Kernel Spectrogram Models for source separation

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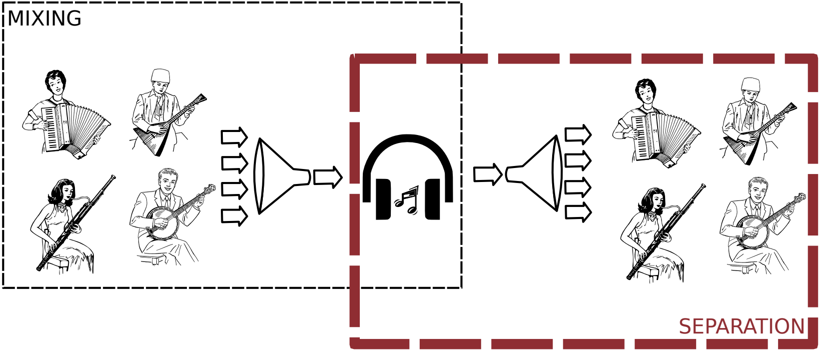
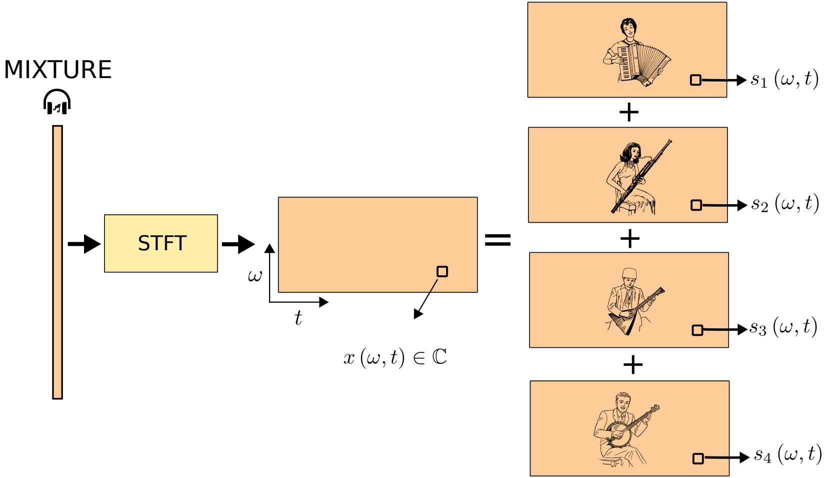
Separating audio sources



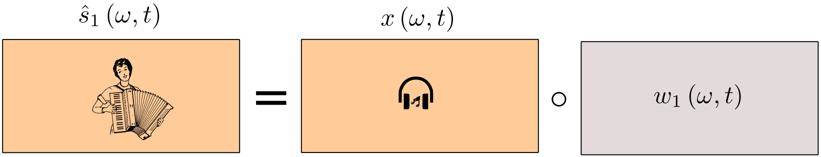
In this presentation: mono mixtures

$\Rightarrow$ General multichannel case in the paper

Notations


MIXTURE
STFT
ω
t
$x(\omega, t) \in \mathbb{C}$
$s_1(\omega, t)$
$s_2(\omega, t)$
$s_3(\omega, t)$
$s_4(\omega, t)$

Time frequency masking



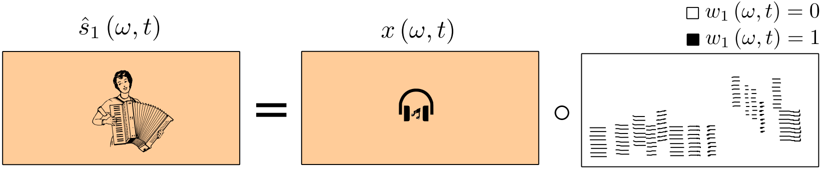
- Each source STFT $s_j(\omega, t)$ is obtained by *filtering* the mixture

$$\hat{s}_j(\omega, t) = w_j(\omega, t)\, x(\omega, t)$$

- Underdetermined separation $\Rightarrow$ w_j varies with both ω and t
- Waveforms obtained by inverse STFT

