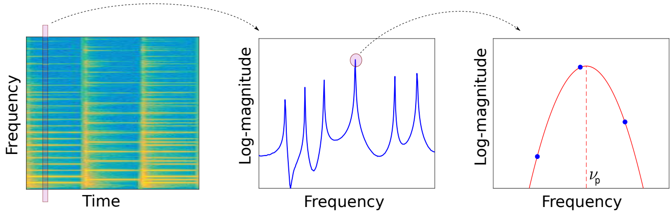

✓ Useful for source separation (and audio inpainting) applications.

✗ The performance is limited due to the simplicity of the model.

Perspective: towards deep phase models

Recently: Some attempts at predicting the phase using DNNs.

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Proposal: Generalize phase models from signal analysis using deep learning.

$$\boldsymbol{\mu}_t = \boldsymbol{\mu}_{t-1} + l\boldsymbol{\nu}_t \quad \rightarrow \quad \boldsymbol{\mu}_t = \underbrace{\mathcal{R}(\boldsymbol{\nu}_t, \boldsymbol{\mu}_{t-1}, \dots, \boldsymbol{\mu}_{t-\tau})}_{\text{temporal dynamics}} \quad \text{with} \quad \boldsymbol{\nu}_t = \underbrace{\mathcal{C}(|\mathbf{x}|_t)}_{\text{frequency extraction}}$$

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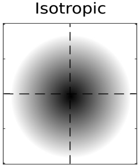
- ▷ Architectural choices (non-linearities, loss functions) adapted to the phase (periodicity).
- ▷ Identify and exploit perceptual phase invariants.

Probabilistic phase modeling

Phase-aware Gaussian models

The ubiquitous isotropic Gaussian model:

$$s \sim \mathcal{N}_{\mathbb{C}}(m, \Gamma) \text{ with } \Gamma = \begin{pmatrix} \gamma & 0 \\ 0 & \gamma \end{pmatrix}$$



Equivalent to assuming a uniform phase $\angle s \sim \mathcal{U}_{[0,2\pi[}$.

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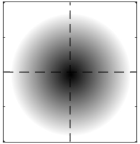

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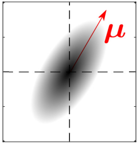
Anisotropic Gaussian model

$$s \sim \mathcal{N}_{\mathbb{C}}(m, \Gamma) \text{ with } \Gamma = \begin{pmatrix} \gamma & c \\ \bar{c} & \gamma \end{pmatrix}$$



c is the *relation* term, defined as a function of the phase parameter μ.

✓ Allows to incorporate phase priors; nice performance boost for source separation applications (e.g., phase-aware Wiener filter).

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Proposal: Combine deep learning and anisotropic modeling, e.g., via anisotropic VAEs.

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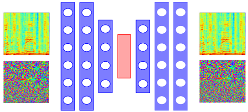

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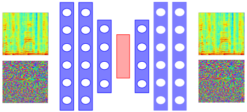

▷ A strong effort in modeling and optimization is needed for deriving appropriate estimation techniques.

Spectrogram inversion algorithms

Spectrogram inversion

Goal: retrieve (complex-valued) STFTs from (non-negative) spectrograms.

- Identify important properties in the STFT domain.
- Promote them by defining an optimization problem.
- Solve it using some optimization strategy.

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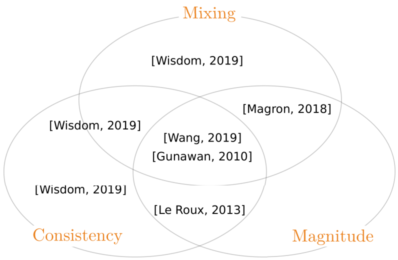
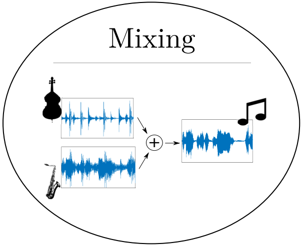
- ▷ Promote them by defining an optimization problem.
- ▷ Solve it using some optimization strategy.

