

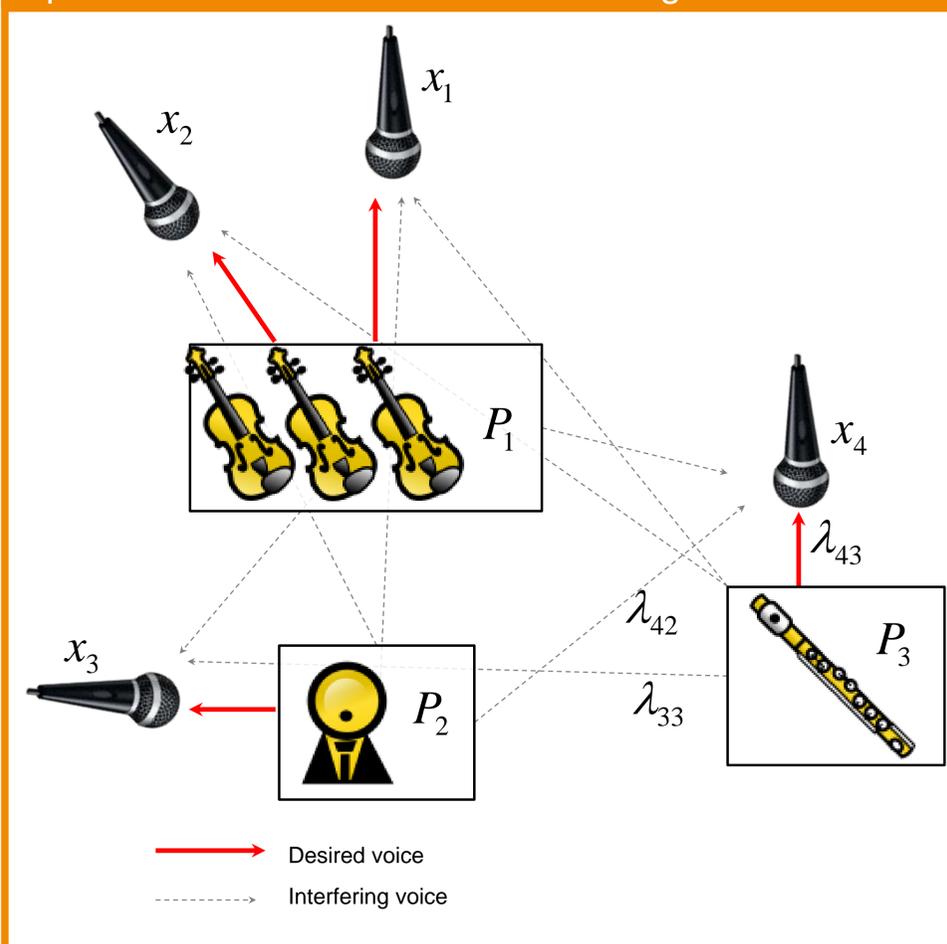
# KERNEL ADDITIVE MODELING FOR INTERFERENCE REDUCTION IN MULTI-CHANNEL MUSIC RECORDINGS

Thomas Prätzlich, Rachel M. Bittner, Antoine Liutkus, and Meinard Müller

## Abstract

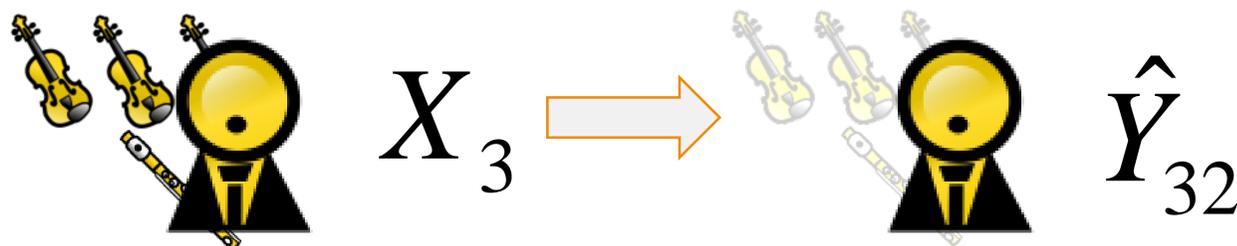
It is difficult to acoustically shield microphones when recording a live music performance. In practice, each microphone also contains interferences from the other voices. In this paper, we aim to reduce these interferences in multi-channel recordings to recover only the isolated voices. Following the recently proposed Kernel Additive Modeling framework, we present a method that iteratively estimates both the power spectral density of each voice and the corresponding strength in each microphone signal. With this information, we build an optimal Wiener filter, strongly reducing interferences. The trade-off between distortion and separation can be controlled by the user through the number of iterations of the algorithm. Furthermore, we present a computationally effective approximation of the iterative procedure. Listening tests demonstrate the effectiveness of the method.