Many different ways to get a Time-Frequency (TF) mask $w_j(\omega, t)$

Time frequency masking



- $s_j(f, t)$ is assumed equal either to $x(\omega, t)$or to 0
- A **classification task** over the mixture STFT x
  $\Rightarrow$ based on **features**
  - pitch detection+harmonics selection (CASA)
  - panning position (DUET)

Y. Han and C. Raphael. Informed source separation of orchestra and soloist. In *Proceedings of the 11th International Society for Music Information Retrieval Conference (ISMIR)*, pages 315–320, 2010

O. Yilmaz and S. Rickard. Blind separation of speech mixtures via time-frequency masking. *IEEE Trans. on Signal Processing*, 52(7):1830–1847, 2004

Getting the mask

Binary masking yields **musical noise**

$\Rightarrow$ Soft masking $w_j(f,t) \in [0\,1]$ is better!

Example: Wiener filtering for Gaussian processes

- Sources energies $f_j(\omega,t) \geq 0$ add up to get mix energy

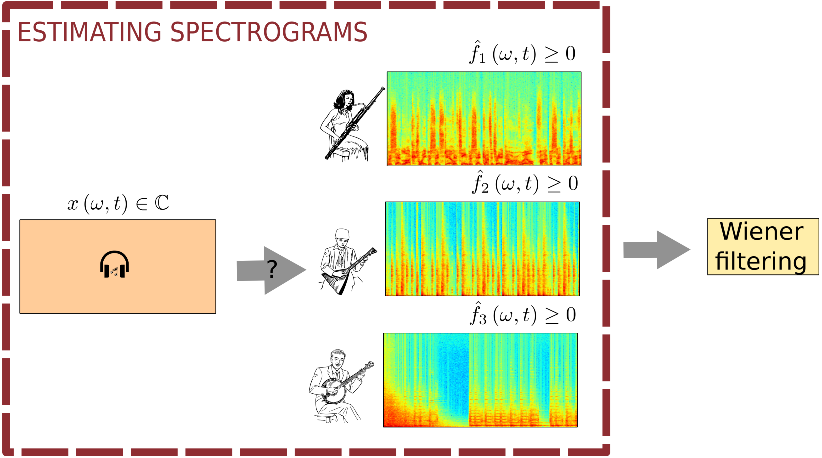
$$\sum_j f_j(\omega,t)$$

- $w_j(f,t)$ taken as proportion of source j in mix

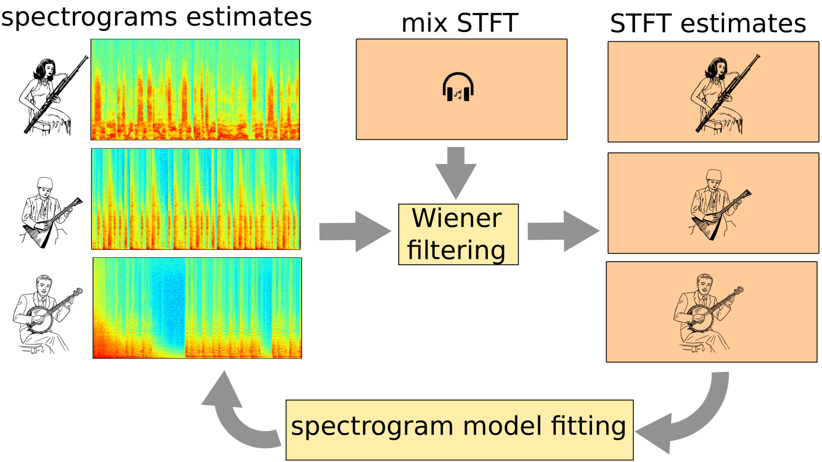
$$w_j(\omega,t) = \frac{f_j(\omega,t)}{\sum_{j'} f_{j'}(\omega,t)} \in [0\,1]$$

L. Benaroya, F. Bimbot, and R. Gribonval. Audio source separation with a single sensor. *IEEE Trans. on Audio, Speech and Language Processing*, 14(1):191–199, January 2006

Time-Frequency masking
challenges



Iterative approaches
main ideas



The need for spectrograms models

Given $\hat{s}_j(\omega, t)$, how to estimate $f_j(\omega, t)$?

