Phase-aware audio source separation

Seminar at the Signal Processing research group - Universität Hamburg
May 27, 2021

Paul Magron

CNRS, IRIT, Université de Toulouse, France

Research field

Audio signal processing

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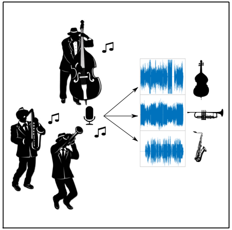

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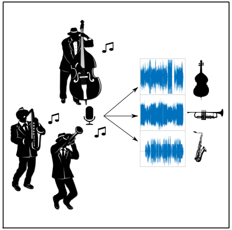

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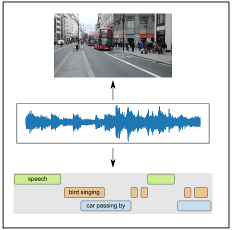

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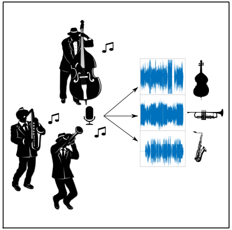

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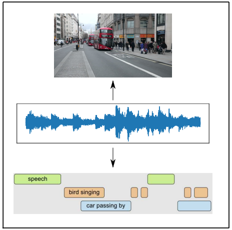

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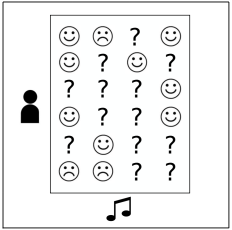

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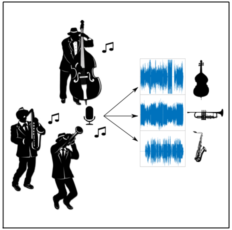

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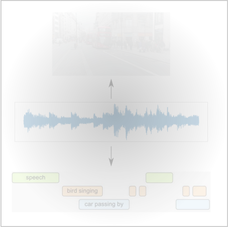

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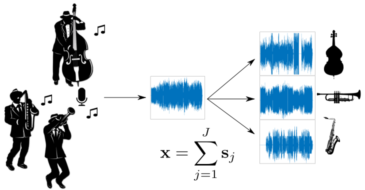
- Time-stretching (transients vs. partials).



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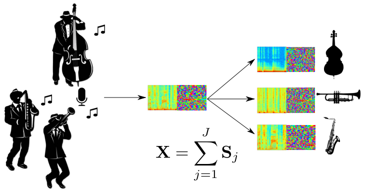
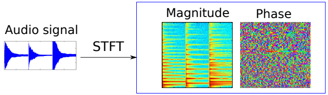
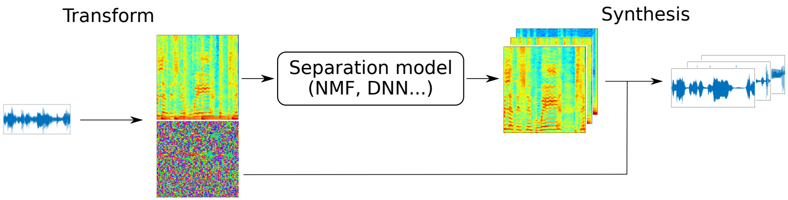


Time-frequency separation = acts on the short-time Fourier transform (STFT).



General framework



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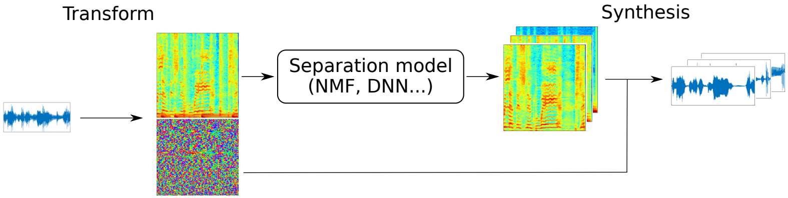

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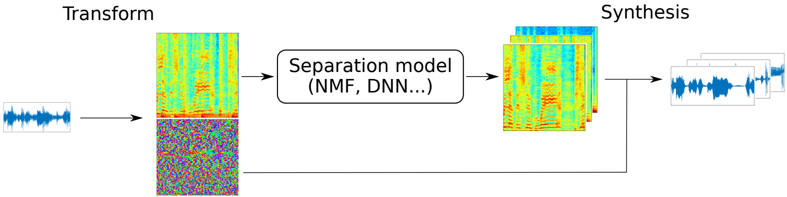

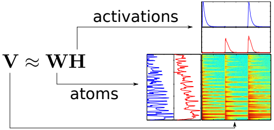

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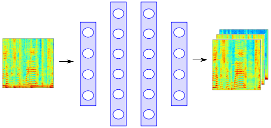
2. Structured model, e.g., nonnegative matrix factorization, deep neural networks.



