

Generalized Constraints for NMF with Application to Informed Source Separation

Content

1. Introduction

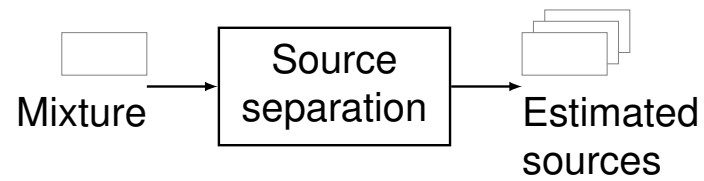
2. NMF-based Informed Source Separation

3. Generalized Constraints for NMF

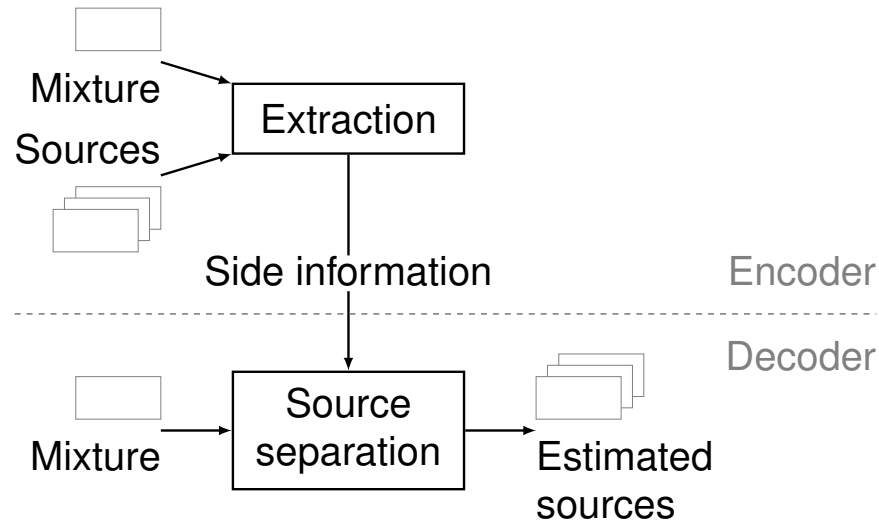
4. Experiments

5. Conclusion

Introduction



Introduction



- Informed source separation (ISS) uses source separation for audio object coding
- Active listening and remixing of music (e.g. karaoke) requires audio objects

