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Frequency Domain Source Separation

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Outline

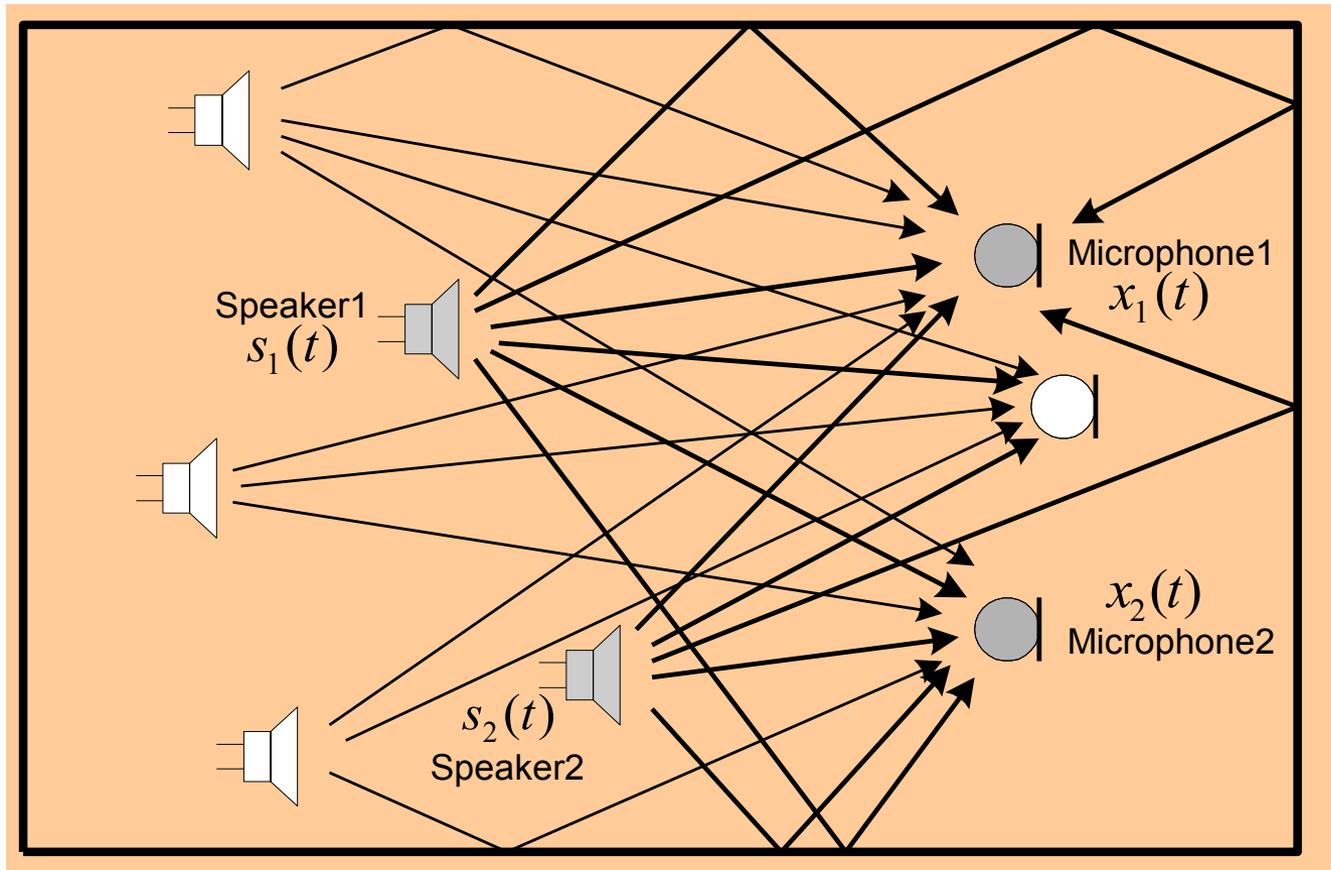


- ❑ Speech separation and cocktail party problem as an example
- ❑ Convolutional source separation and frequency domain methods
- ❑ Computational auditory scene analysis and ideal binary mask
- ❑ Convolutional ICA (in frequency domain) and binary masking
- ❑ Ideal ratio mask and kurtosis ratio
- ❑ Soft time-frequency mask: A model based approach for stereo source separation (determined and underdetermined)
- ❑ Sparse representation and dictionary learning for source separation
- ❑ Underwater acoustic source localisation/separation

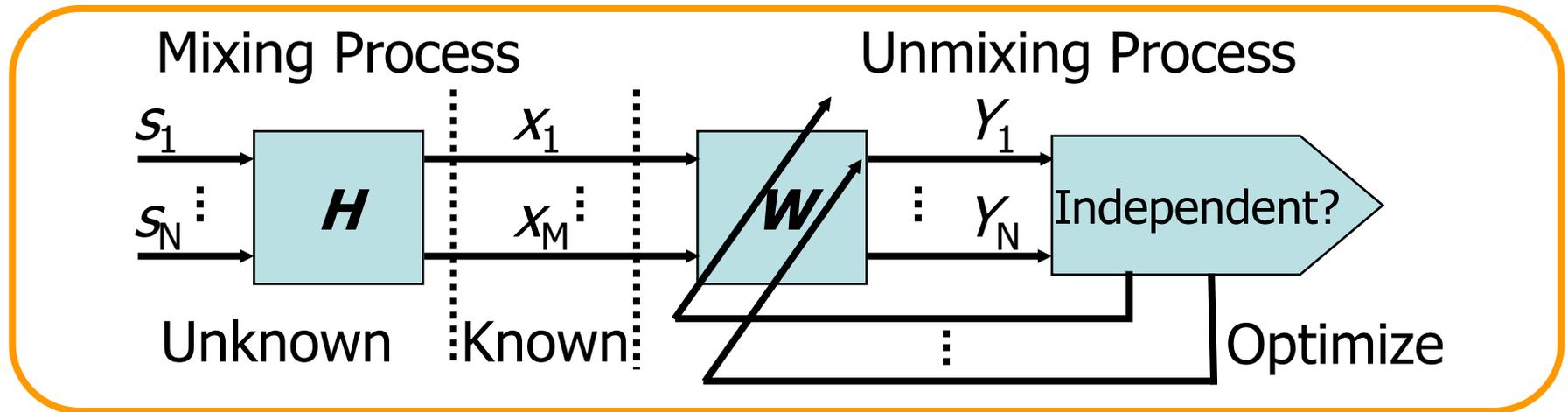
Speech separation problem

- In a natural environment, target speech is usually corrupted by acoustic interference, creating a speech segregation problem
 - Also known as *cocktail-party problem* (Cherry'53) or *ball-room problem* (Helmholtz, 1863)
 - Speech segregation is critical for many applications, such as automatic speech recognition and hearing prosthesis
- Potential techniques for the speech separation problem
 - Beamforming
 - Blind source separation
 - Speech enhancement
 - Computational auditory scene analysis
- “No machine has yet been constructed to do just that [solving the cocktail party problem].” (Cherry'57)

Cocktail party problem



Blind source separation & independent component analysis



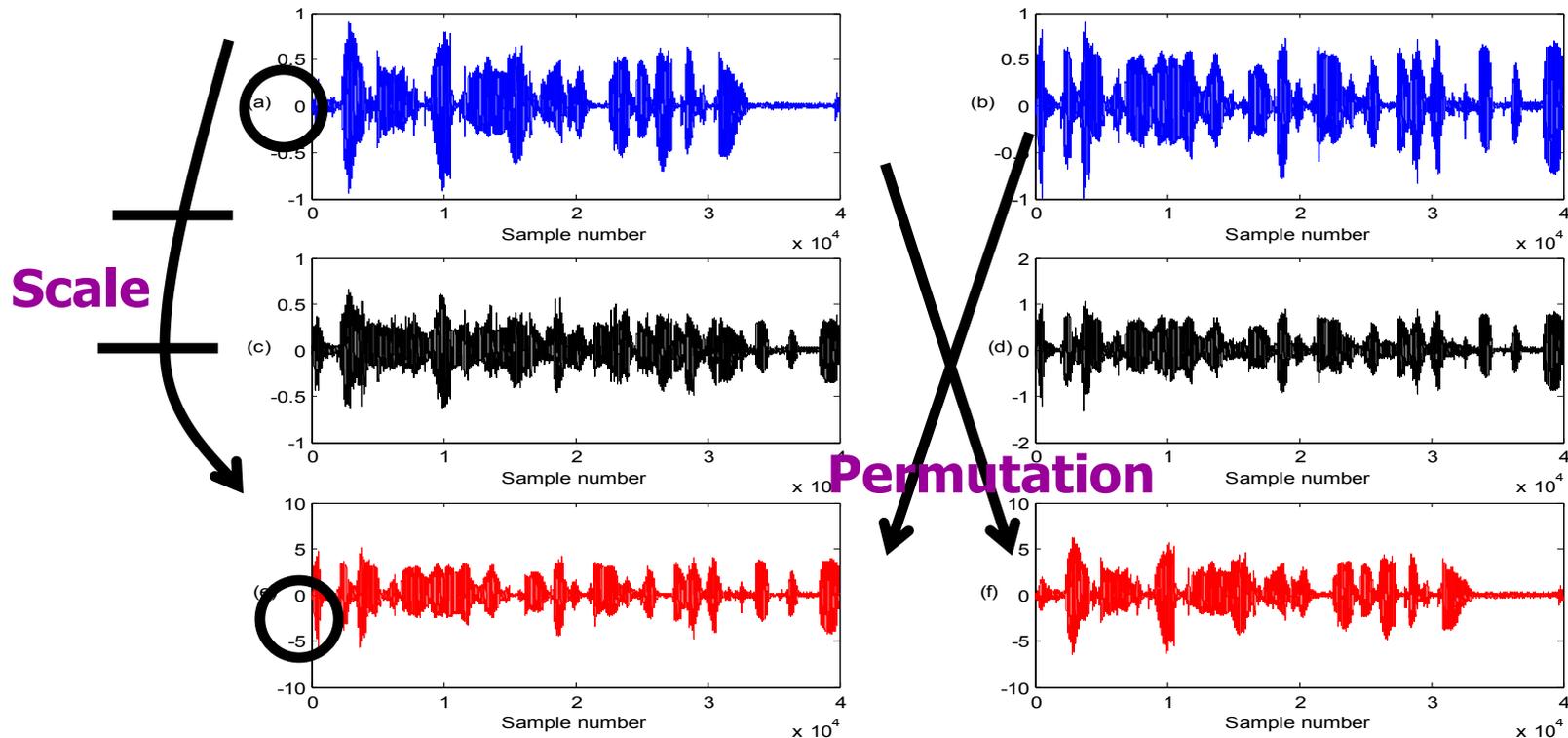
Mixing Model: $\mathbf{x} = \mathbf{H}\mathbf{s}$

De-mixing Model: $\mathbf{y} = \mathbf{W}\mathbf{x} = \mathbf{W}\mathbf{H}\mathbf{s} = \mathbf{P}\mathbf{D}\mathbf{s}$

Diagonal Scaling Matrix

Permutation Matrix

Scale and permutation ambiguities: an example



Blind source separation for instantaneous mixtures with the JADE algorithm (SNR=30dB): (a)(b) original sources; (c)(d) mixtures; (e)(f) separated sources

Convolutional BSS: mathematical model

Compact form: $\mathbf{x} = \mathbf{H} \circledast \mathbf{s}$ **Convolution**

$$\begin{bmatrix} H_{11}(t) & \cdots & H_{1N}(t) \\ \vdots & \ddots & \vdots \\ H_{M1}(t) & \cdots & H_{MN}(t) \end{bmatrix} \begin{bmatrix} s_1(t) \\ \vdots \\ s_N(t) \end{bmatrix} = \begin{bmatrix} x_1(t) \\ \vdots \\ x_M(t) \end{bmatrix}$$

Expansion form:
$$x(n) = \sum_{j=1}^N \sum_{p=0}^{P-1} h_{ij}(p) s_j(n-p)$$

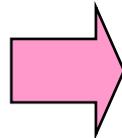
Transform convolutive BSS into the frequency domain

$$\mathbf{x} = \mathbf{H} * \mathbf{s}$$

DFT

$$\begin{bmatrix} x_1(\omega) \\ \vdots \\ x_M(\omega) \end{bmatrix} = \begin{bmatrix} H_{11}(\omega) & \cdots & H_{1N}(\omega) \\ \vdots & \ddots & \vdots \\ H_{M1}(\omega) & \cdots & H_{MN}(\omega) \end{bmatrix} \cdot \begin{bmatrix} s_1(\omega) \\ \vdots \\ s_N(\omega) \end{bmatrix}$$

Convolutive
BSS problem



Multiple complex-valued
instantaneous BSS problems

De-mixing operation

$$\mathbf{Y}(\omega, t) = \mathbf{W}(\omega)\mathbf{X}(\omega, t) \quad \forall \omega$$

where $\mathbf{W}(\omega) \in C^{N \times M} \quad \forall \omega$

$$\mathbf{Y}(\omega, t) = [Y_1(\omega, t), \dots, Y_N(\omega, t)]^T \in C^N$$

Parameters in $\mathbf{W}(\omega)$ determined such that $Y_1(\omega, t), \dots, Y_N(\omega, t)$ become mutually independent.