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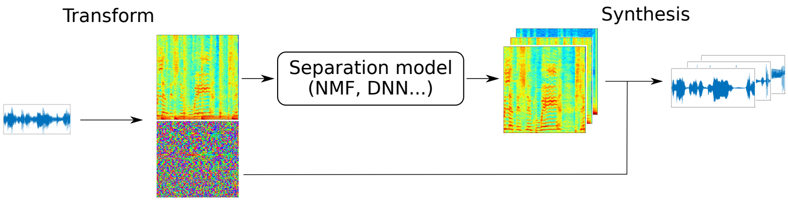
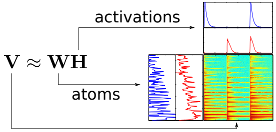
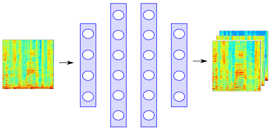




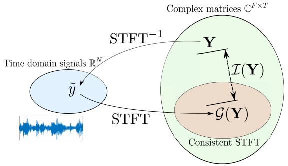


1. Nonnegative representation, e.g., $\mathbf{V} = |\mathsf{STFT}(\mathbf{x})|^2$.
2. Structured model, e.g., nonnegative matrix factorization, deep neural networks.
3. Nonnegative masking and synthesis: $\hat{\mathbf{s}}_j = \mathsf{STFT}^{-1}(\mathbf{M}_j \odot \mathbf{X})$.

The phase problem

Nonnegative masking: $\angle\hat{\mathbf{S}}_j = \angle\mathbf{X}$.

- ✗ Issues in sound quality when sources overlap in the TF domain.
- ✗ *Inconsistency*: $\hat{\mathbf{S}}_j \notin \mathsf{STFT}(\mathbb{R}^N)$.



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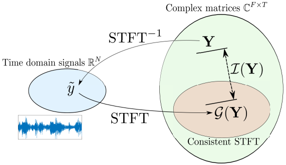

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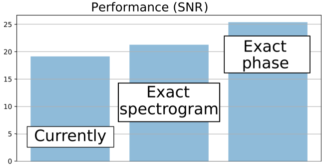
The importance of phase

- ▷ Highlighted in NMF-based [ICASSP '15] and recent DNN-based techniques.
- ▷ Given the current state-of-the-art, there is more potential gain for reconstructing the phase than improving magnitude estimation.



Magron et al., "Phase recovery in NMF for audio source separation: an insightful benchmark", *Proc. IEEE ICASSP*, April 2015.

Phase recovery

Consistency-based approaches

$$\text{Inconsistency:} \quad \mathcal{I}(\mathbf{Y}) = ||\mathbf{Y} - \mathsf{STFT} \circ \mathsf{STFT}^{-1}(\mathbf{Y})||^2$$

- Minimization of $\mathcal{I}$ with alternating projections [Griffin '84].
- Extension to multiple-signals mixtures for source separation [Gunawan '10].
- Combination with Wiener filtering [Le Roux '13].

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My approach

Leveraging **model-based** phase properties in source separation.

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Model-based phase recovery

Probabilistic phase modelling

Joint estimation of magnitude and phase

Perspectives

Model-based phase recovery

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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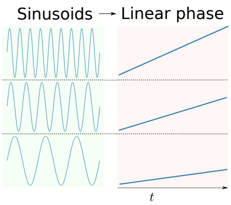
The STFT phase follows: $\mu_{f,t} = \mu_{f,t-1} + 2\pi l \nu_{f,t}$

- l is the hop size of the STFT.
- $\nu_{f,t} = \nu_p$ for channels f under the influence of the frequency peak p.



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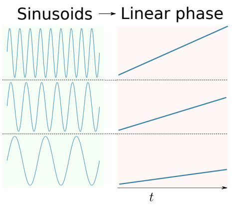

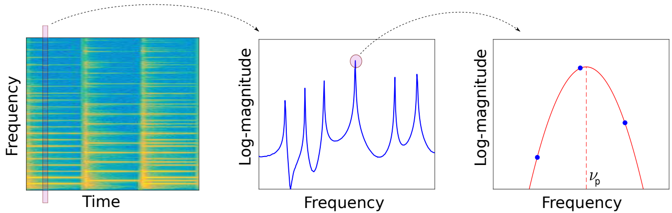

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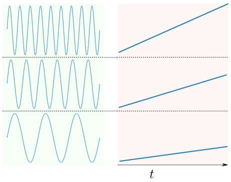
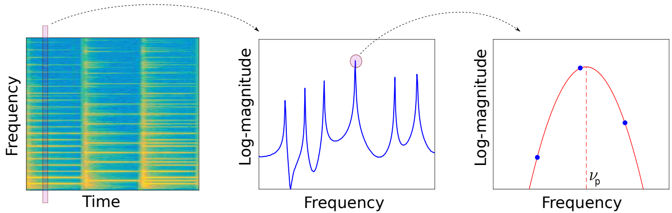


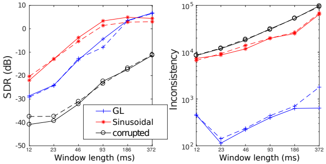


- ✓ Accounting for non-stationary signals.
- ✓ A suitable technique for real-time processing.