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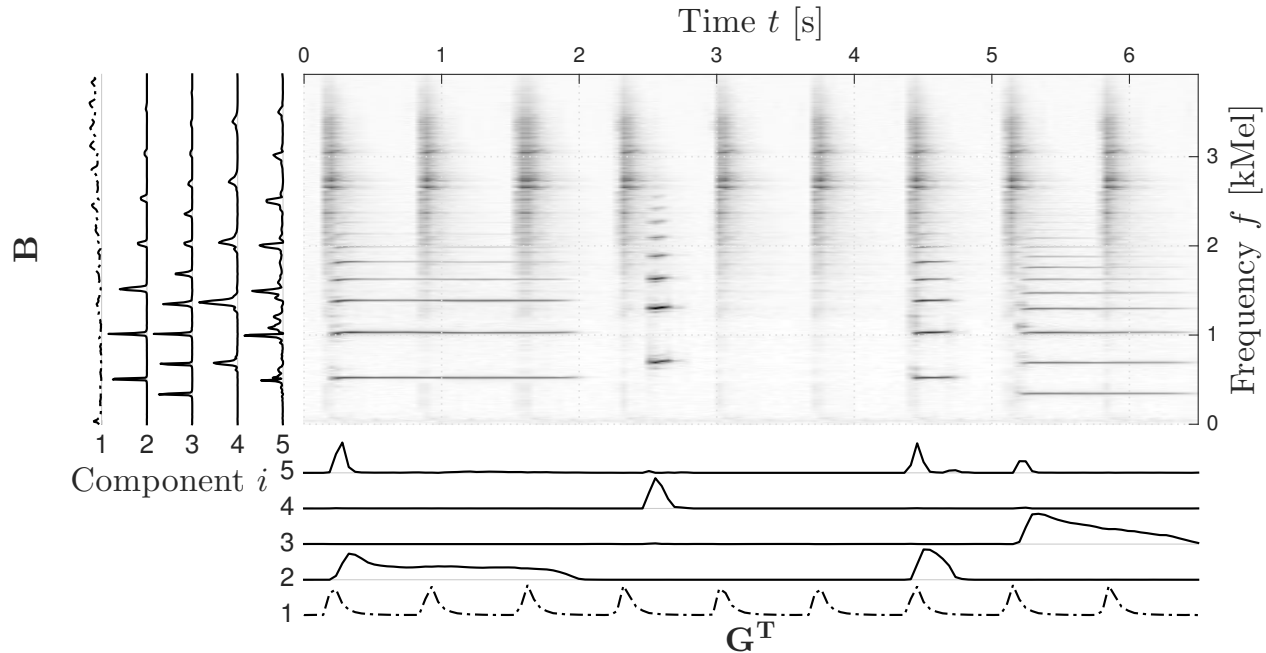
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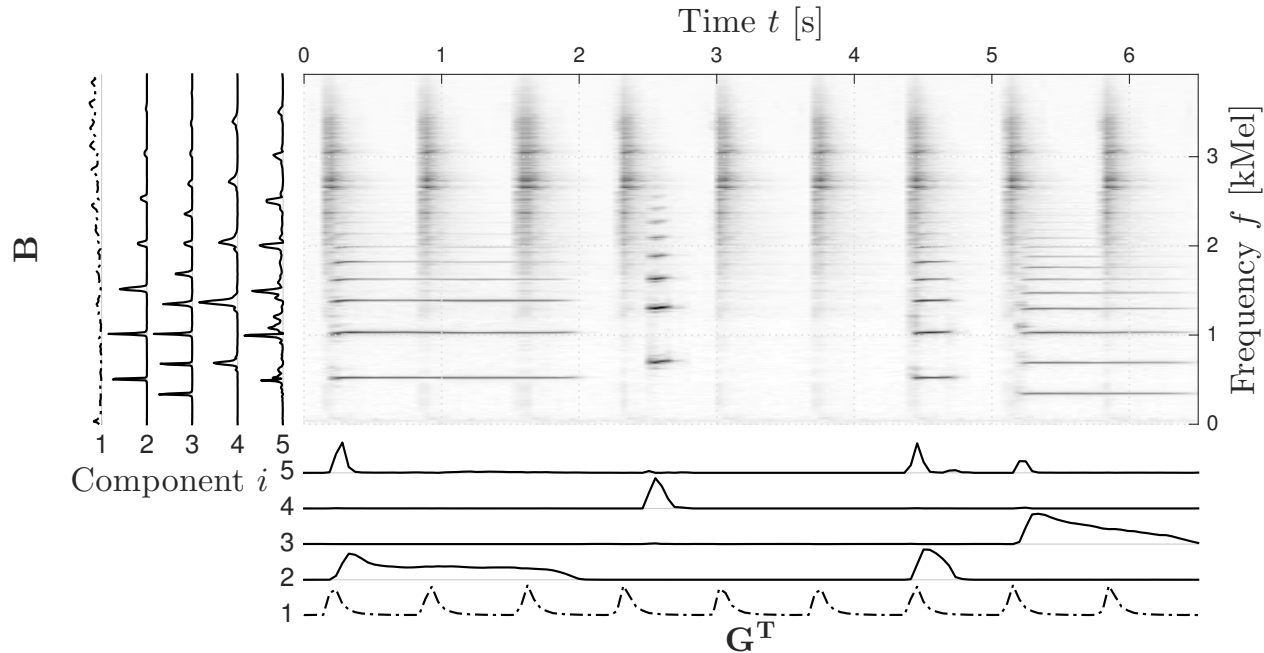
5. Conclusion

Nonnegative matrix factorization



$$\mathbf{X} = |\underline{\mathbf{X}}| \approx \mathbf{B}\mathbf{G}^T, \quad \mathbf{X} \in \mathbb{R}_+^{F \times T}, \mathbf{B} \in \mathbb{R}_+^{F \times I}, \mathbf{G} \in \mathbb{R}_+^{T \times I}$$