L. Parra and C. Spence, "Convolutional blind source separation of nonstationary sources," *IEEE Trans. Speech Audio Process.*, vol. 8, no. 3, pp. 320–327, May 2000.

Exploiting the non-stationarity of signals measured by the cross-spectrum of the output signals,

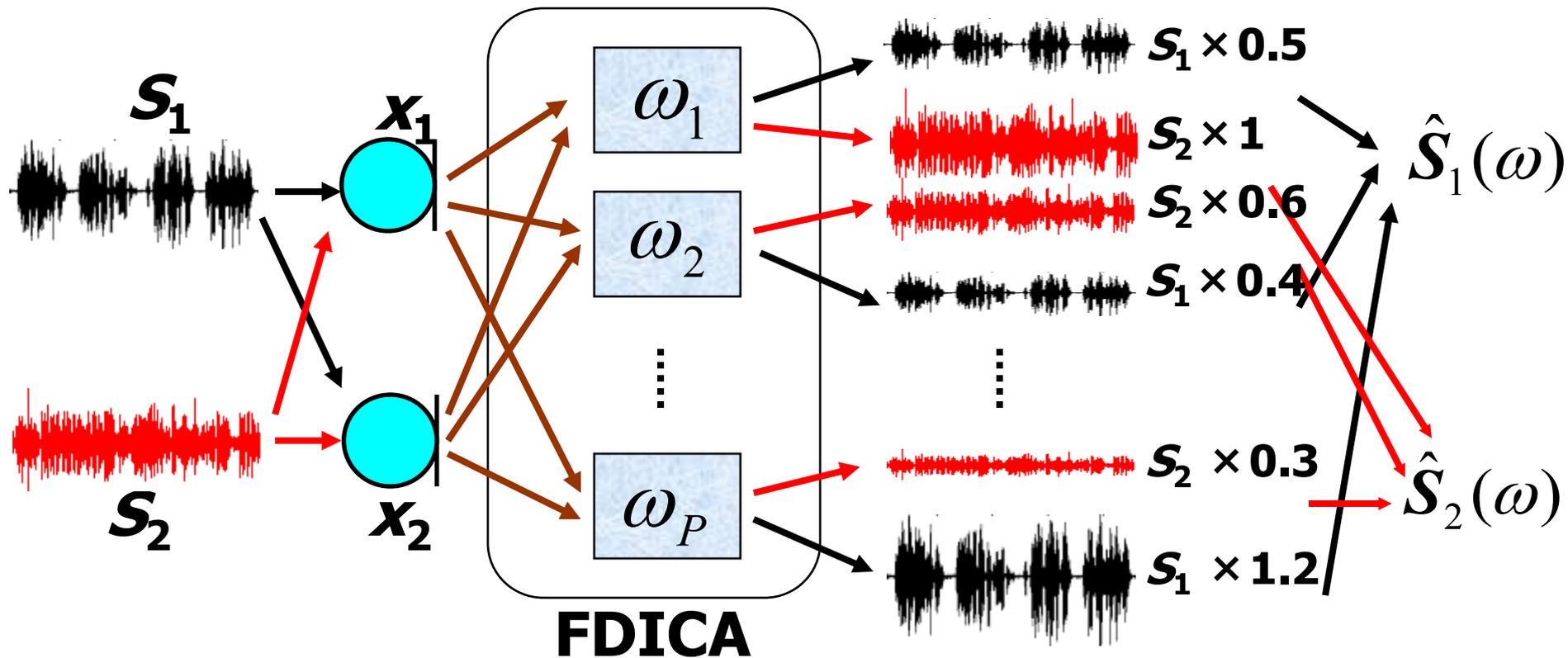
$$\mathbf{R}_Y(\omega, k) = \mathbf{W}(\omega)[\mathbf{R}_X(\omega, k)]\mathbf{W}^H(\omega)$$

Cost Function:

$$J(\mathbf{W}(\omega)) = \arg \min_{\mathbf{W}} \sum_{\omega=1}^T \sum_{t=1}^K F(\mathbf{W})(\omega, t)$$

where $F(\mathbf{W})(\omega, t) = \|\mathbf{R}_Y(\omega, t) - \text{diag}[\mathbf{R}_Y(\omega, t)]\|_F^2$

Frequency domain BSS & permutation problem

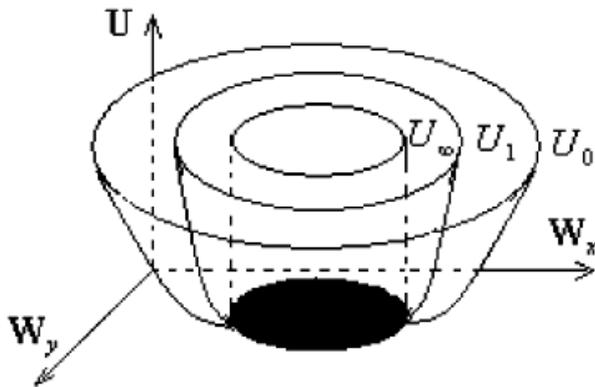


Solutions:

- Beamforming
- Spectral envelope correlation

Constrained convolutive ICA: penalty function approach

- Introducing additional constraints could further improve the separation performance, such as unitary and non-unitary constraints to prevent the degenerate trivial solutions to the unmixing matrix, as shown in Wang et al. (2005).
- Penalty function can be used to convert the constrained optimisation problem into an unconstrained one.



$$\mathfrak{J}(\mathbf{W}(\omega)) = \mathcal{J}(\bar{\mathbf{W}}(\omega)) + \sum_{i=1}^r \kappa_i \mathcal{U}_i(\mathbf{W}(\omega))$$

$$\mathfrak{J}(\mathbf{W}) = \operatorname{argmin}_{\mathbf{W}} \sum_{\omega=1}^T \sum_{k=1}^K \{ \mathcal{F}(\mathbf{W})(\omega, k) + \kappa \mathcal{G}(\mathbf{W})(\omega, k) \}$$

Sound demonstration

	Sources	Mixtures	Parra&Spence	Our approach
Two speaking sentences artificially mixed together				
				
A man speaking with TV on				
				

W. Wang, S. Sanei, and J. A. Chambers, Penalty function based joint diagonalization approach for convolutive blind separation of nonstationary sources, in IEEE Trans. Signal Processing, vol. 53, no. 5, pp. 1654-1669, May 2005.

Auditory scene analysis



- Listeners parse the complex mixture of sounds arriving at the ears in order to form a mental representation of each sound source
- This perceptual process is called auditory scene analysis (Bregman'90)
- Two conceptual processes of auditory scene analysis (ASA):
 - **Segmentation.** Decompose the acoustic mixture into sensory elements (segments)
 - **Grouping.** Combine segments into groups, so that segments in the same group likely originate from the same sound source

Computational auditory scene analysis (CASA)

- Computational auditory scene analysis (CASA) approaches sound separation based on ASA principles
 - Feature based approaches
 - Model based approaches
- CASA has made significant advances in speech separation using monaural and binaural analysis
- CASA challenges
 - Reliable pitch tracking of noisy speech
 - Unvoiced speech
 - Room reverberation

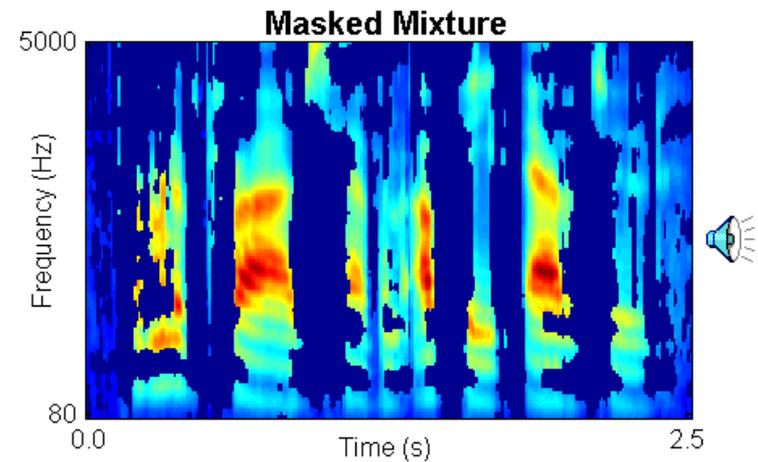
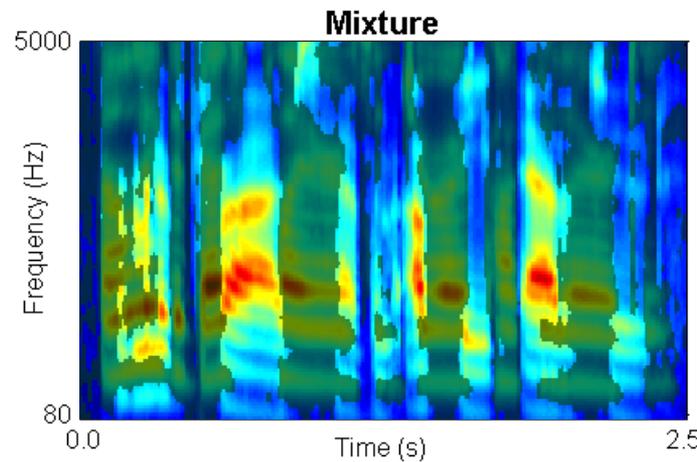
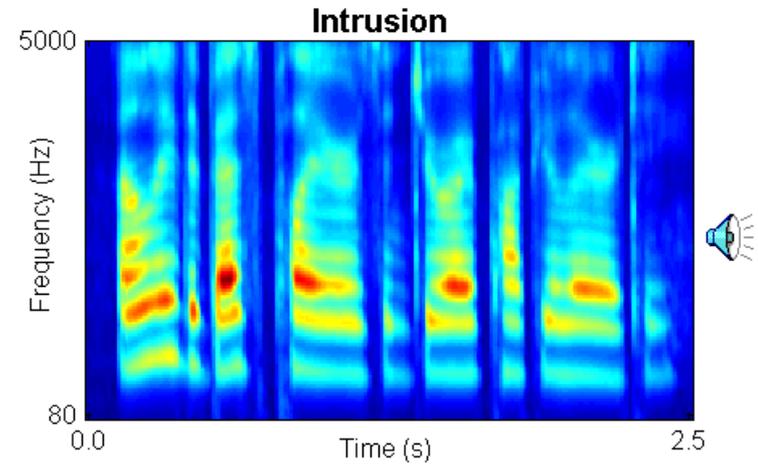
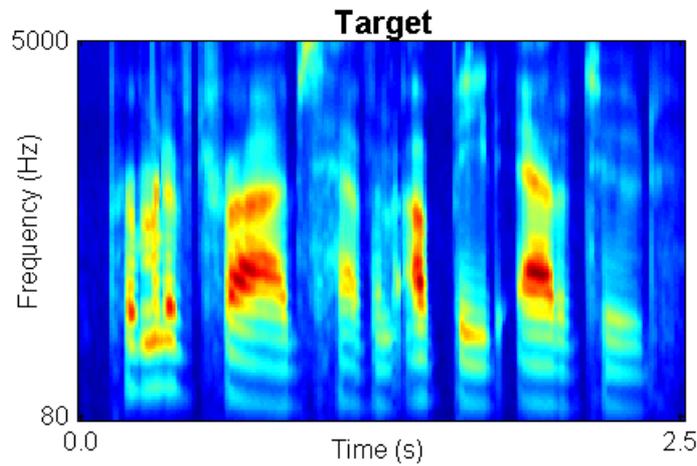
Ideal binary mask (IBM)

- Auditory masking phenomenon: In a narrowband, a stronger signal masks a weaker one
- Motivated by the auditory masking phenomenon, the ideal binary mask has been suggested as a main goal of CASA (D.L. Wang'05)
- The definition of the ideal binary mask

$$m(t, f) = \begin{cases} 1 & \text{if } s(t, f) - n(t, f) \geq \theta \\ 0 & \text{otherwise} \end{cases}$$

- $s(t, f)$: Target energy in unit (t, f)
- $n(t, f)$: Noise energy
- θ : A local SNR criterion in dB, which is typically chosen to be 0 dB
- Optimality: Under certain conditions the ideal binary mask with $\theta = 0$ dB is the optimal binary mask from the perspective of SNR gain
- It does not actually separate the mixture!