Sinusoidal phase model

Restoration of piano pieces:

- ▷ Better performance than the GL algorithm: a lower inconsistency does not mean a higher SDR.
- ▷ The longer the window, the higher SDR (better frequency resolution), but this does not apply to non-stationary signals.
  - ✗ But overall low SDR: error propagates over time frames.



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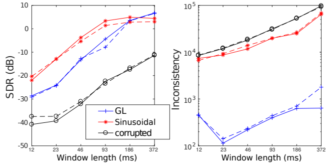
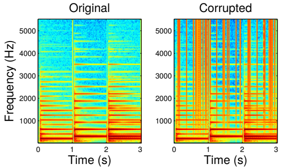




Applications scenarios

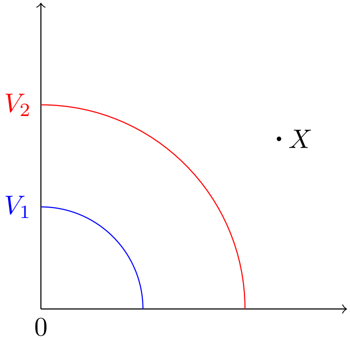
- ▷ Few frames to restore: click removal [EUSIPCO '15].
- ▷ Exploit additional information: source separation.

Magron et al., "Phase reconstruction of spectrograms with linear unwrapping: application to audio signal restoration", *Proc. EUSIPCO*, August 2015.

Source separation algorithm

Problem Given target magnitude values $\mathbf{V}_j$, solve:

$$\min_{\{\hat{\mathbf{S}}_j\}} ||\mathbf{X} - \sum_{j=1}^{J} \hat{\mathbf{S}}_j||^2 \quad \text{s.t.} \quad |\hat{\mathbf{S}}_j| = \mathbf{V}_j$$



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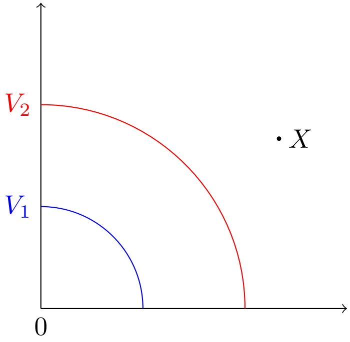
Majorization-Minimization (MM) algorithm

- Introduce auxiliary variables $\mathbf{Y}_j$ s.t. $\mathbf{X} = \sum_j \mathbf{Y}_j$.
- Majorize the loss using the Jensen inequality:

$$||\mathbf{X} - \sum_{j=1}^{J} \hat{\mathbf{S}}_j||^2 \leq \sum_{j=1}^{J} \frac{||\mathbf{Y}_j - \hat{\mathbf{S}}_j||^2}{\lambda_j}$$

- Incorporate the constraints using Lagrange multipliers, and find a saddle point of the resulting functional.
- Iterative procedure: **initialize with the sinusoidal phase**.



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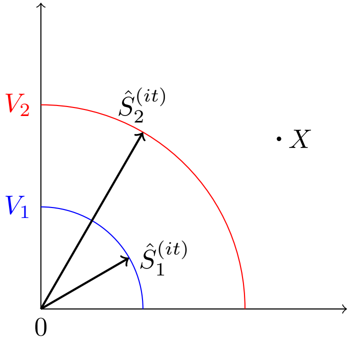

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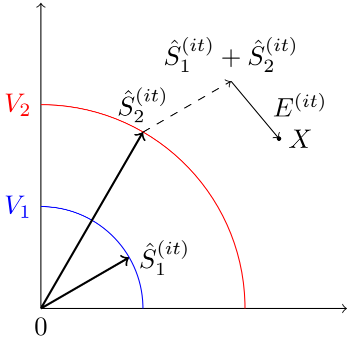

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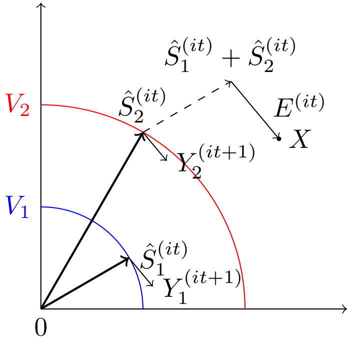

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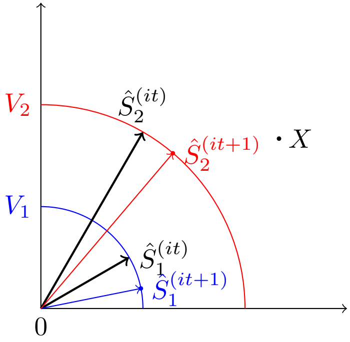

Source separation algorithm - performance

DSD100 dataset: 100 mixtures of 4 sources, ground truth magnitudes.

Magron et al., "Model-based STFT phase recovery for audio source separation", *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, June 2018.