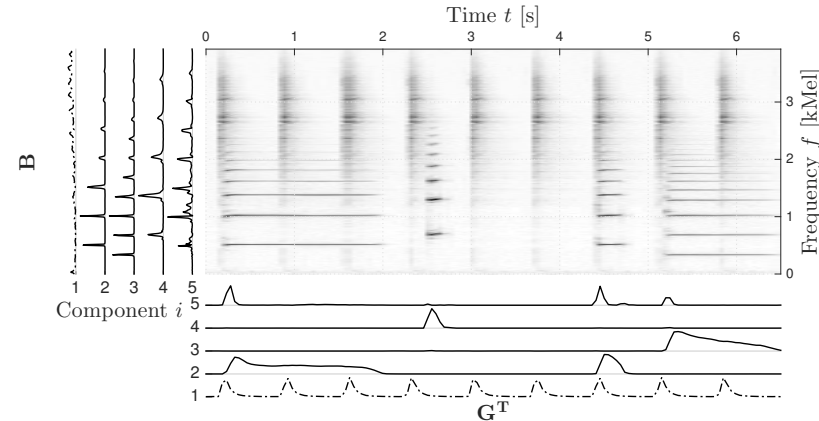
Nonnegative matrix factorization



$$\mathbf{X} = |\underline{\mathbf{X}}| \approx \mathbf{B}\mathbf{G}^T, \quad \mathbf{X} \in \mathbb{R}_+^{F \times T}, \mathbf{B} \in \mathbb{R}_+^{F \times I}, \mathbf{G} \in \mathbb{R}_+^{T \times I}$$

$$\min d_\beta(\mathbf{X}|\mathbf{B}\mathbf{G}^T)$$

Constrained NMF



$$\min d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}}) + \alpha c(\mathbf{G}) + \gamma c(\mathbf{B})$$

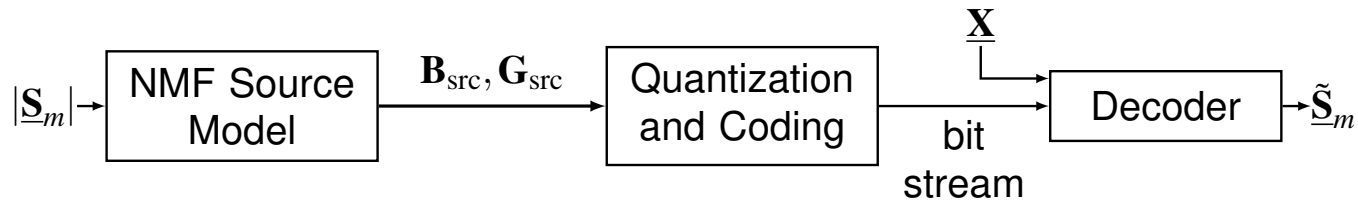
Temporal continuity and temporal sparseness [Virtanen 2007]

$$c_{tc}(\mathbf{G}) = \sum_{i=1}^I \frac{1}{\sigma_i^2} \sum_{t=2}^T [g_{t,i} - g_{t-1,i}]^2 = \sum_i c_{tc}(\mathbf{g}_i)$$

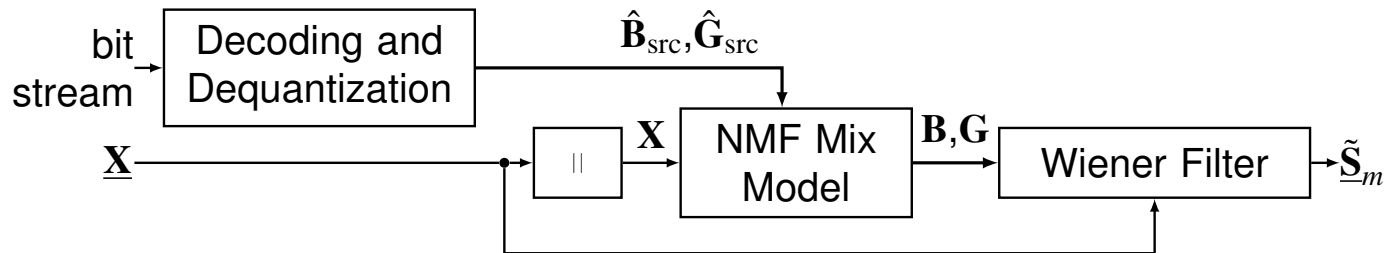
$$c_s(\mathbf{G}) = \sum_{i=1}^I \sum_{t=1}^T \frac{g_{t,i}}{\sigma_i} = \sum_i c_s(\mathbf{g}_i) \quad \text{with } \sigma_i = \sqrt{1/T \sum_t g_{t,i}^2}$$

NMF-based ISS

Encoder



Decoder



[Rohlfing, Becker, Wien 2016]