IBM illustration (after DeLiang Wang)

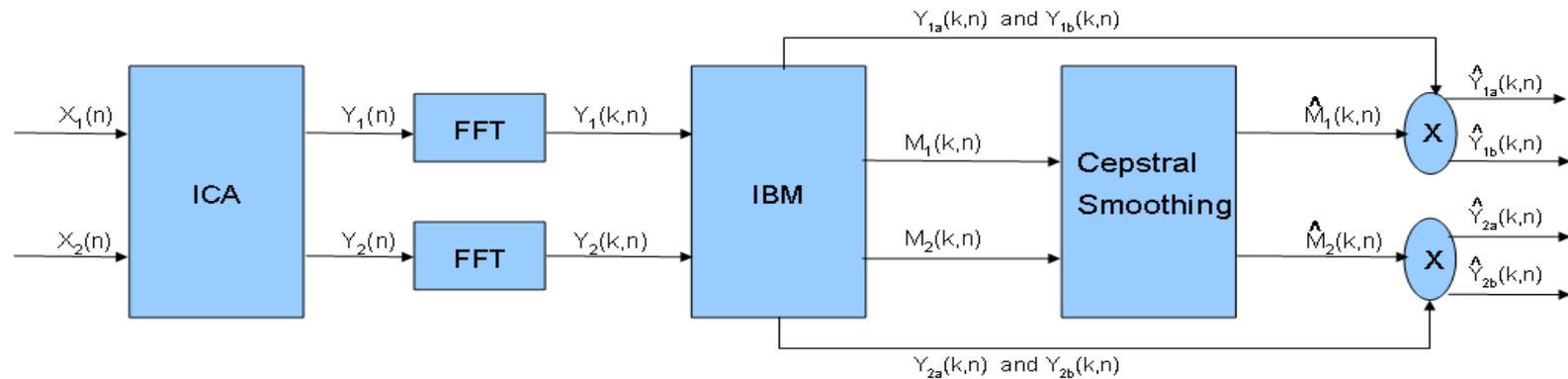


Recent psychophysical tests show that the ideal binary mask results in dramatic speech intelligibility improvements (Brungart et al.'06; Li & Loizou'08)

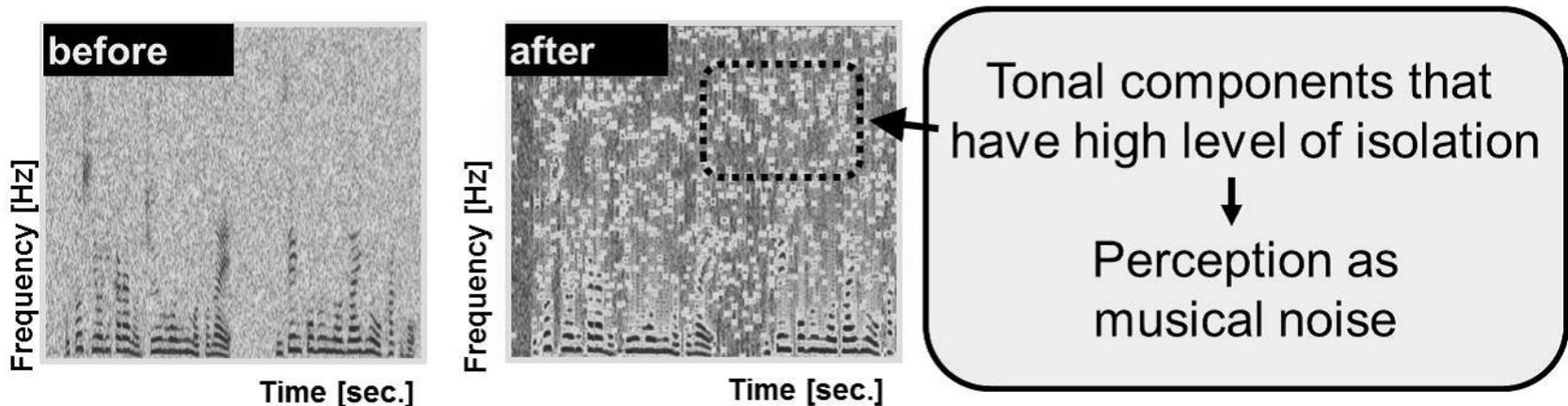
ICA versus IBM

- ICA: Excellent performance if (no or low) reverberation or noise is present in the mixture. For highly reverberant and noisy mixtures, the performance is limited.
- IBM: Excellent performance if both target and background interference are known. Otherwise, the IBM has to be estimated from the acoustic mixture, which however remains an open challenging task!

A multistage approach fusing ICA and IBM



Musical noise



Example of musical noise generation: the input signal on the left plot is corrupted by white Gaussian noise, and the output signal on the right plot is obtained by applying a source separation algorithm to the input. Figure due to Saruwatari and Miyazaki (2014)

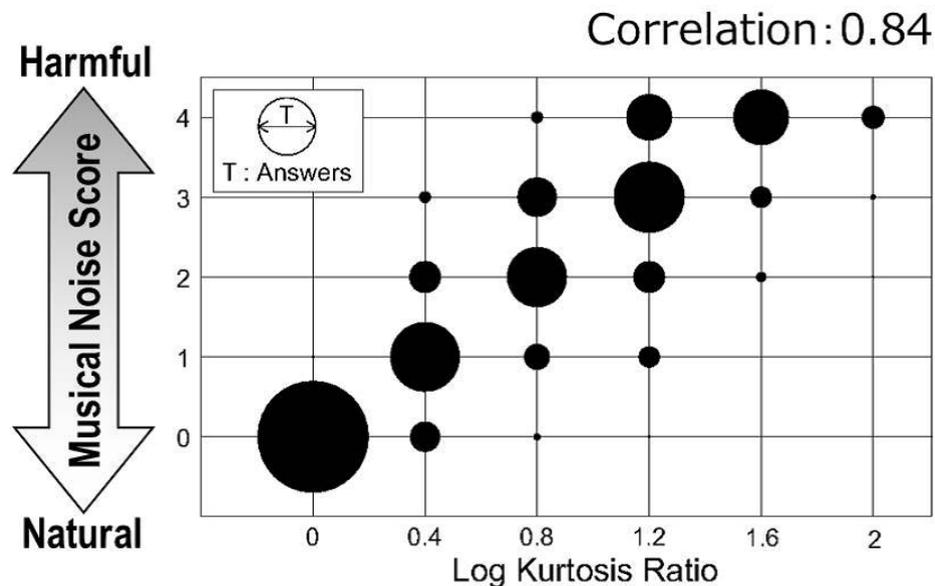
H. Saruwatari and R. Miyazaki, "Statistical analysis and evaluation of blind speech extraction algorithms," in G. Naik and W. Wang (eds), *Blind Source Separation: Advances in Theory, Algorithms and Applications*, Springer, May, 2014

Kurtosis ratio

$$\text{kurtosis ratio} = \frac{\text{kurt}_{\text{proc}}}{\text{kurt}_{\text{org}}},$$

$$\text{kurt} = \frac{\mu_4}{\mu_2^2},$$

$$\mu_m = \int_0^\infty x^m P(x) dx,$$



Relation between kurtosis ratio and human perceptual score of degree of musical noise generation. Figure due to Saruwatari et al. (2014).

H. Saruwatari and R. Miyazaki, "Statistical analysis and evaluation of blind speech extraction algorithms," in G. Naik and W. Wang (eds), *Blind Source Separation: Advances in Theory, Algorithms and Applications*, Springer, May, 2014

Cepstral smoothing to mitigate musical noise

Converting mask from spectral domain to cepstral domain:

$$M_i^c(l, m) = DFT^{-1} \{ \ln(M_i^f(k, m)) |_{k=0, \dots, K-1} \},$$

Smoothing with various smoothing level to different frequency bands (low smoothing to envelop and pitch band to maintain its structure, more smoothing to other band to remove the artefacts):

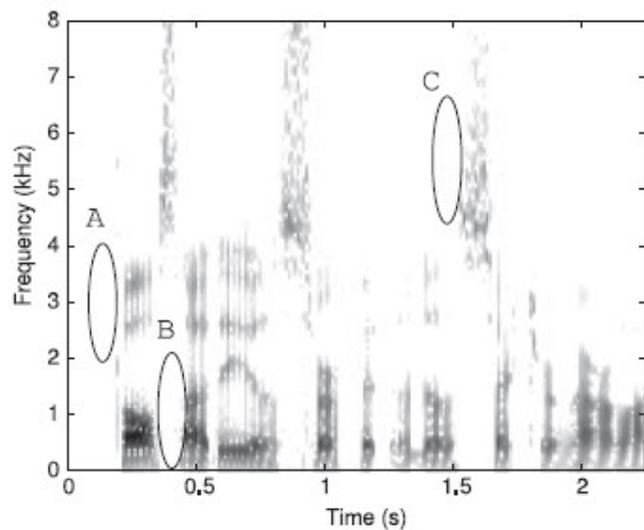
$$\bar{M}_i^s(l, m) = \gamma_l \bar{M}_i^s(l, m-1) + (1 - \gamma_l) M_i^c(l, m) \quad i = 1, 2,$$

$$\gamma_l = \begin{cases} \gamma_{env} & \text{if } l \in \{0, \dots, l_{env}\}, \\ \gamma_{pitch} & \text{if } l = l_{pitch}, \\ \gamma_{peak} & \text{if } l \in \{(l_{env} + 1), \dots, K\} \setminus l_{pitch}, \\ & l_{pitch} = \operatorname{argmax}_l \{ Y^c(l, m) | l_{low} \leq l \leq l_{high} \}, \end{cases}$$

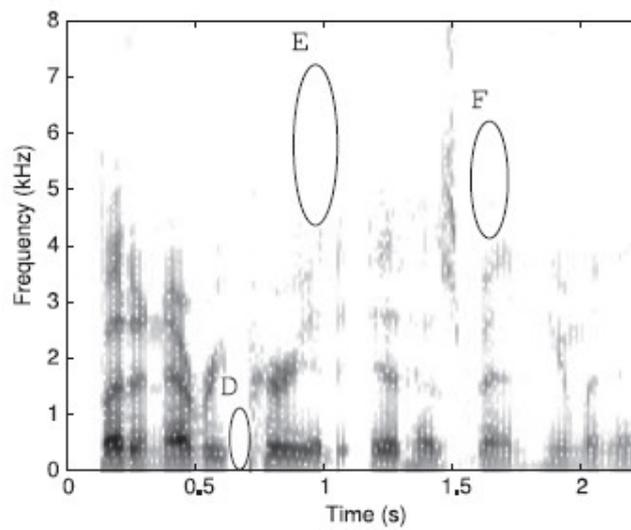
Transform back to the spectral domain:

$$\bar{M}_i^f(k, m) = \exp(DFT \{ \bar{M}_i^s(l, m) |_{l=0, \dots, K-1} \}).$$

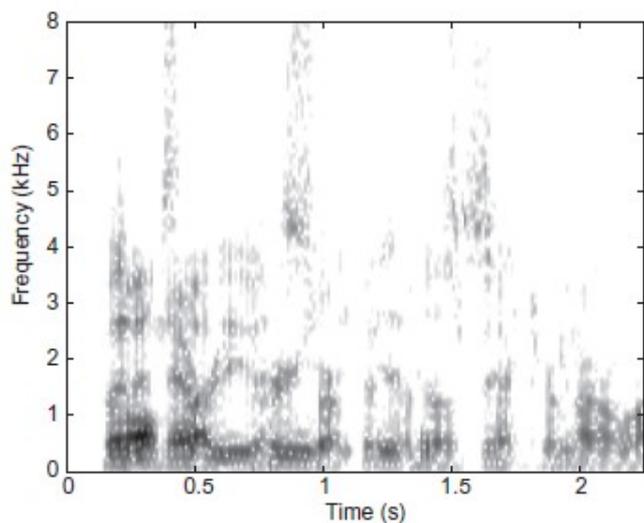
Sources and mixtures



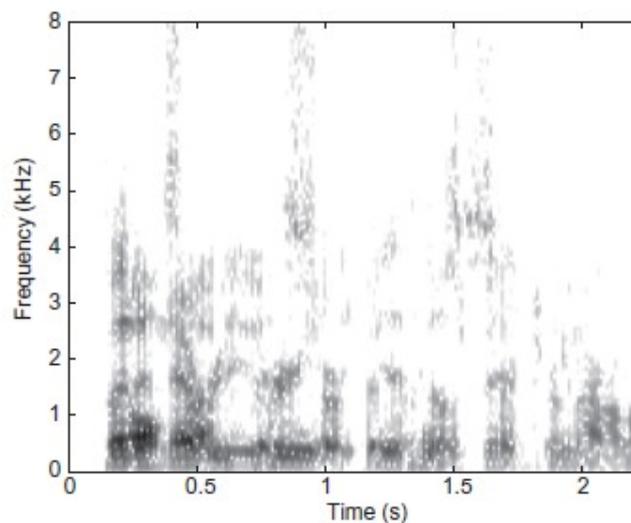
(a)