- ▷ Many algorithms in the literature!
- ▷ Which problem formulation is the most appropriate in practice?
- ▷ Proposal: let's define a general spectrogram inversion framework.



STFT-domain constraints



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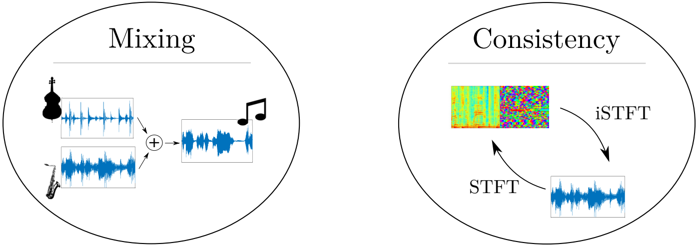

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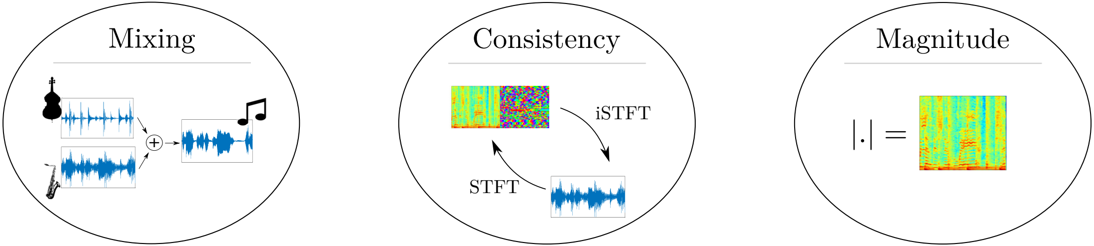

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- Consistency: the estimates (=complex-valued matrices) should be the STFT of time-domain signals.
- Magnitude match: the estimates' magnitude should remain close to the output of the DNN computed beforehand.

Overview

Proposal: A general framework for deriving spectrogram inversion algorithms

- For each property/objective/constraint, define a loss function (and an auxiliary function).
- Combine them (soft penalties / hard constraints) to formulate optimization problems.
- Derive algorithms that alternate projections on the corresponding constraints subspaces.

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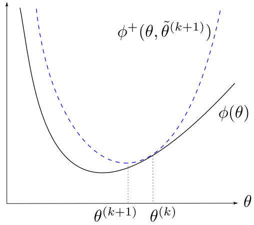
Auxiliary function method

- Considering minimization of ϕ, construct ϕ^+ such that: $\phi(\theta) = \min_{\tilde{\theta}} \phi^+(\theta, \tilde{\theta})$.
- ϕ is non-increasing when minimizing ϕ^+ with respect to θ and $\tilde{\theta}$ alternately.

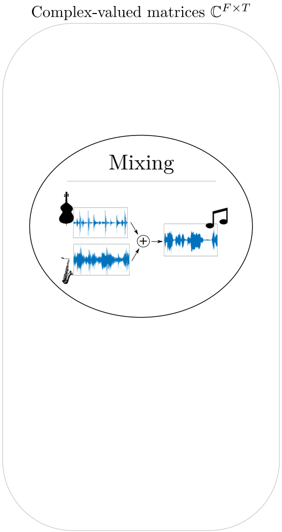
✓ Convergence, successfully used in audio, no hyperparameter to tune.



Mixing constraint

Loss function that promotes conservative estimates:

$$h(\mathbf{S}) = ||\mathbf{X} - \sum_j \mathbf{S}_j||^2$$



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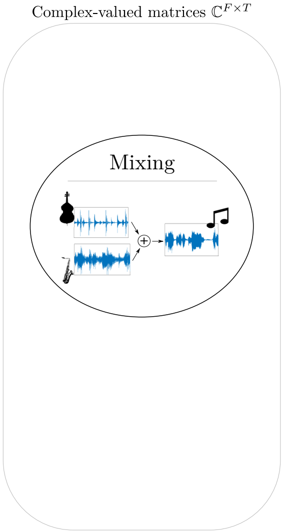
- Auxiliary parameters $\mathbf{Y}$ such that $\sum_j \mathbf{Y}_j = \mathbf{X}$.
- Positive weights $\mathbf{\Lambda}_j$ such that $\sum_j \lambda_{j,f,t} = 1$.
- Then the following is an auxiliary function for h:

$$h^+(\mathbf{S}, \mathbf{Y}) = \sum_{j,f,t} \frac{|y_{j,f,t} - s_{j,f,t}|^2}{\lambda_{j,f,t}}$$