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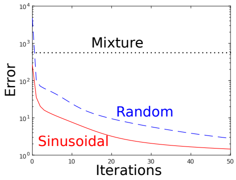

	SDR (dB)	SIR (dB)	SAR (dB)
Mixture	7.5	13.7	8.9
Random	9.5	22.8	9.7
Sinusoidal	**13.6**	**31.0**	**13.7**

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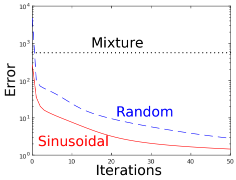

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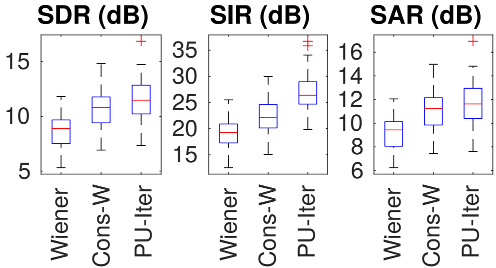
Comparison with Wiener filters:



✓ Leveraging the sinusoidal phase model reduces interference between source estimates.

Magron et al., "Model-based STFT phase recovery for audio source separation", *IEEE/ACM Transactions on Audio, Speech, and Language Processing*, June 2018.

Onsets phase

Onsets play an important perceptual role and initialize the sinusoidal model.

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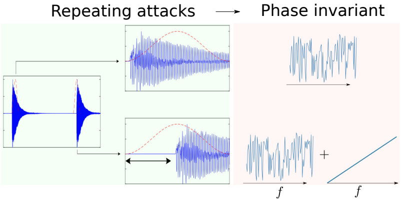
Model of repeated audio events [WASPAA '15]

- ▷ From one onset frame to another, an audio event is the same up to scaling and delay.
- ▷ Consequence on the phase:

$$\mu_{f,t} = \underbrace{\psi_f}_{\text{invariant}} + \underbrace{\eta_t}_{\text{offset}} f$$



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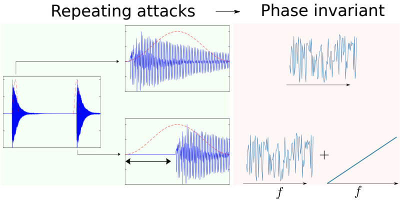

Incorporation in a mixture model

- ▷ Estimation with coordinate descent or MM.
- ▷ Slight improvement over using the mixture's phase.

Magron et al., "Phase reconstruction of spectrograms based on a model of repeated audio events", *Proc. IEEE WASPAA*, October 2015.

How to re-introduce consistency?

A first (naive) approach in the STFT domain:

$$\min_{\{\hat{\mathbf{S}}_j\}} ||\mathbf{X} - \sum_{j=1}^{J} \hat{\mathbf{S}}_j||^2 \quad \text{s.t.} \quad |\hat{\mathbf{S}}_j| = \mathbf{V}_j$$

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Time-domain formulation

$$\min_{\{\hat{\mathbf{s}}_j\}} \sum_j \underbrace{|||\text{STFT}(\hat{\mathbf{s}}_j)| - \mathbf{V}_j||^2}_{\text{magnitude mismatch}} \quad \text{s.t.} \quad \underbrace{\sum_j \hat{\mathbf{s}}_j = \mathbf{x}}_{\text{mixing}}$$

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▷ Optimization with MM: the MISI algorithm, but convergence-guaranteed [Wang '19], [SPL '20].

Wang et al., "A Modified Algorithm for Multiple Input Spectrogram Inversion", *Proc. Interspeech*, September 2019.
Magron and Virtanen, "Online spectrogram inversion for audio source separation", *IEEE Signal Processing Letters*, January 2020.

MISI overview

On top of initial estimates $\hat{\mathbf{s}}_j$, iterate the following:

STFT	$\hat{\mathbf{S}}_j = \text{STFT}(\hat{\mathbf{s}}_j)$
Magnitude modification	$\mathbf{Y}_j = \mathbf{V}_j \odot \frac{\hat{\mathbf{S}}_j}{\lvert\hat{\mathbf{S}}_j\rvert}$
Inverse STFT	$\mathbf{y}_j = \text{iSTFT}(\mathbf{Y}_j)$
Mixing	$\hat{\mathbf{s}}_j = \mathbf{y}_j + \frac{1}{J}\left(\mathbf{x} - \sum_{i=1}^{J} \mathbf{y}_i\right)$

- ▷ Extends the Griffin-Lim algorithm to multiple sources in mixture models.
  - ✗ Offline processing, not applicable in real-time.

Gunawan and Sen, "Iterative phase estimation for the synthesis of separated sources from single-channel mixtures", *IEEE Signal Processing Letters*, May 2010.