(b)



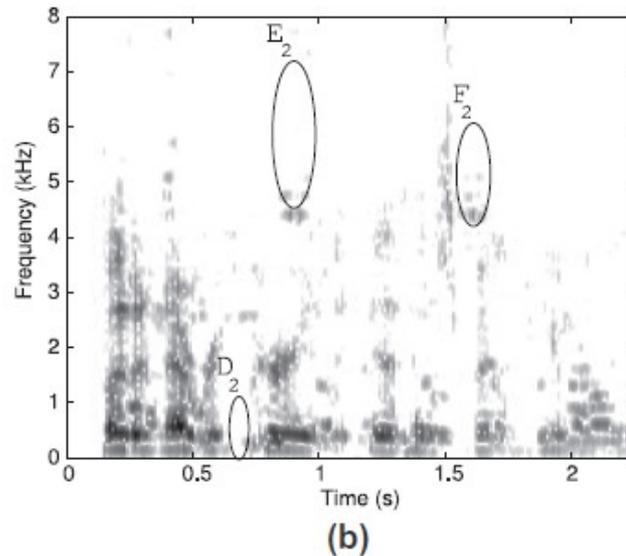
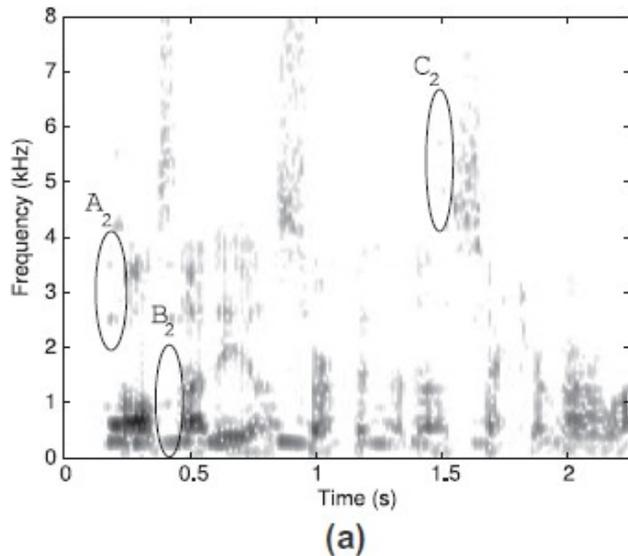
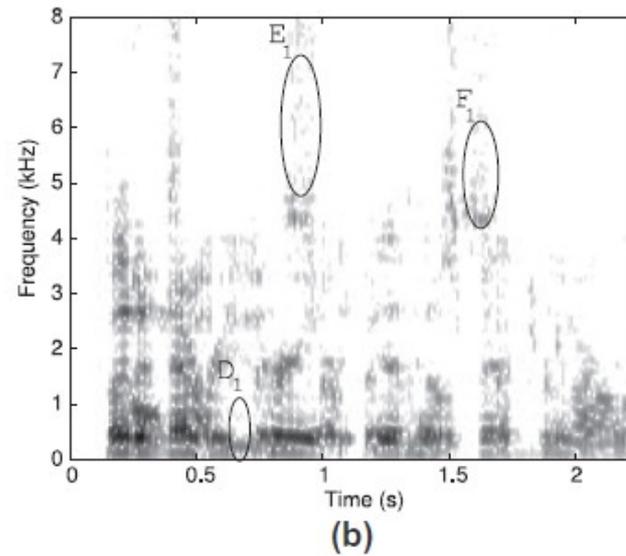
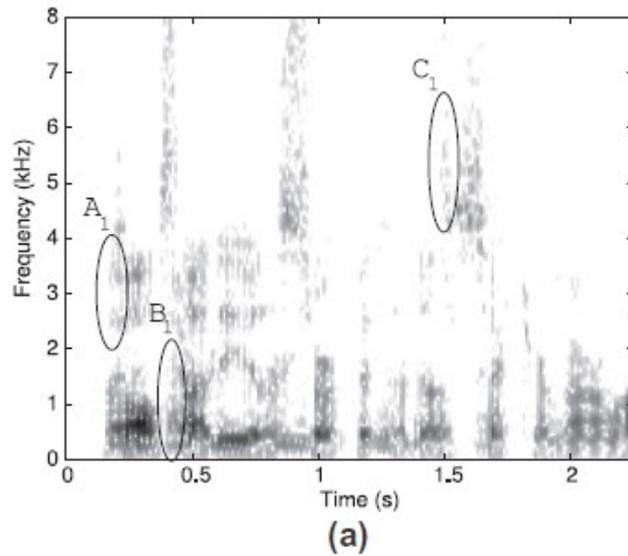
(a)



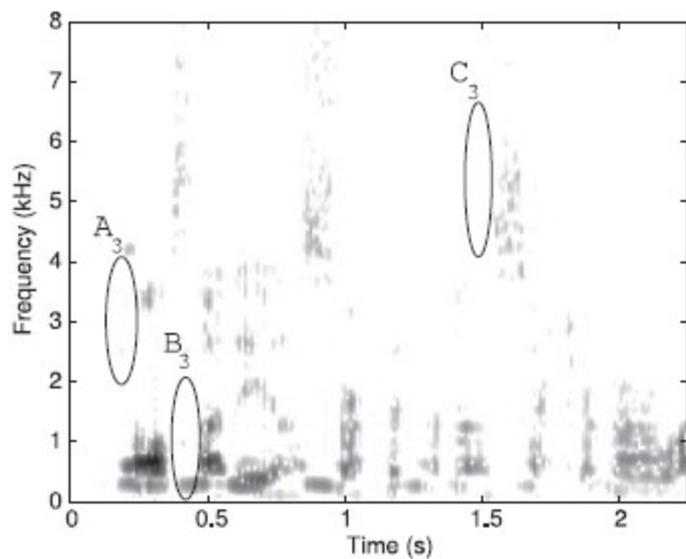
(b)

$T_{60} = 100\text{ms}$
Simulated using
room image
model

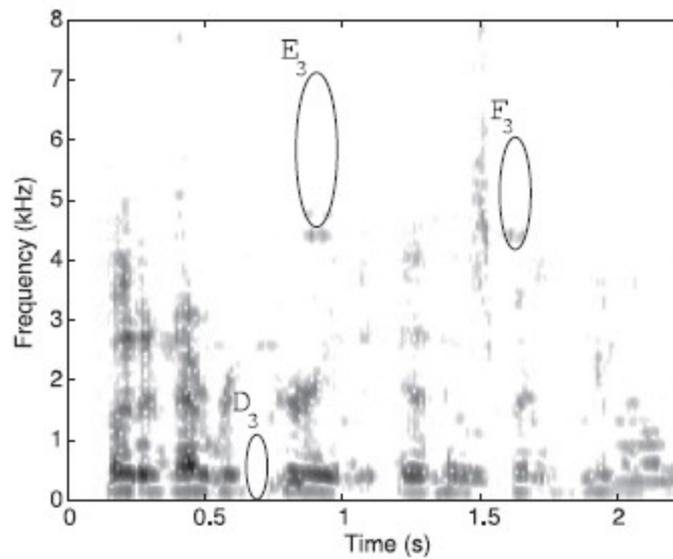
Output of convolutive ICA and IBM



Output of cepstral smoothing



(a)



(b)

Sound demos: simulated reverberant mixtures

	Mixtures $RT_{60}=30\text{ms}$	ConvICA	Estimated IBM	Smoothed IBM
Speakers				
				
	Mixtures $RT_{60}=150\text{ms}$	ConvICA	Estimated IBM	Smoothed IBM
				
				
	Mixtures $RT_{60}=400\text{ms}$	ConvICA	Estimated IBM	Smoothed IBM
				
				

Sound demos: real reverberant mixtures

Separated source signals

Sensor signals



Conv. ICA

Conv. ICA
+IBM

Conv. ICA
+IBM+Cepstral
Smoothing

T. Jan, W. Wang, and D.L. Wang, "A Multistage Approach to Blind Separation of Convolutional Speech Mixtures," *Speech Communication*, vol. 53, pp. 524-539, 2011.

Limitation of the IBM

- Processing artefacts such as musical noise appears to have a deleterious effect on the audio quality of the separated output.
- Not problematic for applications where the output is not auditioned (such as ASR or databasing tasks), but may be problematic for applications (such as speech enhancement or auditory scene reconstruction) where the audio quality is important.
- Recent tests by Hummersone et al. (2014) show that even though the BM gives higher SNR to many other BSS techniques, it gives poorer overall perceptual score (OPS) as compared with these BSS techniques.

C. Hummersone, T. Stokes, and T. Brookes, "On the ideal ratio mask as the goal of computational auditory scene analysis," in *Blind Source Separation: Advances in Theory, Algorithms and Applications*, G. Naik, and W. Wang (ed). , Springer, May, 2014.

Ideal ratio mask (IRM)

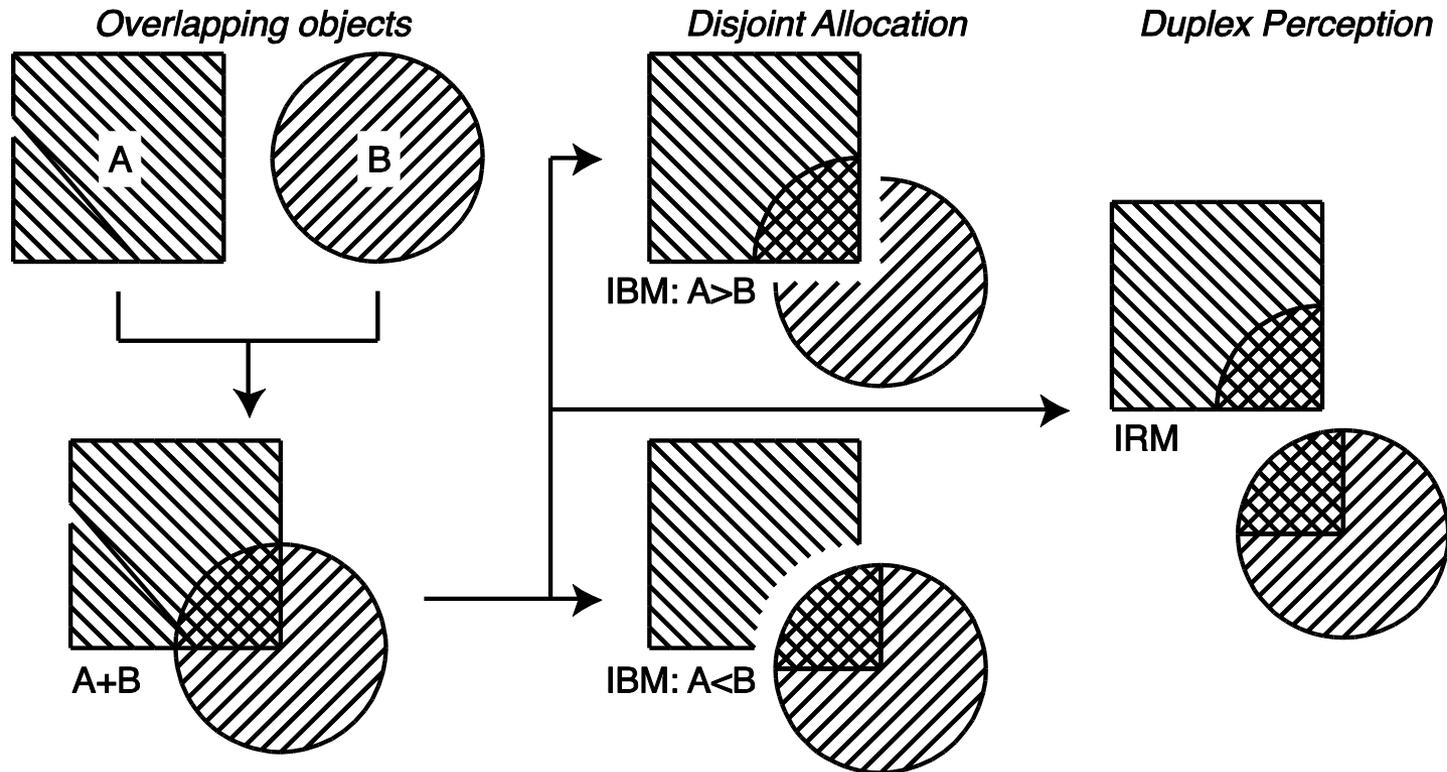
$$m(t, f) = \frac{s(t, f)}{s(t, f) + n(t, f)}$$

S. Srinivasan, N. Roman, and D. Wang, "Binary and ratio time-frequency masks for robust speech recognition," *Speech Commun.*, vol. 48, no. 11, pp. 1486-1501, 2006.