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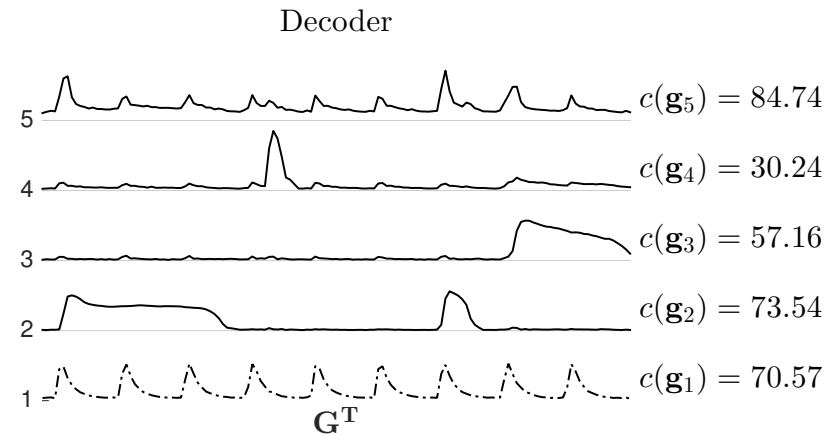
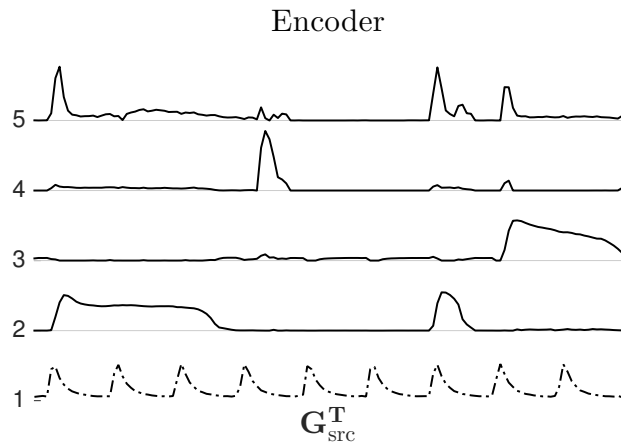
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Generalized Constraints for NMF

Cost function

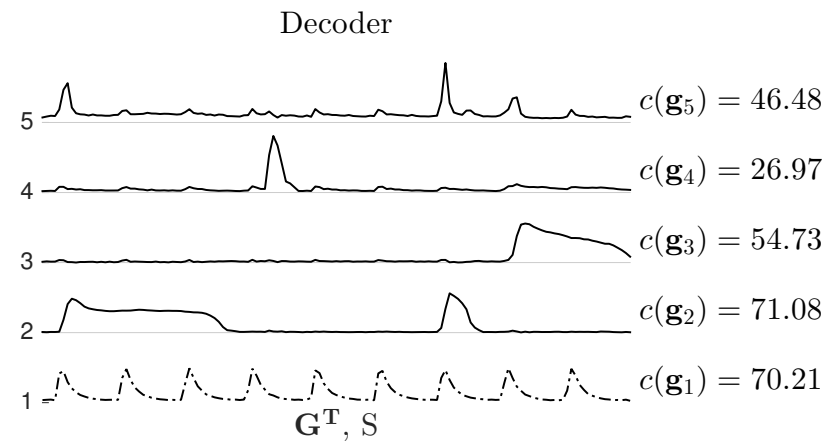
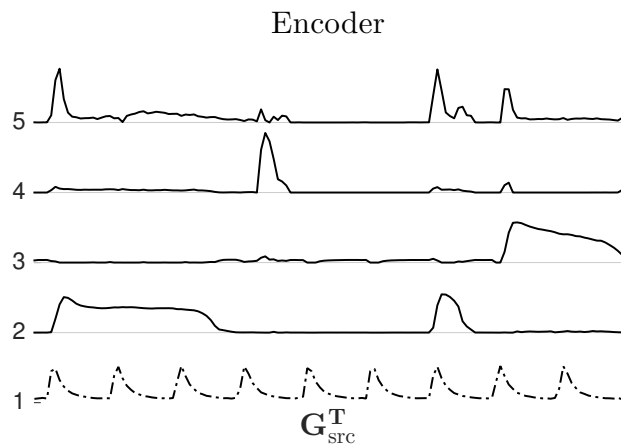
$$\min d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})$$