Online MISI

Problem: MISI involves the inverse STFT, which does not operate online:

$$\hat{\mathbf{s}}_j(n) = \sum_{k=0}^{T-1} \mathbf{s}'_{j,k}(n - tl) \quad \text{with} \quad \mathbf{s}'_{j,k} = \text{iDFT}(\hat{\mathbf{S}}_{j,k}) \odot \mathbf{w}$$

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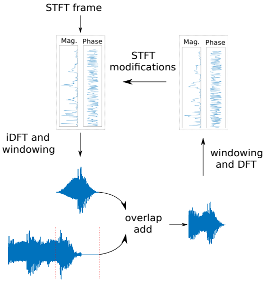
- Only use K look-ahead future frames: allows for real-time processing and alternative initialization (e.g., sinusoidal phase).



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Alternative divergences

Problem setting

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Phase retrieval with beta-divergences

$$\min_{\{\hat{\mathbf{s}}_j\}} \sum_j D_\beta(|\mathsf{STFT}(\hat{\mathbf{s}}_j)|, \mathbf{V}_j) \quad \text{s.t.} \quad \sum_j \hat{\mathbf{s}}_j = \mathbf{x}$$

- Optimization with accelerated gradient descent or ADMM.
- First for single-signal [Vial '21], then extended to multiple-signals [ICASSP '21].
- Experimentally: alternative divergences (e.g., KL) $>$ Euclidean.

Vial et al., "Phase retrieval with Bregman divergences and application to audio signal recovery", *IEEE Journal of Selected Topics in Signal Processing*, January 2021.
Magron et al., "Phase recovery with Bregman divergences for audio source separation", *Proc. IEEE ICASSP*, June 2021.

Probabilistic phase modelling

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Why?

- Modeling uncertainty.
- Incorporating prior information.
- Obtaining estimators with nice statistical properties.
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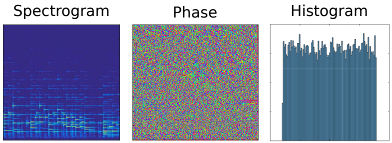
My approach

A phase-aware probabilistic framework for source separation.

Is the phase really uniform?

A simple example (piano piece), where the phase appears uniformly-distributed.



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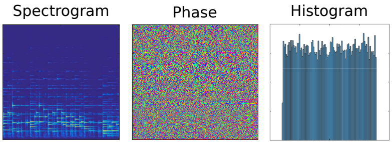

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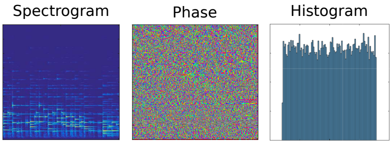

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Interpretation

- ▷ The histogram validates an iid assumption on $\{\phi_{f,t}\}$:

$$\phi_{f,t} \sim \mathcal{D} \text{ and independent } \rightarrow \mathcal{D} = \mathcal{U}_{[0,2\pi[}$$

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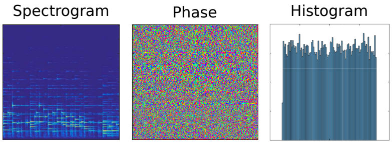

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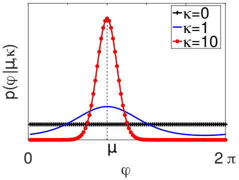
What about the **local structure** of the phase?

Von Mises phase model

Von Mises distribution $\phi_{f,t} \sim \mathcal{VM}(\mu_{f,t}, \kappa)$

- $\mu_{f,t}$ = location parameter (similar to a mean).
- κ = concentration parameter (similar to an inverse variance, quantifies non-uniformity).



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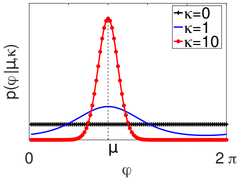

Model

- $\mu_{f,t}$ given by the sinusoidal phase model.

Distribution	Uniform	VM
	$\phi_{f,t} \sim \mathcal{U}_{[0,2\pi[}$	$\phi_{ft} \sim \mathcal{VM}(\mu_{f,t}, \kappa)$
iid	✓	✗
Local structure	✗	✓

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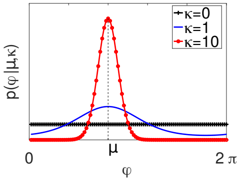

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- Center the phases: $\psi_{f,t} = \phi_{f,t} - \mu_{f,t}$.

Distribution	Uniform	VM	Centered VM
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iid	✓	✗	✓
Local structure	✗	✓	✓

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Von Mises phase model

Model estimation

- For $\mu_{f,t}$: quadratic interpolation (as before).
- For κ: maximum likelihood: $\frac{I_1(\kappa)}{I_0(\kappa)} = \frac{1}{FT} \sum_{f,t} \cos(\psi_{ft})$, solved with fast numerical schemes.

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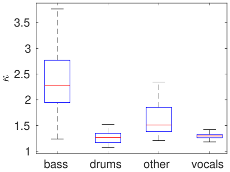

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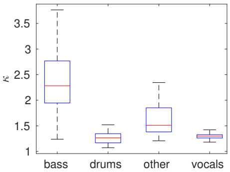
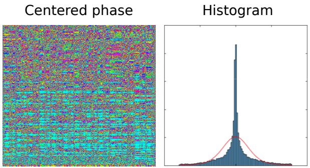
- Both uniform and VM models are statistically relevant.
- They convey different information about the phase (global vs. local).