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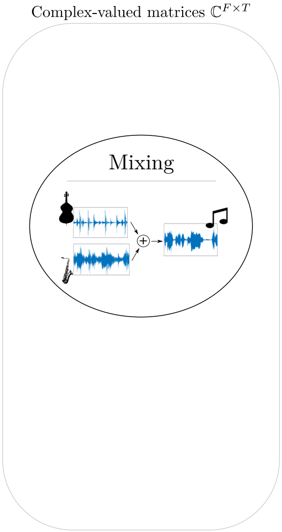
Auxiliary parameters update: $\mathbf{Y}_j = \mathbf{S}_j + \mathbf{\Lambda}_j \odot (\mathbf{X} - \sum_k \mathbf{S}_k)$



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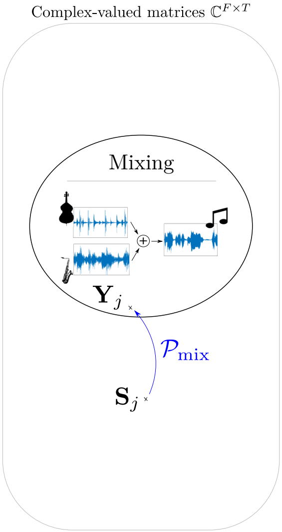
Auxiliary parameters update: $\mathbf{Y}_j = \mathbf{S}_j + \mathbf{\Lambda}_j \odot (\mathbf{X} - \sum_k \mathbf{S}_k)$

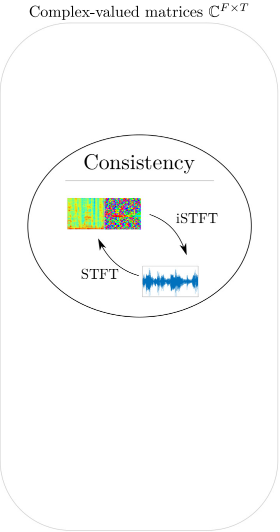
- ▷ Defines a projector $\mathcal{P}_{\text{mix}}$ onto the subspace of matrices complying with the mixing constraint.



Consistency constraint

Loss function that promotes consistent estimates:

$$i(\mathbf{S}) = \sum_j ||\mathbf{S}_j - \mathcal{G}(\mathbf{S}_j)||^2 \text{ with } \mathcal{G} = \text{STFT} \circ \text{iSTFT}$$



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Auxiliary function

- $\mathcal{G}(\mathbf{S}_j)$ is the closest consistent matrix to $\mathbf{S}_j$.
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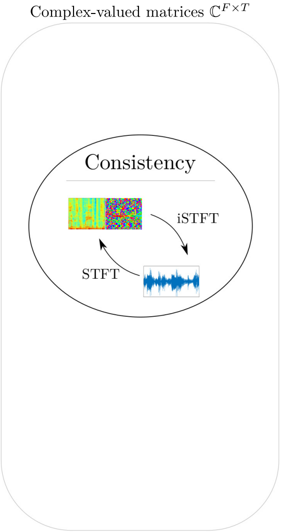

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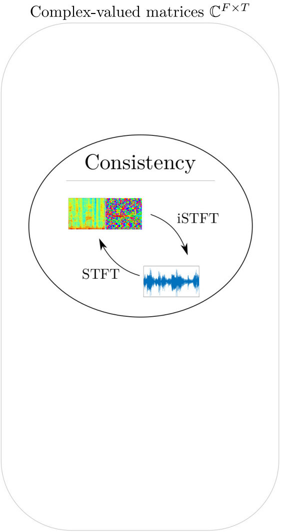