Example: spatial-only models

Assuming a Local Gaussian Model $s_j(\omega, t) \sim \mathcal{N}_c(0, f_j(\omega, t) R_j(\omega))$

- we take $\hat{f}_j(\omega, t) = \underset{f}{\operatorname{argmax}} p\left(s_j(\omega, t) \mid f, \hat{R}_j(\omega)\right)$
- with $R_j(\omega)$ related to spatial positions

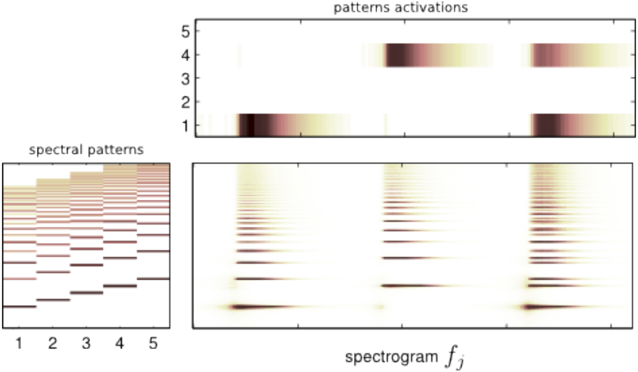
$\Rightarrow$ only works if sources are well separated spatially

We want to improve by using prior knowledge on f_j

N.Q.K. Duong, E. Vincent, and R. Gribonval. Under-determined reverberant audio source separation using a full-rank spatial covariance model. *Audio, Speech, and Language Processing, IEEE Transactions on*, 18(7):1830–1840, sept. 2010

Global spectrogram models

nonnegative matrix factorization



A. Ozerov, E. Vincent, and F. Bimbot. A general flexible framework for the handling of prior information in audio source separation. *Audio, Speech, and Language Processing, IEEE Transactions on*, PP(99):1, 2011

Y. Salaün, E. Vincent, N. Bertin, N. Souviraà-Labastie, X. Jaureguiberry, D. Tran, and F. Bimbot. The Flexible Audio Source Separation Toolbox (FASST) version 2.0. In *ICASSP*, 2014

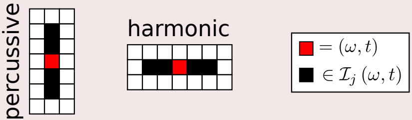
Kernel spectrogram models

principles

- NMF is a **global** single model for all of f_j
- Sometimes, our knowledge is only **local**
  $\Rightarrow$ We assume $f_j(\omega, t)$ is equal to some **neighbours** $\mathcal{I}_j(\omega, t)$

Example: harmonic/percussive local models

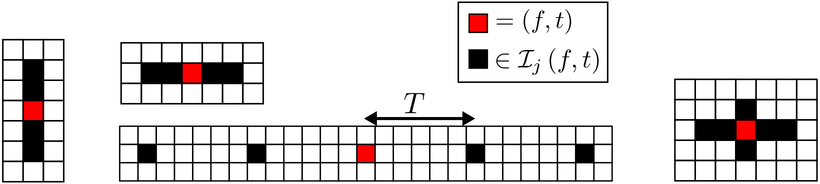
- Percussive sounds are locally constant through frequency
- Harmonic sounds are locally constant through time



D. Fitzgerald. Harmonic/percussive separation using median filtering. In *Proc. of the 13th Int. Conference on Digital Audio Effects (DAFx-10)*, Graz, Austria, September 2010

Kernel spectrogram models
examples

$$\forall\left(\omega', t'\right) \in \mathcal{I}_j\left(\omega, t\right),\ f_j\left(\omega', t'\right) \approx f_j\left(\omega, t\right)$$



D. Fitzgerald. Harmonic/percussive separation using median filtering. In *Proc. of the 13th Int. Conference on Digital Audio Effects (DAFx-10)*, Graz, Austria, September 2010

Z. Rafii and B. Pardo. A simple music/voice separation method based on the extraction of the repeating musical structure. In *Acoustics, Speech and Signal Processing (ICASSP), 2011 IEEE International Conference on*, pages 221 –224, may 2011