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	Phase-aware	Tractable
Isotropic Gaussian	✗	✓

Isotropic Gaussian model

- $s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \Gamma_j)$ with $\Gamma_j = \begin{pmatrix} \gamma_j & 0 \\ 0 & \gamma_j \end{pmatrix}$ (m_j: mean (location) / γ_j: variance (energy)).
- Equivalently in polar coordinates, $s_j = r_j e^{\mathrm{i}\phi_j}$ with:
  - $r_j \sim \mathcal{R}(v_j)$ (Rayleigh magnitude).
  - $\phi_j \sim \mathcal{U}_{[0,2\pi[}$ (uniform phase).

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Rayleigh + von Mises model: uniform $\rightarrow$ von Mises: phase-aware... but not tractable.

Anisotropic Gaussian model

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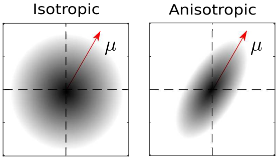

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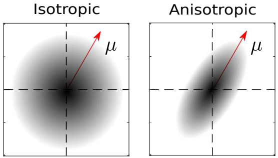

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Model definition: use the moments of the Rayleigh + von Mises model.

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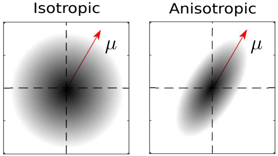

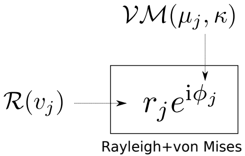

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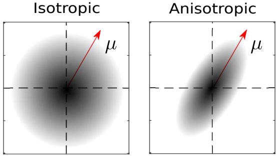

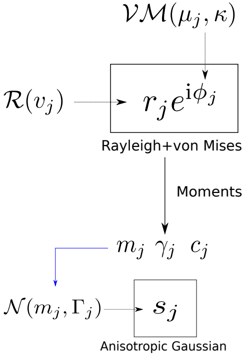

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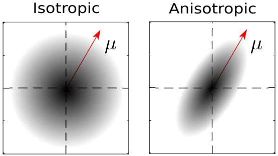
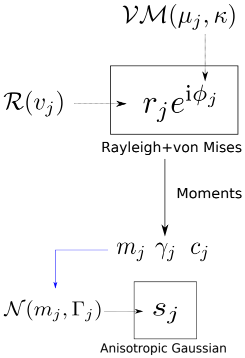


Model definition: use the moments of the Rayleigh + von Mises model. Three parameters:

- v_j: energy (spectrogram model).
- μ_j: phase location (e.g., sinusoidal).
- κ: quantifies anisotropy / non-uniformity.



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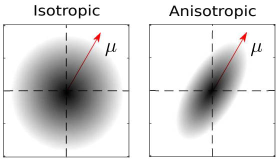
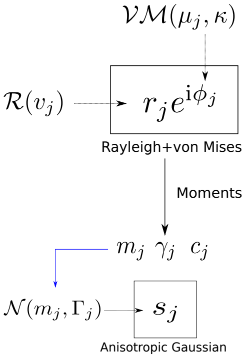
$$s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \Gamma_j) \text{ with } \Gamma_j = \begin{pmatrix} \gamma_j & c_j \\ \bar{c}_j & \gamma_j \end{pmatrix}$$

- ▷ c_j is the *relation* term, non-zero here.



Model definition: use the moments of the Rayleigh + von Mises model. Three parameters:

- ▷ v_j: energy (spectrogram model).
- ▷ μ_j: phase location (e.g., sinusoidal).
- ▷ κ: quantifies anisotropy / non-uniformity.



Anisotropic Gaussian model

Fully tractable, phase-aware, and interpretable.

Application to source separation

Anisotropic Wiener filter [ICASSP '17]

- Posterior mean of the sources: $\hat{\mathbf{S}}_j = \mathbb{E}(\mathbf{S}_j | \mathbf{X})$.
- Optimal in the MMSE sense, conservative set of estimates.
- If $\kappa \to 0$, it reduces to the Wiener filter.

Magron et al., "Phase-dependent anisotropic Gaussian model for audio source separation", *Proc. IEEE ICASSP*, March 2017.

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Performance on the DSD100 dataset:

	SDR	SIR	SAR
Wiener	8.5	19.1	9.1
Anisotropic Wiener	**9.7**	**21.9**	**10.1**

✓ Including phase information in the filter improves the separation quality.

✓ Potential of a phase-aware statistical framework.

Magron et al., "Phase-dependent anisotropic Gaussian model for audio source separation", *Proc. IEEE ICASSP*, March 2017.

Again... consistency?

Reminder: the (anisotropic) Wiener filter produces inconsistent matrices.