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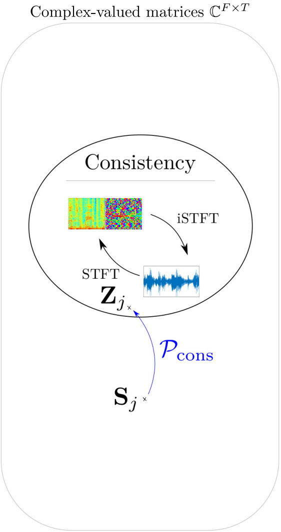
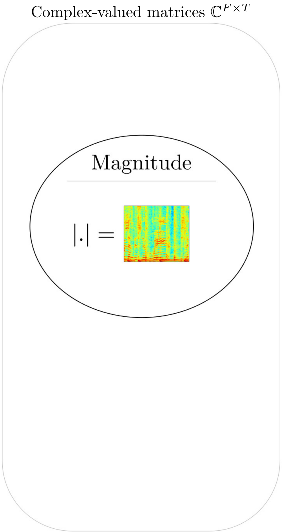


Magnitude constraint

Loss function that ensures the estimates' magnitudes remain close to the target value $\mathbf{V}_j$ estimated beforehand (e.g., using a DNN):

$$m(\mathbf{S}) = \sum_j |||\mathbf{S}_j| - \mathbf{V}_j||^2$$



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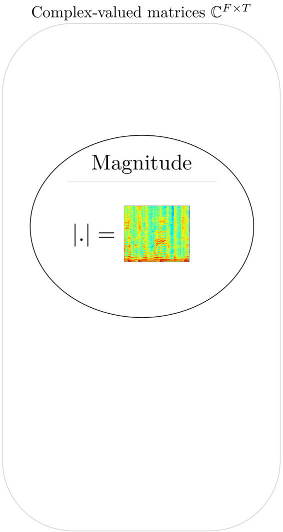

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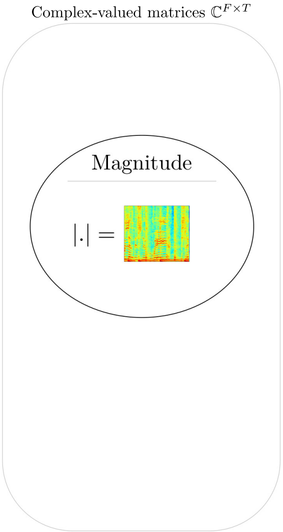

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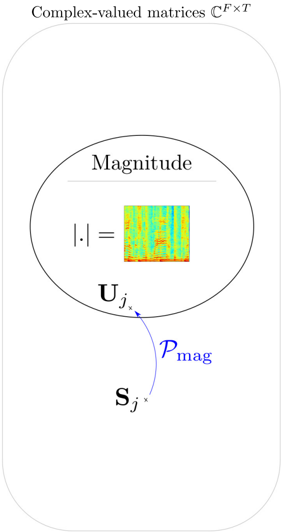

Algorithm derivation example: problem setting

Main problem: optimize the mixing objective + soft consistency penalty + hard magnitude constraint.

$$\min_{\mathbf{S}} h(\mathbf{S}) + \sigma i(\mathbf{S}) \text{ such that } |\mathbf{S}_j| = \mathbf{V}_j$$

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- ▷ Auxiliary parameters updates ($\mathbf{Y}$ and $\mathbf{Z}$) are already known.
- ▷ So let's focus on the update on $\mathbf{S}$.

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New problem

- Incorporate the hard constraint using the method of Lagrange multipliers.
- Find a critical point for:

$$h^+(\mathbf{S}, \mathbf{Y}) + \sigma i^+(\mathbf{S}, \mathbf{Z}) + \sum_{j,f,t} \delta_{j,f,t}(|s_{j,f,t}|^2 - v_{j,f,t}^2)$$

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Update

- Set the partial derivative with respect to $\mathbf{S}$ at 0 and solve:

$$\mathbf{S}_j = \frac{\mathbf{Y}_j + \sigma \mathbf{\Lambda}_j \odot \mathbf{Z}_j}{|\mathbf{Y}_j + \sigma \mathbf{\Lambda}_j \odot \mathbf{Z}_j|} \odot \mathbf{V}_j$$

- Generalizes particular cases from the literature ($\sigma = 0$ and $\sigma = +\infty$).

