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# Complex NMF under phase constraints based on signal modeling

Application to audio source separation

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March 23, 2016



- Source separation
- NMF
- Magnitude Phase retrieval Η Time (s) Magnitude W Time (s) Original spectrogram 500 Frequency (Hz) Frequency (Hz) Frequency (Hz) 10 Magnitude (dB) Time (s) Magnitude (dB)



ELECOM ParisTech



- Wiener filtering commonly used
- Issues when the sources overlap in the TF domain.

How can we improve phase reconstruction in NMF-based source separation?









Phase reconstruction in NMF

Proposed Model

Experimental results



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## Phase reconstruction / NMF Model

- ▶ Non negative data: magnitude spectrogram |X|
- $|X| \approx WH = \sum_k W_k H_k$





# Phase reconstruction / Wiener filtering



• 
$$\phi$$
-source =  $\phi$ -mixture

⊖ Issues in sound quality when sources overlap in the TF domain

$$\ominus \hat{X}_k 
eq$$
 STFT of a  $\hat{x}_k(n)$ 

# Phase reconstruction / Consistency



#### Consistency-based approaches

- Find a  $\hat{X}_k$  that is close to a STFT
- Griffin & Lim, 84 (iterative)
- Leroux, 2008, 2013
- $\ominus$  Magron, Icassp 2015, Consistency  $\Rightarrow$  sound quality

Proposed model / Key ideas

### Our approach

- Phase constraints based on time signal properties
- Complex NMF (CNMF) framework [Kameoka, 2009]

### 2 novelties

- Phase unwrapping
- Repetition of audio events



# Proposed model / Background

### Complex NMF (CNMF) [Kameoka, 2009]

Mixture model:

$$\hat{X}(f,t) = \sum_{k=1}^{K} \underbrace{W(f,k)H(k,t)}_{\mathsf{NMF model}} e^{i\phi_k(f,t)}$$
(2)

Estimation by minimization of

$$\sum_{f,t} |X(f,t) - \hat{X}(f,t)|^2 + \sigma_s 2 \sum_{k,t} H(k,t)^p$$
  
Distance  $D(X,\hat{X})$  Sparsity penalty  $C_s(H)$ 



# Proposed model / Phase unwrapping

- 1. For each source, onset frames are detected  $\rightarrow$  { $T_k$ }
- 2. Each source is modeled as a  $\sum$  of sines:
  - frequency peaks are estimated with QIFFT
  - each channel f is assigned to one sine frequency  $\nu_k(f)$
  - the phase in channel f is mainly governed by  $\nu_k(f)$
- 3. phase unwrapping in channel f:

$$\Delta\phi_k(f,t)=2\pi S\nu_k(f),$$

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Unwrapping cost function:

$$\mathcal{C}_u(\phi) = \sum_{f,k} \sum_{t \neq ext{onsets}} |X(f,t)|^2 |e^{i\Delta\phi_k(f,t)} - e^{2i\pi S 
u_k(f)}|^2$$

# Model of repeated audio events



Two onset signals are equal up to a gain factor and a delay:

$$X(f, t_m) \approx X(f, t_0) \rho e^{i\lambda(m)f}, \text{ with } \lambda(m) = \frac{2\pi\eta(m)}{F}.$$
  
 $\underbrace{\phi(f, t)}_{\text{phase within an onset frame}} \approx \underbrace{\psi(f)}_{\text{reference phase}} + \underbrace{\lambda(t)f}_{\text{offset}}.$ 

# Model of repeated audio events



Repetition cost function:

$$\mathcal{C}_{r}(\phi,\psi,\lambda) = \sum_{f,k} \sum_{t \in \Omega_{k}} |X(f,t)|^{2} |e^{i\phi_{k}(f,t)} - e^{i\psi_{k}(f)}e^{i\lambda_{k}(t)f}|^{2}$$

# **CNMF** under phase constraints

Complete cost function:



- The variables are  $\theta = \{W, H, \phi, \psi, \lambda\};$
- $\sigma_u$ ,  $\sigma_r$  and  $\sigma_s$  are prior weights which promote the constraints.

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### Model estimation:

Minimization of  $C(\theta)$ .

- Coordinate descent method  $\rightarrow$  Iterative procedure.
- Convergence is not guaranteed but observed in practice.

# Protocol & datasets

- Synthetic mixtures of sinusoids;
- Mixtures of piano notes (MAPS database);
- ► *Fs* = 11025 Hz;
- The STFT uses a 46 ms-long Hann window and 75 % overlap.



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#### Methods:

- NMF-W: 30 iterations of KLNMF + Wiener filtering;
- CNMF: 10 iterations of CNMF without phase constraints;
- ► **CNMF**- $\phi$ : 10 iterations of CNMF with phase constraints; **Score**:
  - ▶ BSS Eval [Vincent, 2006]  $\rightarrow$  SDR, SIR and SAR.

## Influence of the weights

- Sparsity: p = 1 and  $\sigma_s = ||X||^2 K^{-(1-p/2)} 10^{-5}$ .
- Sinusoids:



Piano notes:



=I ECO

## Influence of the weights

• With  $\sigma_r = 0.2$ :



 $\rightarrow$  ( $\sigma_u, \sigma_r$ ) = (0.2, 0.2) for robustness and higher scores.



# Source separation

Reconstruction of a B2 piano note partial from a mixture made up of two piano notes (E2 and B2):



## Source separation

Separation results:

Data	Method	SDR	SIR	SAR
Synthetic sinsuoids	NMF-W	12.1	17.5	14.1
	CNMF	12.0	14.6	16.1
	$CNMF$ - $\phi$	14.0	20.7	15.4
Piano notes	NMF-W	12.9	23.3	14.5
	CNMF	13.5	20.0	14.8
	$CNMF$ - $\phi$	14.0	24.0	14.6

- Improved interference rejection.
- Slight increase of SDR.

# Source separation - Realistic data

- 100 songs (rock, pop, electro...) from the Demixing Secret Database;
- The optimal weights are learned on 50 songs;
- Source separation is performed on the other 50.



### Source separation - Realistic data



- Significant increase in interference rejection;
- The trade-off between SDR, SIR and SAR highly depends on the weights values.

### Source separation - Realistic data



# **Conclusion**

### Complex NMF with signal model-based phase constraints

- A promising approach for separating overlapping sources in the TF domain;
- Better interference rejection than traditional Wiener filtering or unconstrained CNMF;
- The repetition constraints does not significantly improve the results.

#### Further work

- High sensitivity to the weight parameters;
- Optimization scheme is not efficient
  - $\rightarrow$  New formulation of the problem: probabilistic framework.



### Thank you!

#### Webpage: http://perso.telecom-paristech.fr/~magron/