Generalized Constraints for NMF

Cost function

$$\min d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}}) + \alpha \underbrace{\sum_{i=1}^I c(\mathbf{g}_i)}_{=c(\mathbf{G})}$$

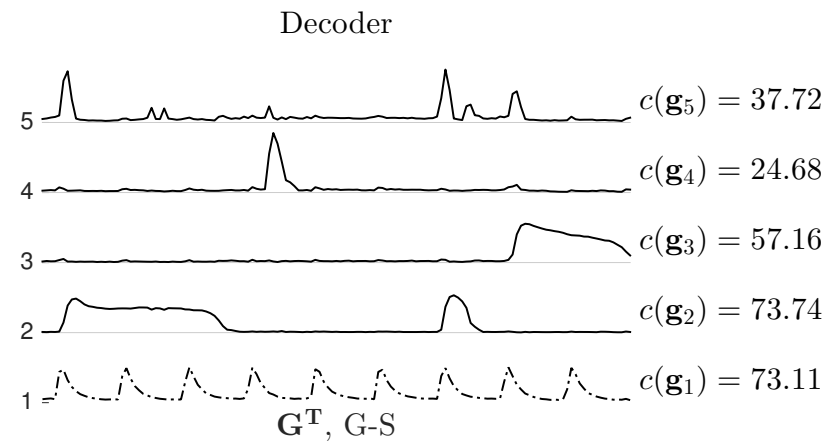
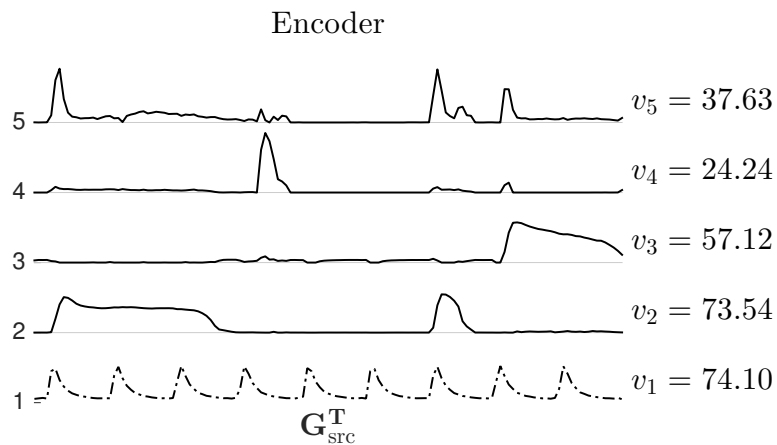


Generalized Constraints for NMF

Cost function

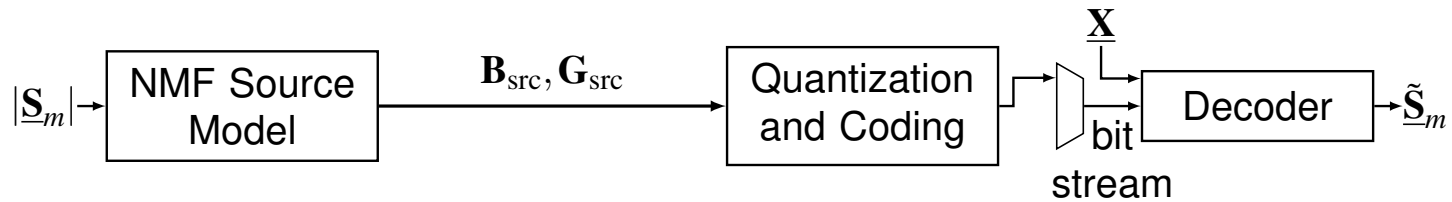
$$\min d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}}) + \alpha \underbrace{\sum_{i=1}^I |c(\mathbf{g}_i) - \hat{v}_i|^p}_{=\bar{c}_p(\mathbf{G})}$$