Algorithm derivation example: illustration

Compact update rule using the projectors: $\mathcal{P}_{\mathsf{mag}}\left(\mathcal{P}_{\mathsf{mix}}(\mathbf{S}) + \sigma \mathbf{\Lambda} \odot \mathcal{P}_{\mathsf{cons}}(\mathbf{S})\right)$

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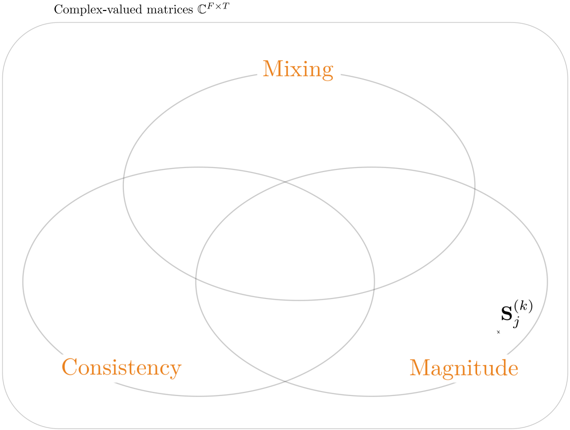

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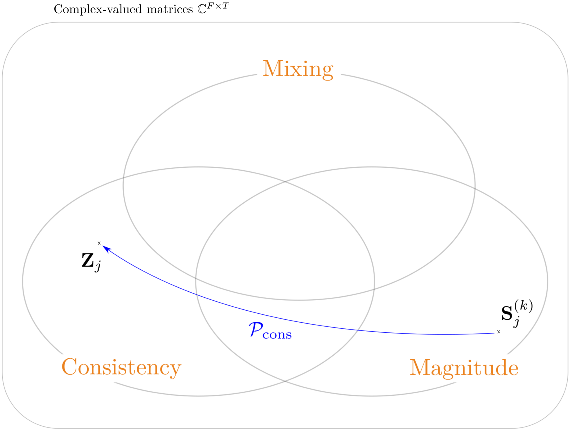

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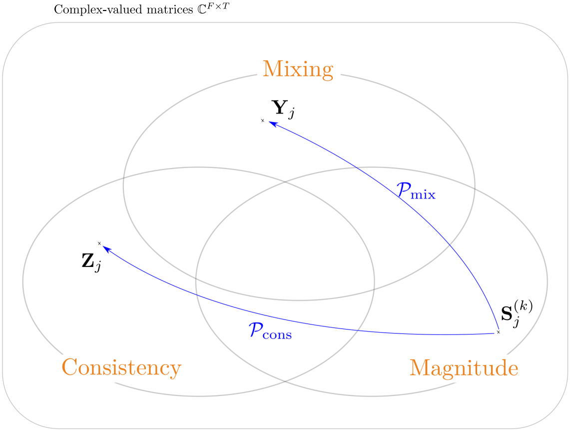

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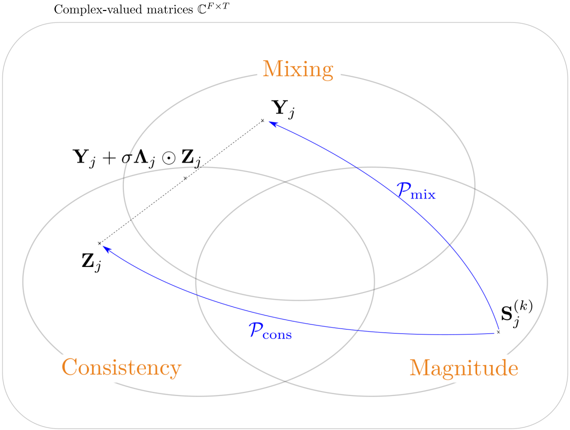