In terms of Hummersone et al. (2014), IRM has the following properties:

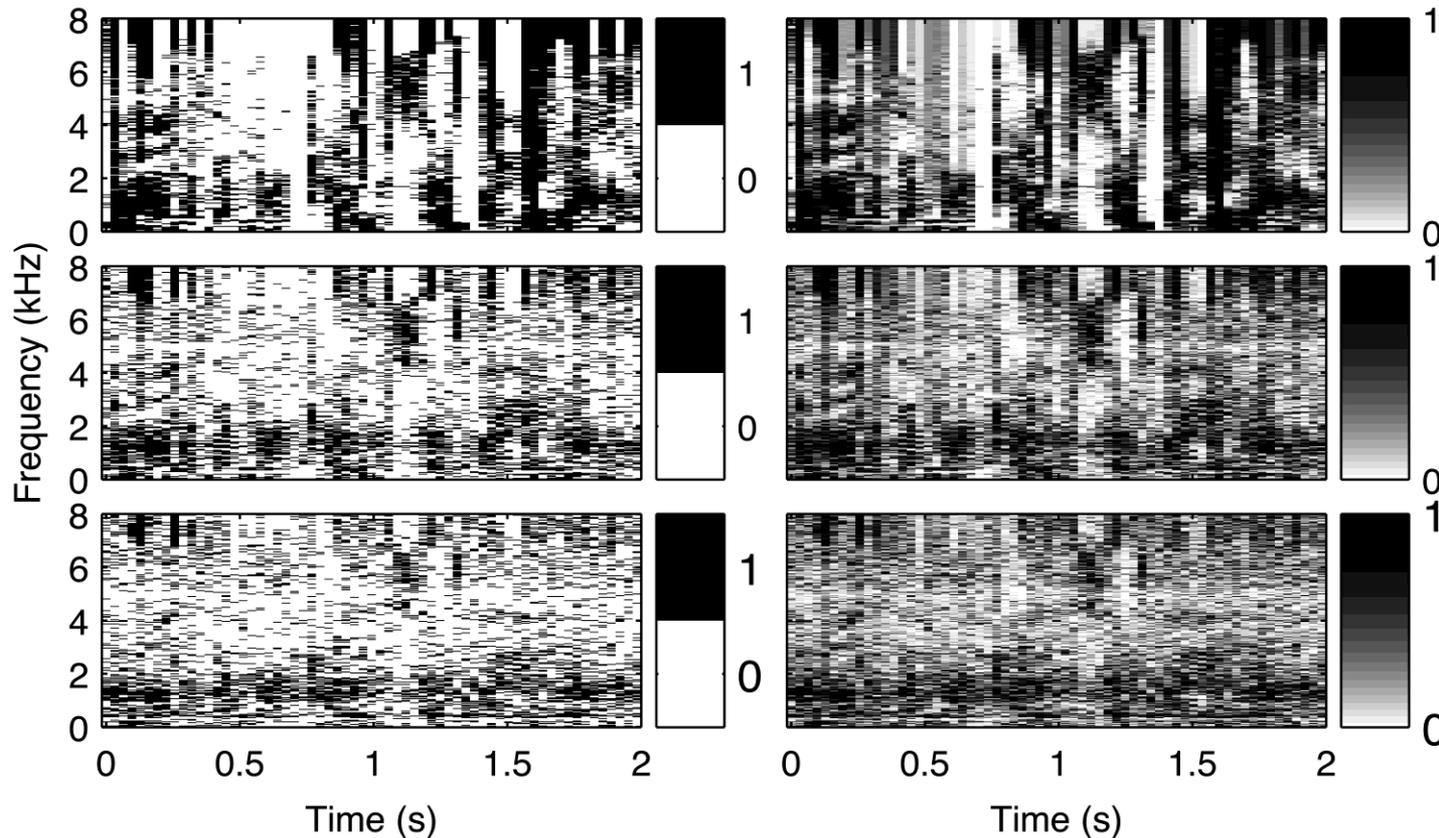
- **Flexible**: any source can be designated as the target, and the sum of remaining sources is typically designated as the interference.
- **Well-defined**: the interference component may constitute any number of sources.
- **Optimality**: closely related to the ideal Wiener filter, which is the optimal linear filter with respect to MMSE.
- **Psychoacoustic principles**: IRM is perhaps a better approximation of auditory masking and ASA principles than the IBM.

IRM v.s. IBM



Visual analogies of disjoint allocation and duplex perception when objects overlap (left), the disjoint allocation case (middle) is analogous to IBM, while the duplex perception case is analogous to the IRM (right). Plots taken from Hummersone et al. (2014).

IRM v.s. IBM



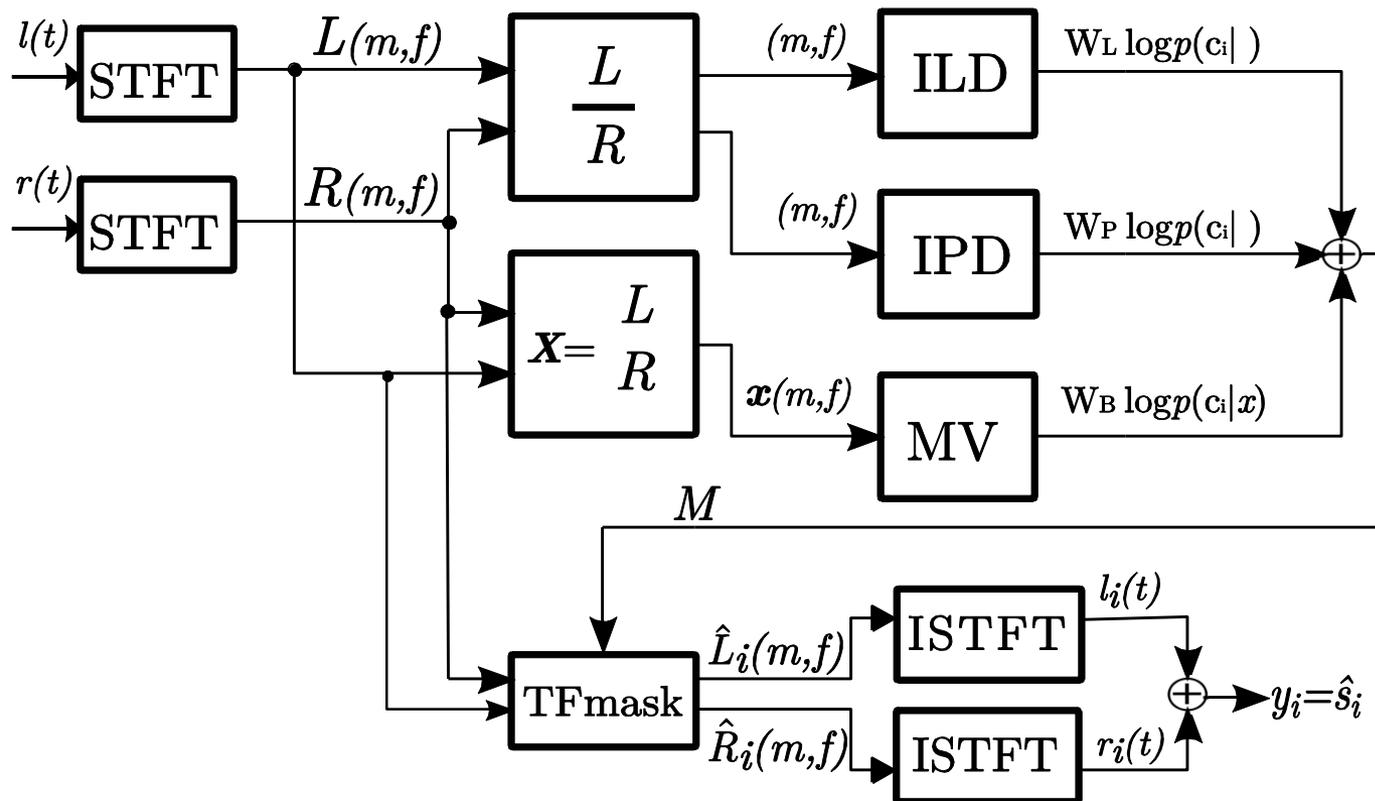
Examples of ideal (top row) and “estimated” masks (middle and bottom rows, with error perturbations). Binary masks (left column) and ratio masks (right column). Plots due to Hummersone et al. (2014).

Soft time-frequency mask:

a model based approach for binaural source separation

- ❑ Information considered: mixing vector (MV), binaural cues (interaural level difference (ILD), interaural phase difference (IPD))
- ❑ Model and algorithm used:
 - For each time-frequency point, the cues are modelled as Gaussian distributed, and a mixture of Gaussians are therefore used to model the joint distribution of the cues.
 - The model parameters estimated and refined using the expectation maximisation (EM) algorithm
- ❑ Soft mask generation: the probability that each source present at each time-frequency point of the mixtures is therefore estimated by the EM which leads to a soft mask that can be used to separate the sources.

Soft mask



A. Alinaghi, P. Jackson, Q. Liu, and W. Wang, "Joint Mixing Vector and Binaural Model Based Stereo Source Separation", *IEEE Transactions on Audio Speech and Language Processing*, 2014. (in press)

Signal model

$$x_k(t) = \sum_{i=1}^N s_i(t) * h_{ik}(t) * n_k^c(t) + n_k^a(t),$$



Sparsifying the mixtures with a time-frequency transform, such as STFT

$$X_k(m, f) = \sum_{i=1}^N S_i(m, f) \cdot H_{ik}(f) \cdot N_k^c(m, f) + N_k^a(m, f),$$



Assuming the sparsity, each time-frequency point will be dominated by one source

$$X_k(m, f) \approx X_{k|i}(m, f) \cdot N_k^c(m, f) + N_k^a(m, f)$$

where $X_{k|i}(m, f) = S_i(m, f) \cdot H_{ik}(f)$

Estimating cues from mixtures: mixing vector

$$\mathbf{x}(m, f) \approx S_i(m, f)\mathbf{h}_i(f) + \mathbf{n}^a(m, f),$$

$$\begin{aligned}\tilde{\mathbf{x}}(m, f) &= \frac{\mathbf{x}(m, f)}{\|\mathbf{x}(m, f)\|}, \\ &\approx \tilde{S}_i(m, f) \cdot \tilde{\mathbf{h}}_i(f) + \tilde{\mathbf{n}}^a(m, f).\end{aligned}$$

$$\mathbf{z}(m, f) = \frac{\mathbf{W}(f)\tilde{\mathbf{x}}(m, f)}{\|\mathbf{W}(f)\tilde{\mathbf{x}}(m, f)\|},$$

$$p_B^i(m, f) = \frac{\exp\left(-\frac{\|\mathbf{z} - (\mathbf{a}_i^H \mathbf{z}) \cdot \mathbf{a}_i\|^2}{\gamma_i^2}\right)}{(\pi\gamma_i^2)^{M-1}},$$

$$\mathbf{a}_i(f) \approx \frac{\mathbf{W}(f)\tilde{\mathbf{h}}_i(f)}{\|\mathbf{W}(f)\tilde{\mathbf{h}}_i(f)\|}.$$

H. Sawada, S. Araki, and S. Makino, "Underdetermined convolutive blind source separation via frequency bin-wise clustering and permutation alignment," *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 19, no. 3, pp. 516–527, March 2011.