here: $v_i = c(\mathbf{g}_{\text{src},i})$

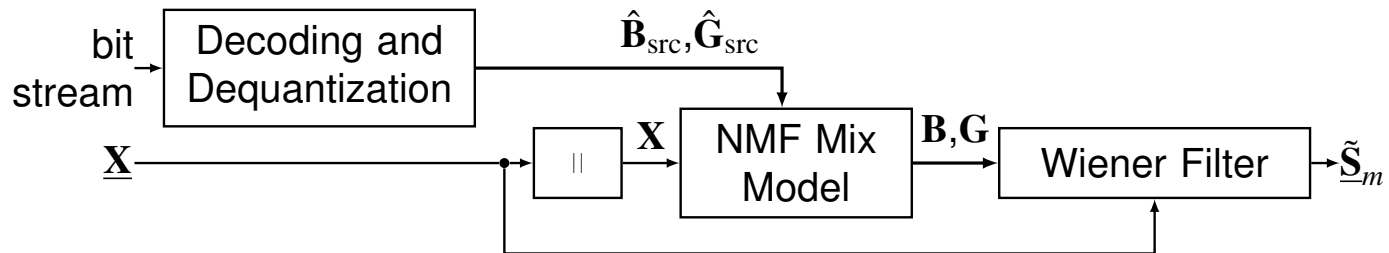


NMF-based ISS – revised

Encoder

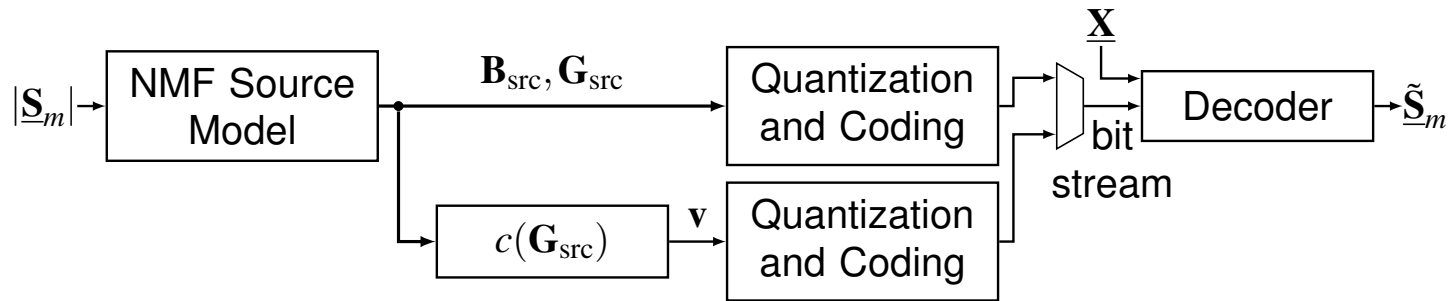


Decoder

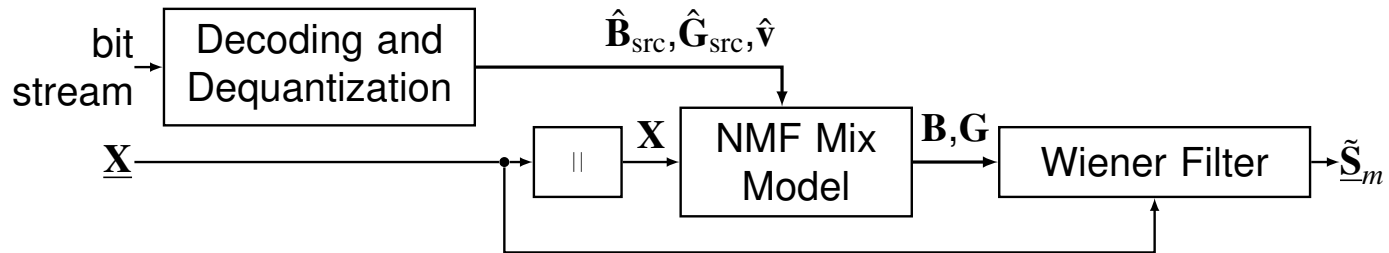