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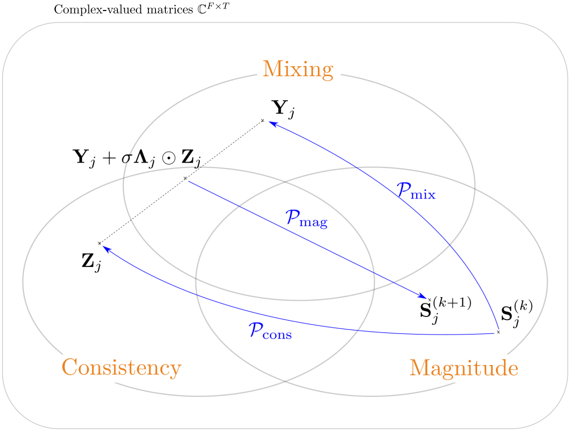

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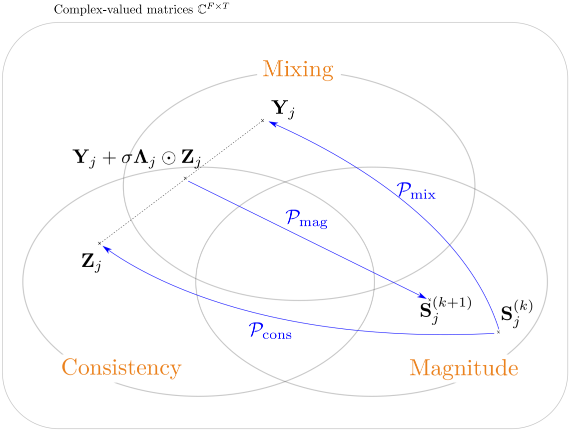

Check our EUSIPCO paper for all problem formulations / update schemes.

Experiments

Task: speech enhancement

- ▷ Clean speech (VoiceBank) + noise (DEMAND: living room, bus, and public square noises).
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	Accurate magnitudes	Less accurate magnitudes
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- ▷ Some novel algorithms are interesting alternatives.
- ▷ Perspectives: unfold these into neural networks for time-domain training.

Conclusion

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From nonnegative to time-domain deep learning.

✓ Performance in controlled conditions, no more phase problem.

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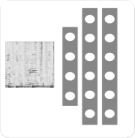
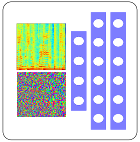
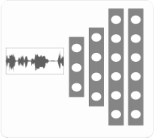

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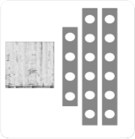 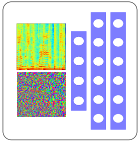 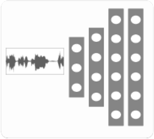

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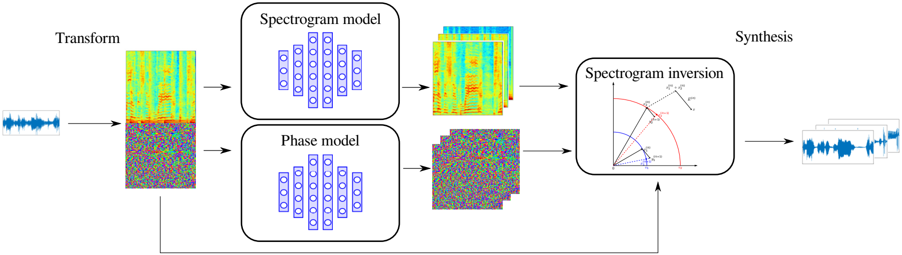
- ✓ Robustness/flexibility of time-frequency processing.
- ✓ Performance of processing all the data exhaustively.
- ✗ Using a real/imaginary part decomposition of the STFT is sub-optimal.

The proposed alternative

- ▷ The room for improvement of phase recovery: more potential gain than with magnitudes.
- ▷ Move towards **deep phase recovery** for increased performance.



Work in progress:

- ▷ Design deep phase prior models.
- ▷ Unfold iterative algorithms into neural networks for time-domain separation.

Thanks!

https://magronp.github.io/

https://github.com/magronp/