## Input Data: Multi-Channel Recording

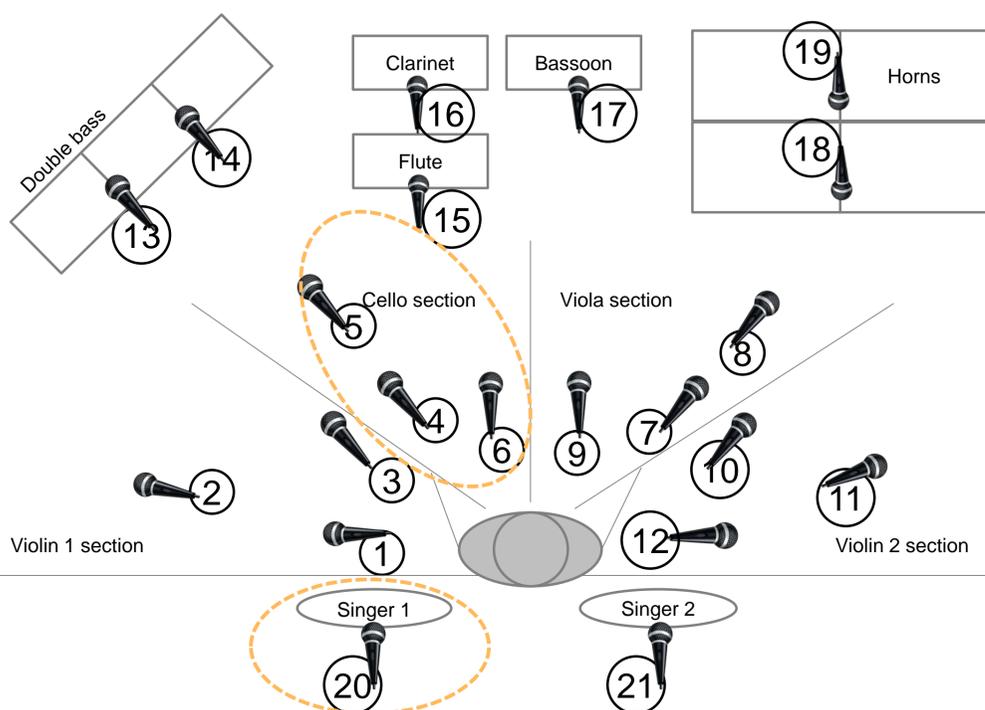


## Goal 1: Interference Reduction

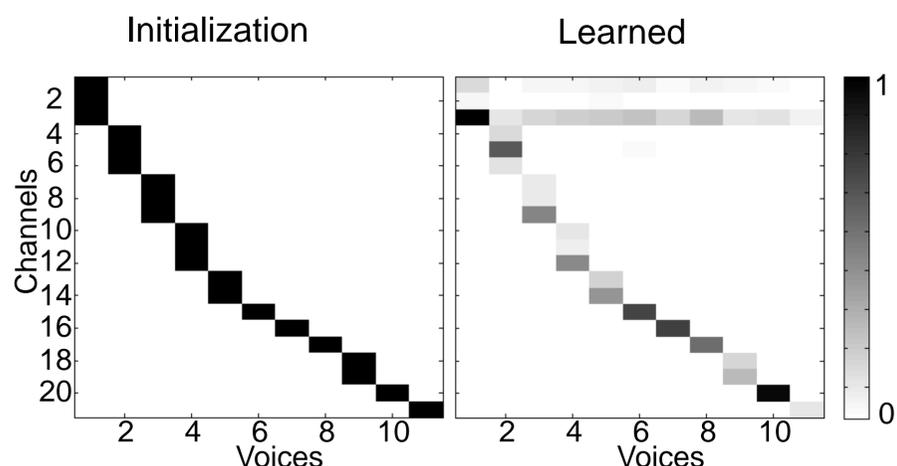
**Example task:** Remove interferences from strings and flute in the singer's microphone channel