NMF-based ISS – revised

Encoder



Decoder



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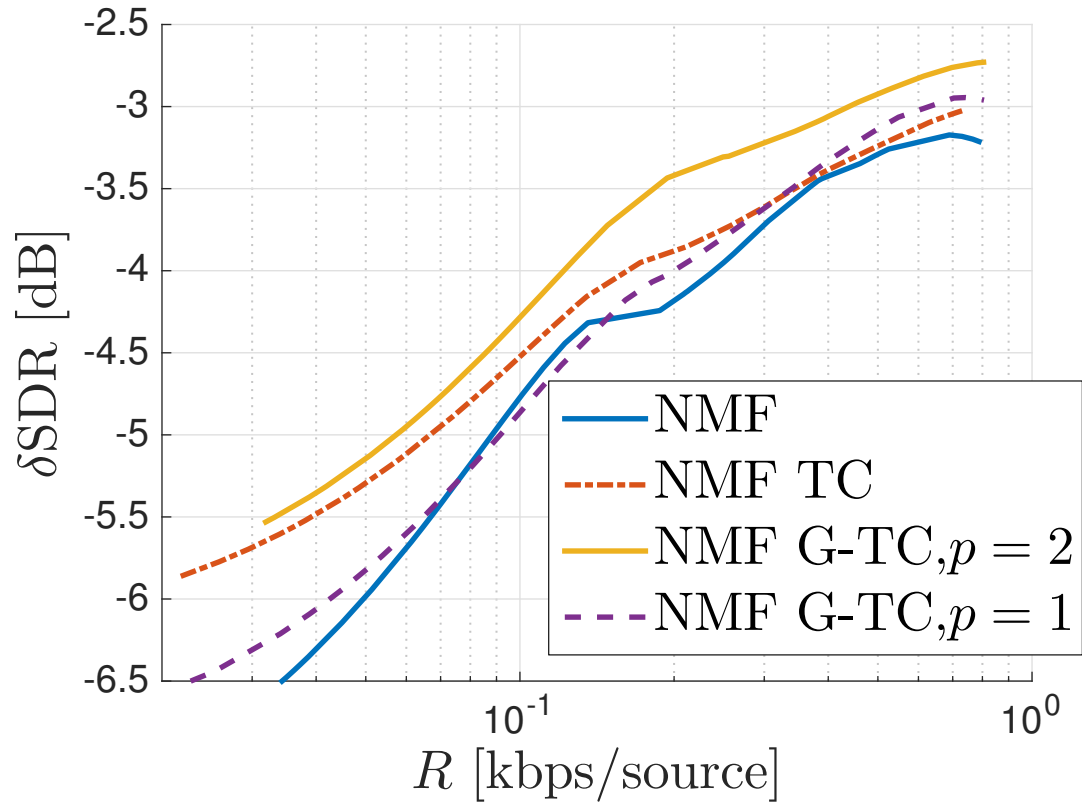
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Setup

