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Audio Inpainting, Source Separation, Audio Compression All with a Unified Framework Based on NTF Model

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Keywords: Audio Inpainting, Source Separation, Informed Source Separation (ISS), Compressive Sampling, Nonnegative Tensor Factorization (NTF)

We propose a general signal recovery algorithm, that can recover J audio source signals in time, $s_{jt}^\tau, j \in \llbracket 1, J \rrbracket, t \in \llbracket 1, T \rrbracket$, given the quantized source samples, y_{jt}^τ , each observed on the support Ω_j^τ and the quantized mixture samples, $x_t^\tau = \sum_{j=1}^J s_{jt}^\tau + a_t^\tau$, observed on Ξ^τ with quantization noise a_t^τ . The sources are modelled in the short time Fourier transform (STFT) domain with a normal distribution ($s_{jfn} \sim \mathcal{N}_c(0, v_{jfn})$) where the variance tensor $\mathbf{V} = [v_{jfn}]_{j,f,n}$ has the following low-rank non-negative tensor factorization (NTF) structure [7], $v_{jfn} = \sum_{k=1}^K q_{jk} w_{fk} h_{nk}$. This model is parametrized by $\theta = \{\mathbf{Q}, \mathbf{W}, \mathbf{H}\}$, with $\mathbf{Q} = [q_{jk}]_{j,k} \in \mathbb{R}_+^{J \times K}$, $\mathbf{W} = [w_{fk}]_{f,k} \in \mathbb{R}_+^{F \times K}$ and $\mathbf{H} = [h_{nk}]_{n,k} \in \mathbb{R}_+^{N \times K}$.

We propose to recover the source signals with a generalized expectation-maximization (GEM) algorithm [4] based on multiplicative update (MU) rules [5]. The Algorithm is briefly described in Algorithm 1. Using the proposed approach, it is possible to solve a number of existing and new problems in audio signal processing:

- **Audio inpainting:** It is possible to recover arbitrary time domain losses in audio signals for applications such as signal declipping. NTF

model is used for the *first time* for the recovery of arbitrary time domain losses [3].

- **Joint audio inpainting and source separation:** It is possible to jointly perform audio inpainting and source separation to improve the performance of both tasks. Audio inpainting and source separation are performed jointly for the *first time* [1].
- **Compressed sampling-based informed source separation:** It is possible to recover the sources from their random samples and the mixture via compressive sampling-based informed source separation. This new ISS scheme uses a simple encoder that has properties of distributed coding [8, 6] and it competes with traditional ISS. The concept of distributed coding and of compressive sampling based scheme is introduced for the *first time* in the informed source separation problem [2].

The presentation and the poster will include various new results for the proposed algorithm with comparisons to state of the art methods in the different problems discussed above.

* The first and second authors have contributed equally for this work.

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Algorithm 1 GEM algorithm for NTF model estimation. Details can be found in [1, 2, 3]

- 1: **procedure** ESTIMATESOURCES-NTF($\Xi^\tau, x^\tau, \{y_{jt}^\tau\}_{j=1}^J, \{\Omega_j^\tau\}_{j=1}^J$)
 - 2: Initialize non-negative $\mathbf{Q}, \mathbf{W}, \mathbf{H}$ randomly and apply any known prior on $\mathbf{Q}, \mathbf{W}, \mathbf{H}$
 - 3: **repeat**
 - 4: Estimate sources (s_{jfn}), given $\mathbf{Q}, \mathbf{W}, \mathbf{H}, x^\tau, \Xi^\tau, \{y_{jt}^\tau\}_{j=1}^J, \{\Omega_j^\tau\}_{j=1}^J$ with Wiener filtering
 - 5: Apply constraints in the time domain, and estimate posterior power spectra of the sources ($\tilde{\mathbf{P}}$)
 - 6: Update $\mathbf{Q}, \mathbf{W}, \mathbf{H}$ given $\tilde{\mathbf{P}}$ using MU rules
 - 7: **until** convergence criteria met
 - 8: **end procedure**
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