## Goal 2: Learning of Interference Matrix



## Interference Matrix



Learn contribution of each voice into each channel with Non-Negative Matrix Factorization (NMF)

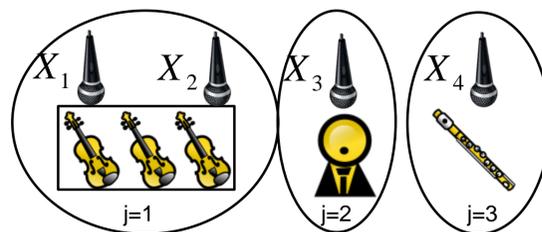
# KERNEL ADDITIVE MODELING FOR INTERFERENCE REDUCTION IN MULTI-CHANNEL MUSIC RECORDINGS

Thomas Prätzlich, Rachel M. Bittner, Antoine Liutkus, and Meinard Müller

## Algorithm

### 1. Input:

- STFT for each channel  $i$
- Assignment of each voice  $j$  to a set of channels according to  $\varphi$
- Minimal interference  $\rho$
- Optional: A kernel for each voice



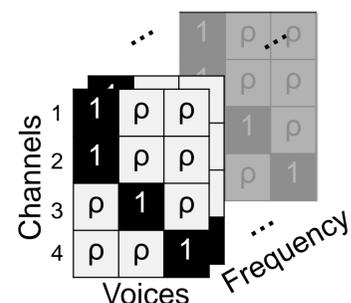
$\varphi(1) = \{1,2\}$   
 $\varphi(2) = \{3\}$   
 $\varphi(3) = \{4\}$

### 2. Initialization

- For each frequency, initialize interference matrix with voice channel assignment and minimal interference  $\rho$
- Set initial estimate of voice's images to STFT of associated microphone signal

$$\forall (i, j, \omega), \lambda_{ij}(\omega) = \begin{cases} 1 & \text{if } i \in \varphi(j) \\ \rho & \text{otherwise,} \end{cases}$$

$\hat{Y}_{11} = X_1$	$\hat{Y}_{21} = X_2$	
$\hat{Y}_{32} = X_3$		
$\hat{Y}_{43} = X_4$		



### 3. Parameter Fitting

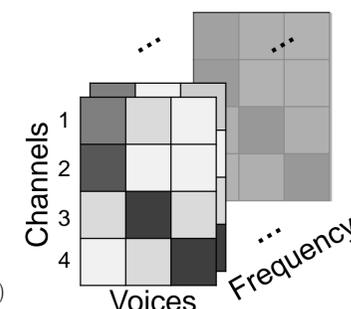
- For each voice: Update the Power Spectral Densities (PSD) according to frequency dependent interference matrix
- Optional: Apply a voice specific kernel median filter on each PSD that captures characteristics of each voice
- Update interference matrix with NMF
- Rescale each PSD and normalize

$$P_j(\omega, t) \leftarrow \frac{1}{|\varphi(j)|} \sum_{i \in \varphi(j)} \frac{1}{\lambda_{ij}(\omega)} |\hat{Y}_{ij}(\omega, t)|^2$$

$$\lambda_{ij}(\omega) \leftarrow \lambda_{ij}(\omega) \cdot \frac{\sum_{t=1}^{N_t} \hat{V}_i(\omega, t)^{\beta-2} V_i(\omega, t) P_j(\omega, t)}{\sum_{t=1}^{N_t} \hat{V}_i(\omega, t)^{\beta-1} P_j(\omega, t)}$$

$$V_i(\omega, t) \triangleq |X_i(\omega, t)|^2$$

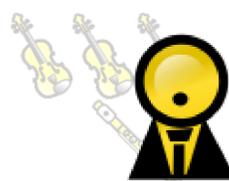
$$\hat{V}_i(\omega, t) \triangleq \sum_j \lambda_{ij}(\omega) P_j(\omega, t)$$