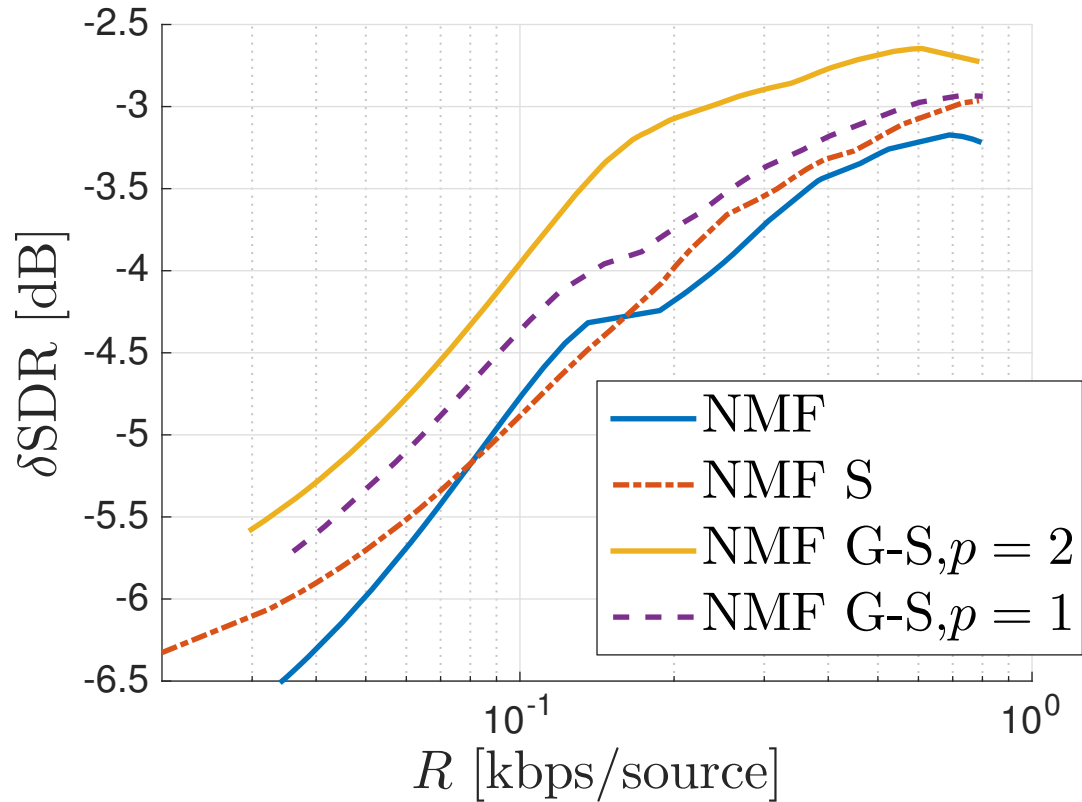
Dataset and metrics

- 5 monaural mixtures from QUASI database (3 to 6 sources), 20s long
- Quality measure: signal-to-distortion ratio (SDR), in relation to oracle SDR (optimal TF-masking): δSDR . Parameter bit rate R in kbps / source.

Results Generalized Temporal Continuity



Results Generalized Temporal Sparseness



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Conclusion and Outlook

Conclusion

- Proposed NMF with generalized constraints
- Generalization due to convergence towards certain target values
- Application to informed source separation

Outlook

- Use generalized constraints for blind source separation
- Transmit target values per NMF iteration

Thank you for your attention

Any questions?

Update rules

Cost function

$$\begin{aligned} & \min d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}}) + c(\mathbf{B}) + c(\mathbf{G}) \\ \text{with } \nabla_{\mathbf{B}}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}}) &= \underbrace{\nabla_{\mathbf{B}}^{+}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})}_{\geq 0} - \underbrace{\nabla_{\mathbf{B}}^{-}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})}_{\geq 0} \\ \nabla_{\mathbf{G}}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}}) &= \dots \\ \nabla_{\mathbf{G}}c(\mathbf{G}) &= \dots \end{aligned}$$

Update rules

$$\begin{aligned} b_{fi} &\leftarrow b_{fi} \frac{[\nabla_{\mathbf{B}}^{-}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})]_{fi}}{[\nabla_{\mathbf{B}}^{+}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})]_{fi}} \\ g_{ti} &\leftarrow g_{ti} \frac{[\nabla_{\mathbf{G}}^{-}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})]_{ti} + \alpha [\nabla_{\mathbf{G}}^{-}c(\mathbf{G})]_{ti}}{[\nabla_{\mathbf{G}}^{+}d_{\beta}(\mathbf{X}|\mathbf{B}\mathbf{G}^{\mathbf{T}})]_{ti} + \alpha [\nabla_{\mathbf{G}}^{+}c(\mathbf{G})]_{ti}} \end{aligned}$$

Update rules generalization

Cost function

$$\min \quad d_\beta(\mathbf{X}|\mathbf{B}\mathbf{G}^T) + \alpha \underbrace{\sum_{i=1}^I |c(\mathbf{g}_i) - \hat{v}_i|^p}_{=\bar{c}_p(\mathbf{G})}$$

Update rules $p = 1$

$$\begin{aligned} [\nabla^+ \bar{c}_1(\mathbf{G})]_{ti} &= \begin{cases} [\nabla^+ c(\mathbf{G})]_{ti} & \text{if } c(\mathbf{g}_i) > \hat{v}_i \\ [\nabla^- c(\mathbf{G})]_{ti} & \text{otherwise.} \end{cases} \\ [\nabla^- \bar{c}_1(\mathbf{G})]_{ti} &= \begin{cases} [\nabla^- c(\mathbf{G})]_{ti} & \text{if } c(\mathbf{g}_i) > \hat{v}_i \\ [\nabla^+ c(\mathbf{G})]_{ti} & \text{otherwise.} \end{cases} \end{aligned}$$

Update rules $p = 2$

$$\begin{aligned} [\nabla^+ \bar{c}_2(\mathbf{G})]_{ti} &= 2 \left\{ c(\mathbf{g}_i) [\nabla^+ c(\mathbf{G})]_{ti} + \hat{v}_i [\nabla^- c(\mathbf{G})]_{ti} \right\} \\ [\nabla^- \bar{c}_2(\mathbf{G})]_{ti} &= 2 \left\{ c(\mathbf{g}_i) [\nabla^- c(\mathbf{G})]_{ti} + \hat{v}_i [\nabla^+ c(\mathbf{G})]_{ti} \right\} . \end{aligned}$$