Estimating cues from mixtures: ILD/IPD cues

$$\alpha(m, f) = dB \left(\frac{|X_1(m, f)|}{|X_2(m, f)|} \right) \\ \approx dB \left(\frac{|H_{i1}(f)|}{|H_{i2}(f)|} \right) + dB \left(\frac{|N_1^c(m, f)|}{|N_2^c(m, f)|} \right),$$

$$\phi(m, f) = \angle \left(\frac{X_1(m, f)}{X_2(m, f)} \right) \\ \approx \angle \left(\frac{H_{i1}(f)}{H_{i2}(f)} \right) + \angle \left(\frac{N_1^c(m, f)}{N_2^c(m, f)} \right)$$

$$p_L^i(m, f) = \mathcal{N}(\alpha(m, f) | \mu_i(f), \eta_i^2(f)),$$

$$p_P^{i,\tau}(m, f) = \mathcal{N}(\hat{\phi}(m, f; \tau(f)) | \xi_{i\tau}(f), \sigma_{i\tau}^2(f))$$

M. I. Mandel, R. J. Weiss, and D. P. W. Ellis, "Model-based expectation maximization source separation and localization," *IEEE Trans. Audio, Speech, Lang. Process.*, vol. 18, no. 2, pp. 382–394, February 2010.

Log-likelihood of the observations:

$$\begin{aligned}\mathcal{L}(\Theta) &= \sum_{m,f} \log p(\phi(m, f), \alpha(m, f), \mathbf{z}(m, f) | \Theta) \\ &= \sum_{m,f} \log \sum_{i,\tau} \left\{ \psi_{i\tau} \cdot p_{P}^{i,\tau}(m, f) \cdot \right. \\ &\quad \left. p_L^i(m, f) \cdot p_B^i(m, f) \right\},\end{aligned}$$

Model parameters:

$$\Theta = \{ \xi_{i\tau}, \sigma_{i\tau}, \mu_i, \eta_i, \mathbf{a}_i, \gamma_i \psi_{i\tau} \}$$

Parameter estimation via expectation maximization

- The **E-step** calculates the **expected value of the log-likelihood function** with respect to the observations of the IPD, ILD, and MV, under the current estimates of the parameters.
 - In other words, given the estimated parameters Θ and the observations, and assuming the statistical independence of the cues, the probability of each source occupying at each time-frequency point of the mixture is calculated:

$$\nu_{i\tau}(m, f) = K \cdot \psi_{i\tau} \cdot p_P^{i,\tau}(m, f) \cdot p_L^i(m, f) \cdot p_B^i(m, f)$$

Parameter estimation via expectation maximization

□ The M-step calculates the model parameters (mean and variance):

ILD:

$$\mu_i(f) = \frac{\sum_{m,\tau} \alpha(m, f) \nu_{i\tau}(m, f)}{\sum_{m,\tau} \nu_{i\tau}(m, f)},$$

$$\eta_i^2(f) = \frac{\sum_m (\alpha(m, f) - \mu_i(f))^2 \sum_{\tau} \nu_{i\tau}(m, f)}{\sum_{m,\tau} \nu_{i\tau}(m, f)}.$$

IPD:

$$\xi_{i\tau}(f) = \frac{\sum_m \hat{\phi}(m, f; \tau) \nu_{i\tau}(m, f)}{\sum_m \nu_{i\tau}(m, f)},$$

$$\sigma_{i\tau}^2(f) = \frac{\sum_m (\hat{\phi}(m, f; \tau) - \xi_{i\tau}(f))^2 \nu_{i\tau}(m, f)}{\sum_m \nu_{i\tau}(m, f)}.$$

MV:

$$\mathbf{R}_i(f) = \sum_{m,\tau} \nu_{i\tau}(m, f) \mathbf{z}(m, f) \mathbf{z}^H(m, f),$$

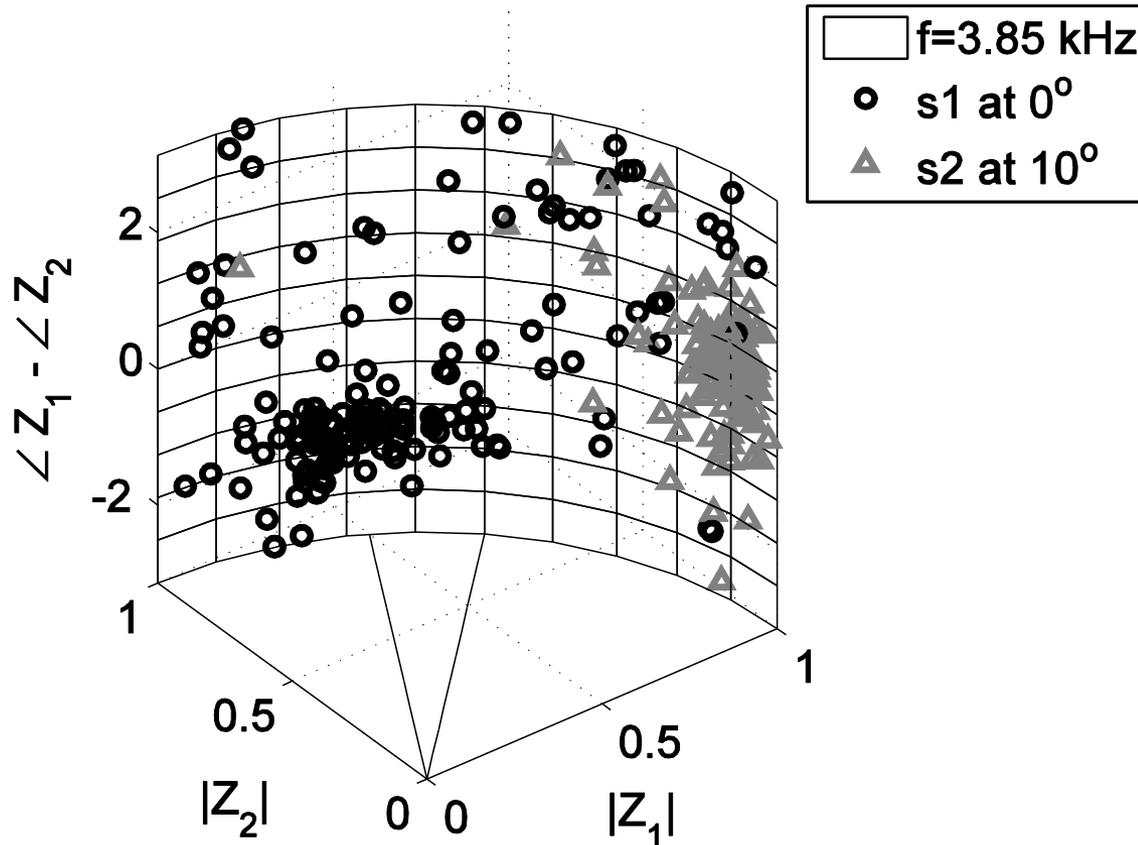
$$\mathbf{a}_i(f) = \text{eigenvector}(\mathbf{R}_i(f))_{\max(\lambda)},$$

$$\gamma_i^2(f) = \frac{\sum_{m,\tau} \nu_{i\tau}(m, f) \|\mathbf{z} - (\mathbf{a}_i^H \mathbf{z}) \cdot \mathbf{a}_i\|^2}{(M - 1) \sum_{m,\tau} \nu_{i\tau}(m, f)},$$

Weights:

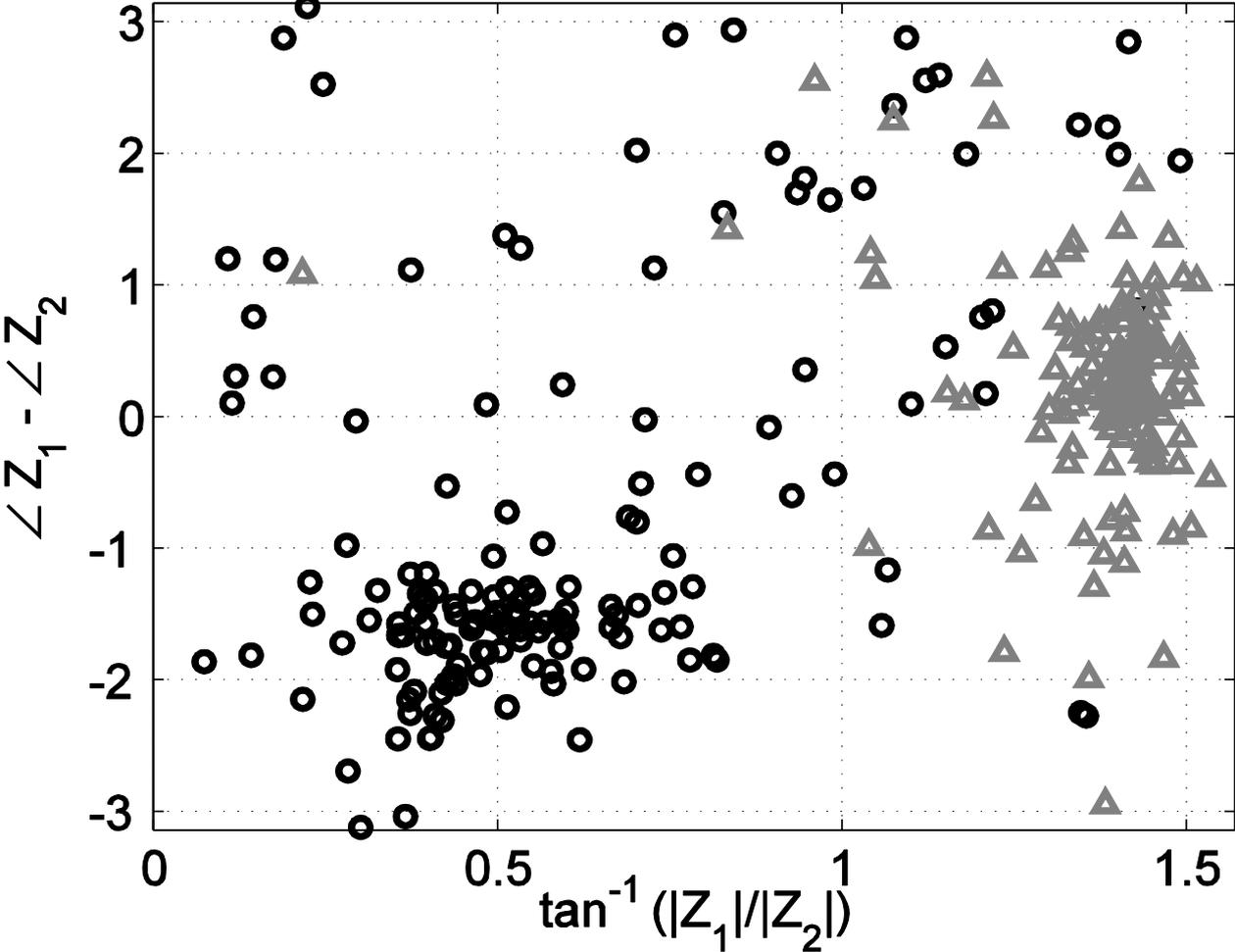
$$\psi_{i\tau} = \frac{1}{TF} \sum_{m,f} \nu_{i\tau}(m, f)$$