### 4. Separation Step / Output: Update the voice's images

$$\hat{Y}_{ij}(\omega, t) = \frac{\lambda_{ij}(\omega) P_j(\omega, t)}{\sum_{j'=1}^J \lambda_{ij'}(\omega) P_{j'}(\omega, t)} X_i(\omega, t)$$

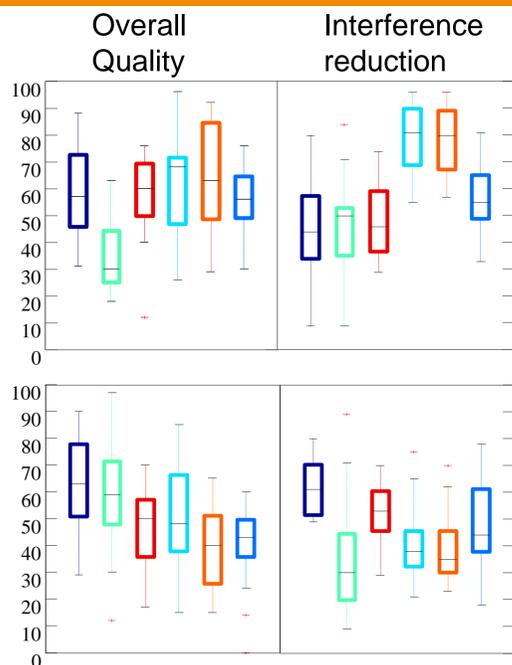
$$\triangleq W_{ij}(\omega, t) X_i(\omega, t),$$



$$\hat{Y}_{32} = W_{32} \otimes X_3$$

### 5. Iteration: For another iteration, return to step (3)

## Evaluation – Listening Test



### Cello microphone (4)

- Use information from the whole cello section (4)(5)(6)
- More microphones are beneficial for interference reduction

### Singer 1 (20)

- 1 microphone
- More iterations may decrease the overall quality

- Kokkinis 2012 [1]
- KAMIR  $\rho = 1, \varphi(j) = j, 1$  iteration
- KAMIR  $\rho = 0.1, \varphi_2, 1$  iterations
- KAMIR  $\rho = 0.1, \varphi_2, 4$  iterations
- KAMIR  $\rho = 0.1, \varphi_2, 4$  iterations, interference matrix learned
- KAMIR  $\rho = 0.1, \varphi_2, 1$  iteration, interference matrix learned, sigmoid on gains

$\varphi_2$ : as initialization of interference matrix on first page

## References

- [1] Elias K. Kokkinis, Joshua D. Reiss, and John Mourjopoulos, "A Wiener filter approach to microphone leakage reduction in close-microphone applications," *IEEE Transactions on Audio, Speech & Language Processing*, vol. 20, no. 3, pp. 767–779, 2012.
- [2] Antoine Liutkus, Derry Fitzgerald, Zafar Rafii, Bryan Pardo, and Laurent Daudet, "Kernel Additive Models for Source Separation," *IEEE Transactions on Signal Processing*, June 2014.
- [3] Accompanying website: <http://www.audiolabs-erlangen.de/resources/MIR/2015-ICASSP-KAMIR>

## Acknowledgments

This work has been supported by the BMBF project *Freischütz Digital* (Funding Code 01UG1239A to C). The International Audio Laboratories Erlangen are a joint institution of the Friedrich-Alexander-Universität Erlangen-Nürnberg (FAU) and Fraunhofer IIS.