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$$\{\text{posterior distribution of the isotropic sources }\}$$

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CW	✗	✓
AW	✓	✗

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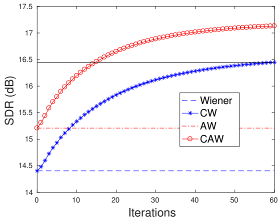

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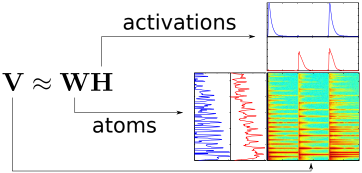
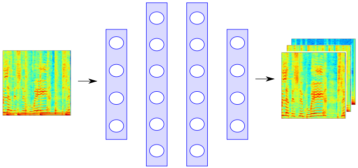
Joint estimation of magnitude and phase

Realistic source separation

Goal: estimate the magnitude **and** the phase of the sources.

▷ Needs an additional spectrogram-like model and estimation technique.





Approaches

▷ Two-stage: first estimate the magnitude, and then recover the phase.

▷ One-stage: jointly estimate the magnitude and the phase.

Two-stage approaches

NMF + phase recovery [the previous papers]

- ▷ Phase recovery induces a slight improvement (interference reduction).

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NMF + phase recovery [the previous papers]

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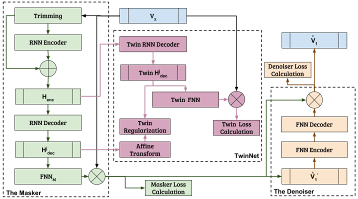
DNN + phase recovery [Interspeech ’18, IWAENC ’18]

- ▷ More significant results (DNNs > NMF).
- ▷ Phase recovery makes sense on top of good magnitude estimates.

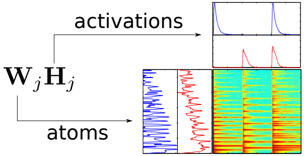


Magron et al., “Reducing interference with phase recovery in DNN-based monaural singing voice separation”, *Proc. Interspeech*. September 2018.
Drossos et al., “Harmonic-percussive source separation with deep neural networks and phase recovery”, *Proc. IWAENC*, September 2018.

Complex NMF

NMF-based spectrogram decomposition

$$|\mathbf{X}| \approx \mathbf{WH} = \sum_{j=1}^{J} \mathbf{W}_j \mathbf{H}_j$$



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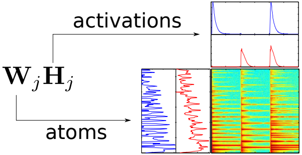

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Phase-constrained complex NMF [ICASSP '16]

✓ Assumes additivity of the sources, and factorize each source spectrogram.

$$\mathbf{X} \approx \sum_{j=1}^{J} \mathbf{W}_j \mathbf{H}_j e^{\mathrm{i}\boldsymbol{\mu}_j}$$

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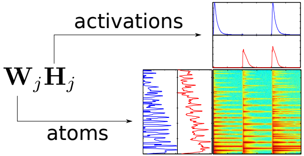

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$$\mathbf{X} \approx \sum_{j=1}^{J} \mathbf{W}_j \mathbf{H}_j e^{\mathrm{i}\boldsymbol{\mu}_j} \xrightarrow[\text{estimation}]{} \min_{\mathbf{W},\mathbf{H},\boldsymbol{\mu}} ||\mathbf{X} - \sum_{j=1}^{J} [\mathbf{W}_j \mathbf{H}_j] e^{\mathrm{i}\boldsymbol{\mu}_j}||^2 + \mathcal{C}(\boldsymbol{\mu})$$

- ▷ Regularize the phases with model-based properties.
- ▷ Optimization with coordinate descent or MM.

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Extending complex NMF to beta-divergences

Problem

- NMF can be estimated using a variety of loss functions (e.g., beta-divergences).
- Complex NMF is estimated using the Euclidean distance.
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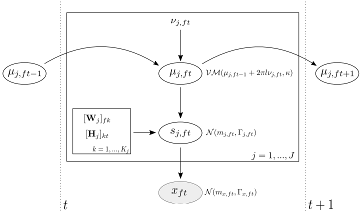
Complex ISNMF [TASLP '19]

Anisotropic Gaussian sources

$$s_j \sim \mathcal{N}_{\mathbb{C}}(m_j, \begin{pmatrix} \gamma_j & c_j \\ \bar{c}_j & \gamma_j \end{pmatrix})$$

- The moments depend on three parameters.
- NMF on the energy parameter: $v_j = w_j h_j$.
- Markov chain prior on the phase parameter μ_j.



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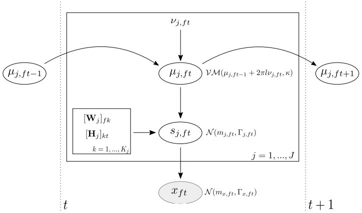

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Complex ISNMF

- ▷ Estimation with an expectation-maximization algorithm:
  - ▷ E-step: compute the posterior moments.
  - ▷ M-step: minimize some Itakura-Saito divergence to estimate the parameters.
- ▷ Better results than the Euclidean (complex) NMF and the (nonnegative) ISNMF.