2D representation of the observation vectors

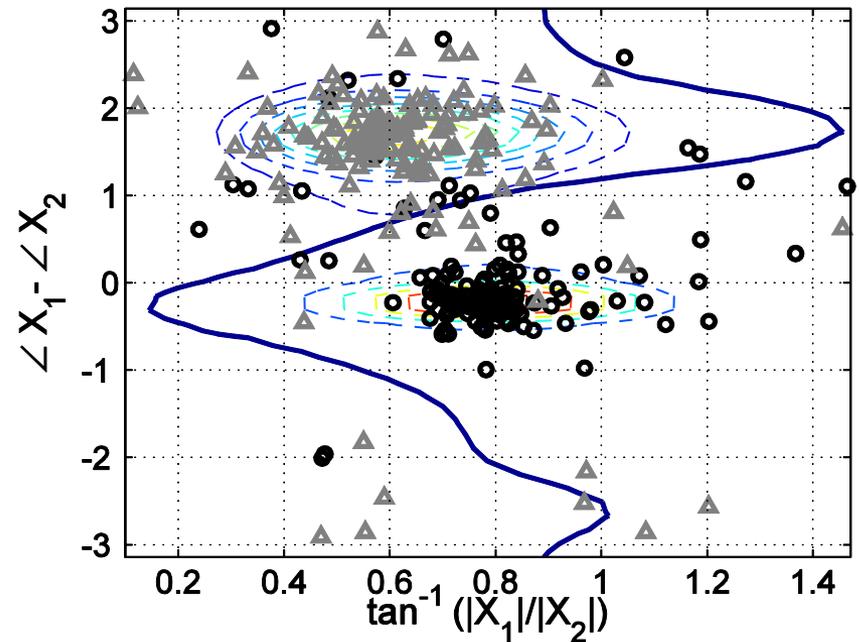
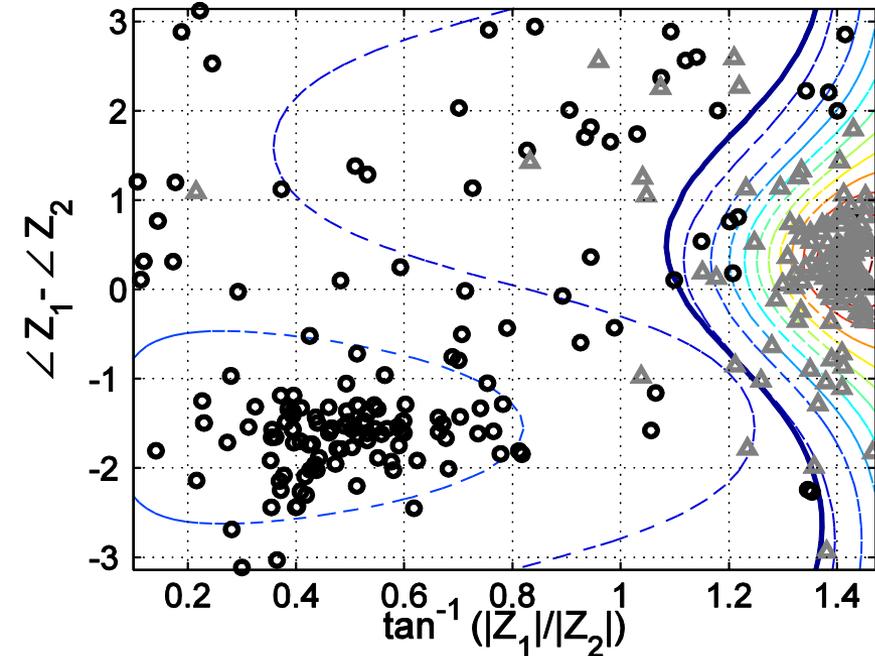


A unit cylinder wall is used to visualise the observation vectors after normalisation and whitening, in frequency channel 3.85 kHz, for two different sources that are close to each other.

Unwrapped 2D plane

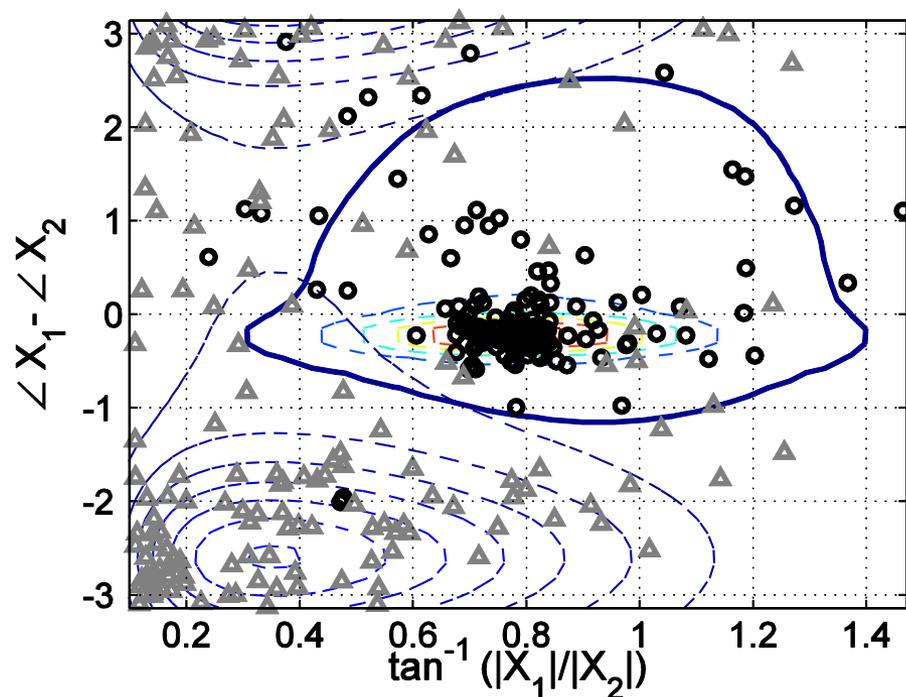
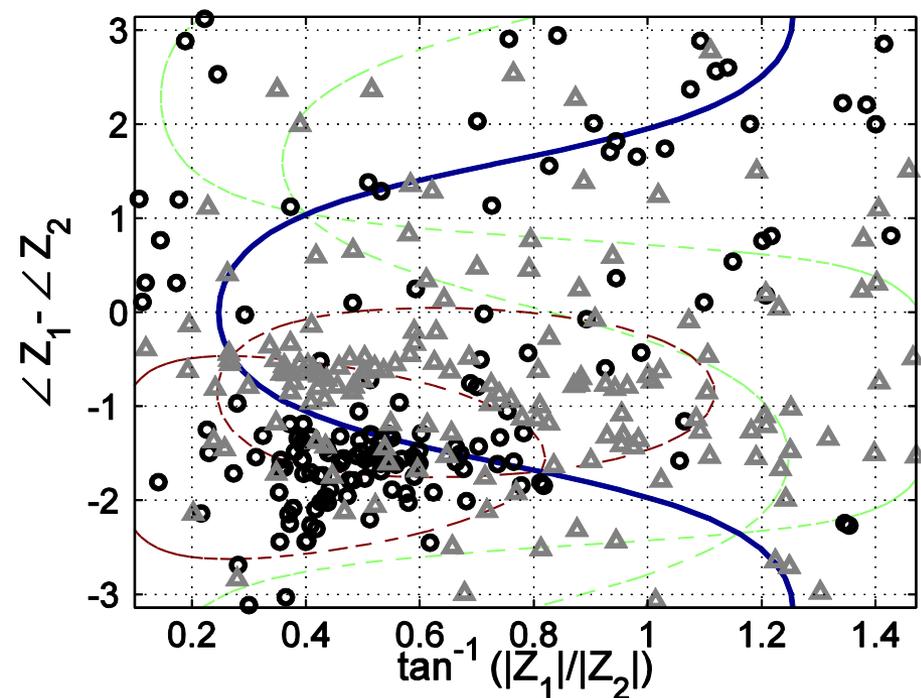


MV v.s. binaural cues: closely spaced sources



Scatter plot and probability contours (dashed lines) for sources in room A at 0° in circles, and 10° in triangles with decision boundaries by solid lines based on **mixing vectors** and **binaural cues** in the frequency band of 3.85 kHz.

MV v.s. binaural cues: sources placed far from each other



Scatter plot and probability contours (dashed lines) for sources in room A at 0° in circles, and 80° in triangles with decision boundaries by solid lines based on **mixing vectors** and **binaural cues** in the frequency band of 3.85 kHz.

MV v.s. binaural cues: KL divergence measure

$$\kappa^{\text{MV}}(f) = \sum_m \left\{ p(\mathbf{z}(m, f) | \mathbf{a}_1(f), \gamma_1(f)) \cdot \log \frac{p(\mathbf{z}(m, f) | \mathbf{a}_1(f), \gamma_1(f))}{p(\mathbf{z}(m, f) | \mathbf{a}_2(f), \gamma_2(f))} \right\},$$

$$p(\mathbf{z}(m, f) | \mathbf{a}_i(f), \gamma_i(f)) = \frac{\exp\left(-\frac{\|\mathbf{z} - (\mathbf{a}_i^H \mathbf{z}) \cdot \mathbf{a}_i\|^2}{\gamma_i^2}\right)}{(\pi \gamma_i^2)^{M-1}},$$

$$\kappa^{\text{Binaural}}(f) = \sum_m p(\mathbf{x}(m, f) | 1) \log \frac{p(\mathbf{x}(m, f) | 1)}{p(\mathbf{x}(m, f) | 2)},$$

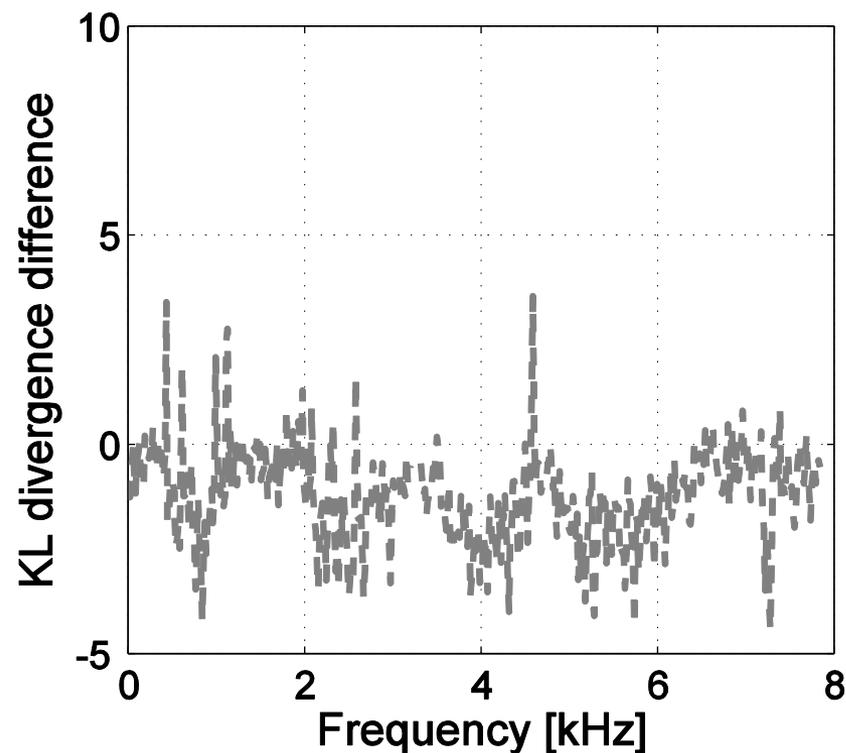
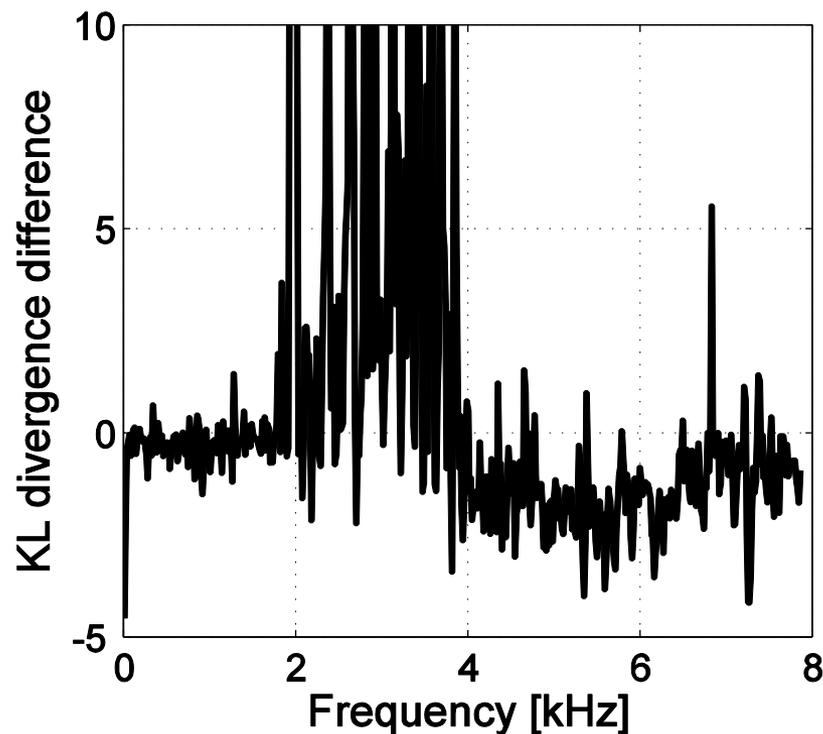
where $p(\mathbf{x}(m, f) | i) = p_P^i(m, f) \cdot p_L^i(m, f)$

$$p(\alpha(m, f) | i) = \mathcal{N}(\alpha(m, f) | \mu_i(f), \eta_i^2(f))$$

$$p(\hat{\phi}(m, f) | i, \tau) = \mathcal{N}(\hat{\phi}(m, f; \tau(f)) | \xi_{i\tau}(f), \sigma_{i\tau}^2(f))$$

MV v.s. binaural cues:

KL divergence difference ($KL^{MV} - KL^{Binaural}$)



The difference between the KL divergences obtained respectively from the MV and the binaural models. The KL divergence between the two source models is calculated based on binaural cues and MV cues in room A ($RT=0.32s$), where one source is placed at 0° and the other at 10° (left plot), and 80° (right plot) respectively.