D. FitzGerald. Vocal separation using nearest neighbours and median filtering. In *Proceedings of the 23nd IET Irish Signals and Systems Conference*, pages 583–588, Maynooth, 2012

Z. Rafii and B. Pardo. Music/voice separation using the similarity matrix. In *Proceedings of the 13th International Conference on Music Information Retrieval (ISMIR)*, pages 583–588, 2012

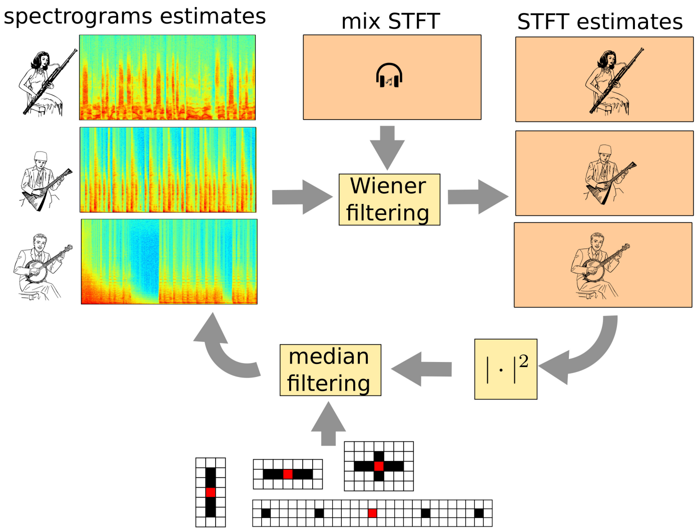
Kernel spectrogram models
objective

Combining all those local models together!

Example: voice/music separation

- Musical background
  5 sources repeating at different scales (beat, downbeat, ...)
  +1 source which is stable along time (strings, synths)
- Voice
  with a locally constant spectrogram (cross-like kernel)

Kernel backfitting algorithm



Kernel backfitting algorithm

monochannel version

Input

Mixture STFT $x(\omega, t)$

Neighbourhoods $\mathcal{I}_j(\omega, t)$, also called "proximity kernels"

Initialization:

$\forall j, \hat{f}_j(\omega, t) \leftarrow |x(\omega, t)|^2$: simply take mix spectrogram

Iterate

Separation with Wiener filtering

compute estimates $\hat{s}_j(\omega, t) = \left[\hat{f}_j(\omega, t) / \sum_{j'} \hat{f}_{j'}(\omega, t)\right] x(\omega, t)$

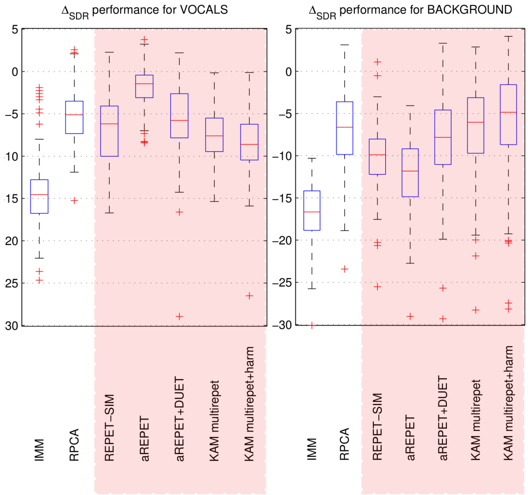
Spectrograms fitting

$\hat{f}_j(\omega, t) \leftarrow$ median filter $|\hat{s}_j(l)|^2$ with kernel $\mathcal{I}_j(\omega, t)$

Output: source estimates $\hat{s}_j$

BSSeval results

on "pet shop sessions" by the Beach Boys



Demo

external demo

Conclusion

- A general framework for combining different kernel models
- Handles multichannel mixtures
- State-of-the-art performance for music separation
- Easy to implement and fast algorithms
  ⇒ full demo at `www.loria.fr/~aliutkus/kam/`

To go further

Formalization

⇒ optimization framework with robust cost-functions

⇒ equivalence with EM algorithm in some cases

Combination with other techniques

Learning source kernels automatically?

⇒ maximizing size of kernel (robustness)

⇒ maximizing invariance to median filtering