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Perspectives

From nonnegative to time-domain deep learning

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- ✓ Performance in controlled conditions.
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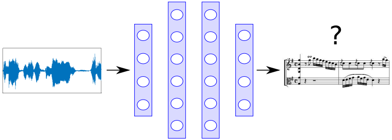

From nonnegative to time-domain deep learning

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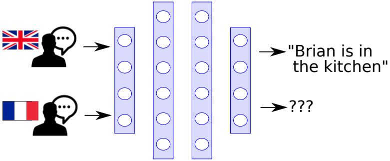

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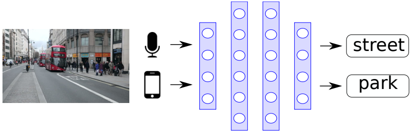

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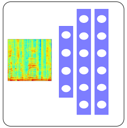

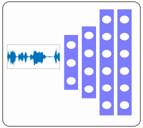

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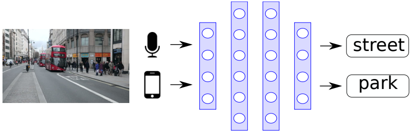
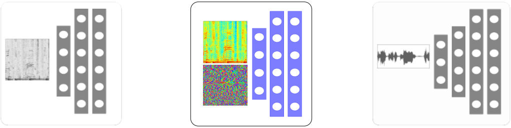


Major challenges

- ▷ Complexity and diversity of acoustic scenes: need for **flexible** systems.
- ▷ Energetic impact of deep learning: need for more **data-efficiency** [Strubell '19].

Strubell et al., "Energy and policy considerations for deep learning in NLP", *Proc. ACL*, July 2019.

An alternative



Complex-domain deep learning

- ✓ Robustness/flexibility of time-frequency processing [Ditter '20].
- ✓ Performance of processing all the data exhaustively.

Ditter and Gerkmann, "A multi-phase gammatone filterbank for speech separation via Tasnet", *Proc. IEEE ICASSP*, May 2020.

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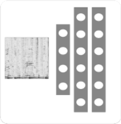

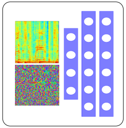

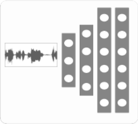

Complex-domain deep learning

- ✓ Robustness/flexibility of time-frequency processing [Ditter '20].
- ✓ Performance of processing all the data exhaustively.

- ▷ How to handle phase in deep learning?
- ▷ How to promote robustness in complex-valued systems?
- ▷ How to efficiently use time-domain data?

Ditter and Gerkmann, "A multi-phase gammatone filterbank for speech separation via Tasnet", *Proc. IEEE ICASSP*, May 2020.

Complex-valued networks

Deep phase processing

✓ Generalize phase models from signal analysis with deep learning.

$$\boldsymbol{\mu}_t = \boldsymbol{\mu}_{t-1} + 2\pi l \boldsymbol{\nu}_t \quad \rightarrow \quad \boldsymbol{\mu}_t = \underbrace{\mathcal{R}(\boldsymbol{\nu}_t, \boldsymbol{\mu}_{t-1}, \ldots, \boldsymbol{\mu}_{t-\tau})}_{\text{temporal dynamic}} \quad \text{with} \quad \boldsymbol{\nu}_t = \underbrace{\mathcal{C}(|\mathbf{x}|_t)}_{\text{frequency extraction}}$$

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

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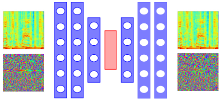
Joint magnitude and phase processing.

✓ Exploit a polar decomposition for structuring the data.

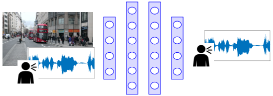
- ▷ Joint latent representation from magnitude and phase.
- ▷ (Variational) anisotropic auto-encodeurs.



Complex-valued networks

Promoting robustness

- Noise-invariance by complex domain adaptation.
- Reverberation-invariance through leveraging spatial models.



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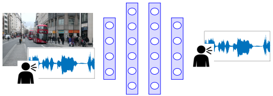
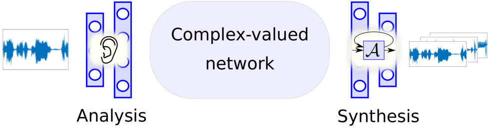


Conjunction with time-domain approaches

✓ Network design in the complex domain, refine the transform with time-domain training data.

- ▷ Direct transform: perceptually-motivated filterbanks.
- ▷ Inverse transform: deep unfolding of phase recovery algorithm.



Conclusion

Main messages

- ▷ The room for improvement of phase recovery: more potential gain than with magnitudes.
- ▷ A promising approach: leveraging model-based phase properties.
- ▷ Incorporate phase in deep learning for complex-valued networks: performance and robustness.

`https://magronp.github.io/`

`https://github.com/magronp/`