MV v.s. binaural cues: High reverberations

$$\kappa_B^n(f) = \sum_m \left\{ p(\mathbf{z}(m, f) | \mathbf{a}(f), \gamma(f)) \cdot \log \frac{p(\mathbf{z}(m, f) | \mathbf{a}(f), \gamma(f))}{p(\mathbf{z}(m, f) | \mathbf{a}^n(f), \gamma^n(f))} \right\}.$$

-	additive noise	convolutive noise
mixing vector (MV)	2.10	2.31
IPD	2.70	2.01
ILD	3.39	3.29

KL divergence between the clean and noisy signal models for three different cues and two types of noise averaged over all frequencies.

Sound demos

2-source case:

Mandel et al. Sawada et al. Alinaghi et al. Original

left  es1    

right  es2    

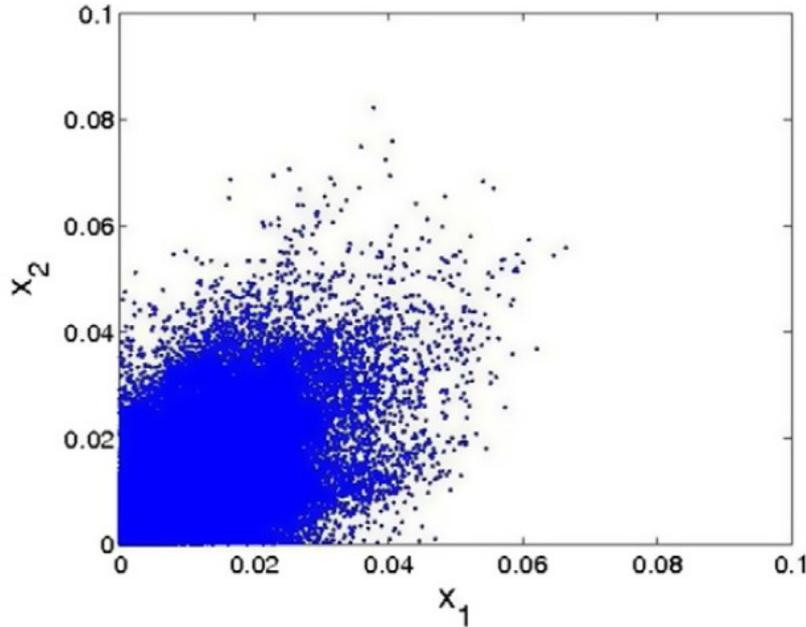
3-source case:

left  es1    

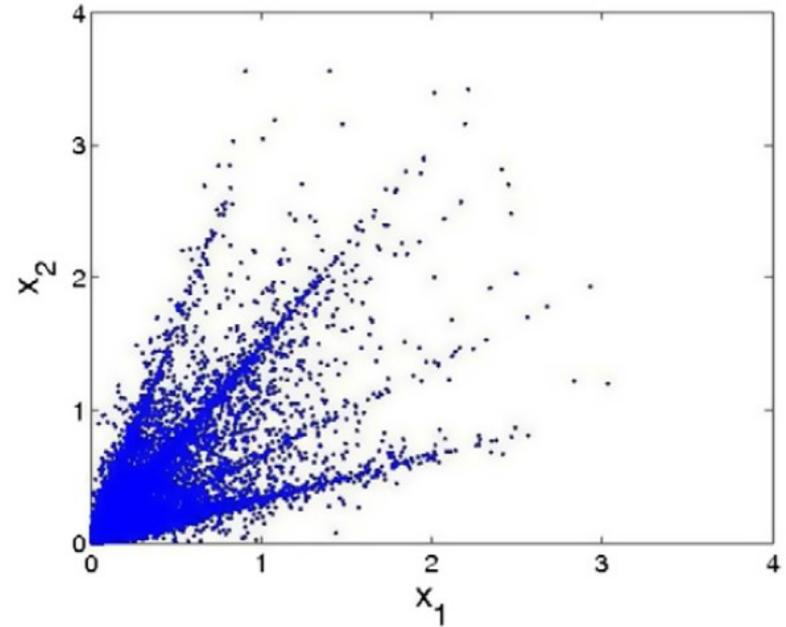
right  es2    

es3    

Sparse representation based source separation



Time domain



Time-frequency domain

$$\begin{pmatrix} \mathbf{x}_1 \\ \mathbf{x}_2 \end{pmatrix} = \begin{pmatrix} a_{11} & a_{12} & a_{13} & a_{14} \\ a_{21} & a_{22} & a_{23} & a_{24} \end{pmatrix} \begin{pmatrix} \mathbf{s}_1 \\ \vdots \\ \mathbf{s}_4 \end{pmatrix}$$

Source separation formulated as a compressed sensing problem

Reformulation:

$$\underbrace{\begin{pmatrix} x_1(1) \\ \vdots \\ x_1(T) \\ \vdots \\ \vdots \\ x_M(1) \\ \vdots \\ x_M(T) \end{pmatrix}}_{\mathbf{b}} = \underbrace{\begin{pmatrix} \Lambda_{11} & \cdots & \Lambda_{1N} \\ \vdots & \ddots & \vdots \\ \Lambda_{N1} & \cdots & \Lambda_{MN} \end{pmatrix}}_{\mathbf{M}} \underbrace{\begin{pmatrix} s_1(1) \\ \vdots \\ s_1(T) \\ \vdots \\ \vdots \\ s_N(1) \\ \vdots \\ s_N(T) \end{pmatrix}}_{\mathbf{f}}$$

- The above problem can be interpreted as a **signal recovery problem** in compressed sensing, where \mathbf{M} is a measurement matrix, and \mathbf{b} is a compressed vector of samples in \mathbf{f} . Λ_{ij} is a diagonal matrix whose elements are all equal to a_{ij} .

- A **sparse representation** may be employed for \mathbf{f} , such as:

$$\mathbf{f} = \Phi \mathbf{c}$$

- Φ is a **transform dictionary**, and \mathbf{c} is the weighting coefficients corresponding to the dictionary atoms.

Source separation formulated as a compressed sensing problem (cont.)



Reformulation:

$$\mathbf{b} = \overline{\mathbf{M}}\mathbf{c} \quad \text{and} \quad \overline{\mathbf{M}} = \mathbf{M}\Phi$$

- According to compressed sensing, if $\overline{\mathbf{M}}$ satisfies the restricted isometry property (RIP), and also \mathbf{c} is sparse, the signal \mathbf{f} can be recovered from \mathbf{b} using **an optimisation process**.
- This indicates that source estimation in the underdetermined problem can be achieved by computing \mathbf{c} using **signal recovery algorithms** in compressed sensing, such as:
 - ✓ Basis pursuit (BP) (Chen et al., 1999)
 - ✓ Matching pursuit (MP) (Mallat and Zhang, 1993)
 - ✓ Orthogonal matching pursuit (OMP) (Pati et al., 1993)
 - ✓ L1 norm least squares algorithm (L1LS) (Kim et al., 2007)
 - ✓ Subspace pursuit (SP) (Dai et al., 2009)
 - ✓ ...

Dictionary learning for sparse representations



- Sparse decompositions of a signal highly rely on the fit between the dictionary and the data, leading to the important problem of dictionary design:
 - **Predefined transform**, such as DCT, DFT, etc.
 - **Learned dictionary** (via a training process), such as MOD, K-SVD, GAD, and SimCO.
 - Learning dictionary Φ from training data

Dictionary learning

Problem:

$$\min_{\Phi, \mathbf{C}} \|\mathbf{X} - \Phi \mathbf{C}\|_F^2$$

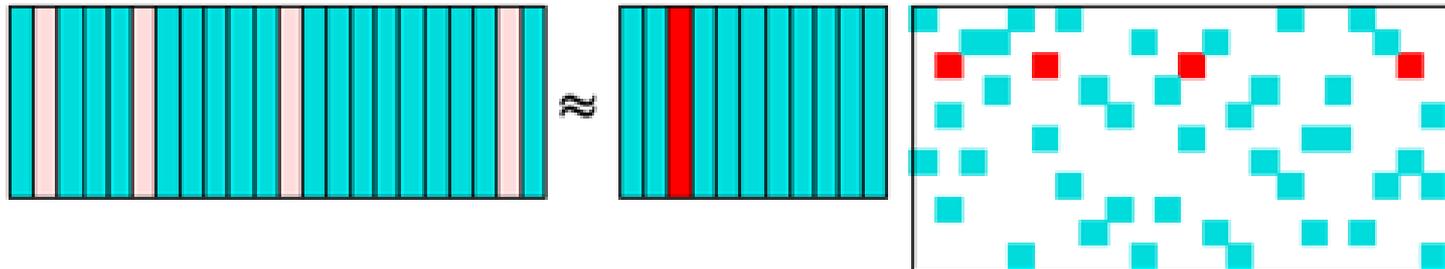
$\mathbf{X} \in \mathbb{R}^{m \times n}$: Training data

$\Phi \in \mathbb{R}^{m \times d}$: An overcomplete dictionary

$\mathbf{C} \in \mathbb{R}^{d \times n}$: Sparse coefficients

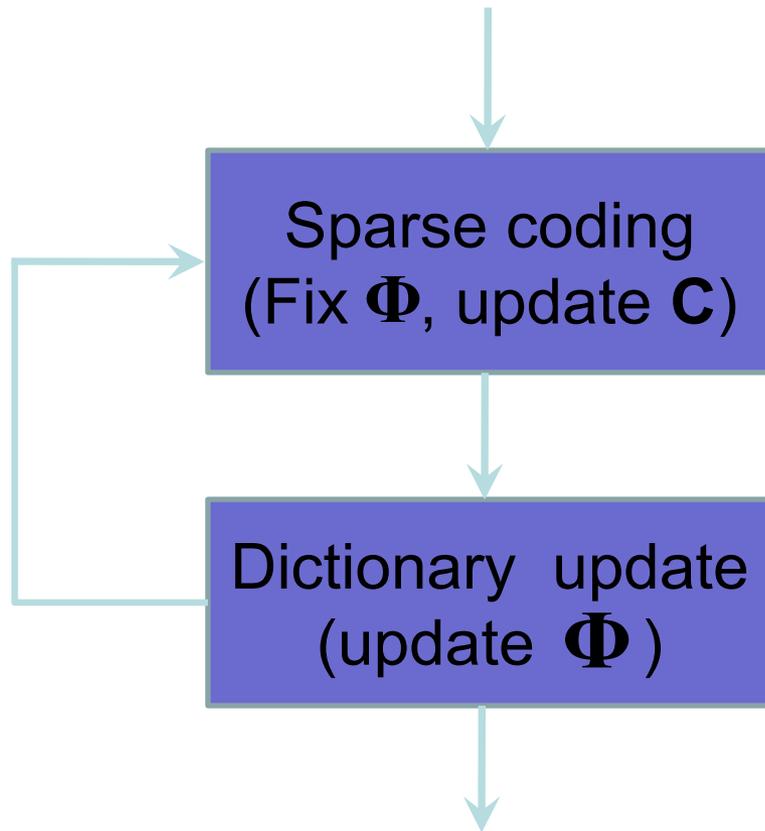
Applications:

- Signal denoising
- Source separation
- Speaker tracking



Optimisation process in dictionary learning

Optimisation process:

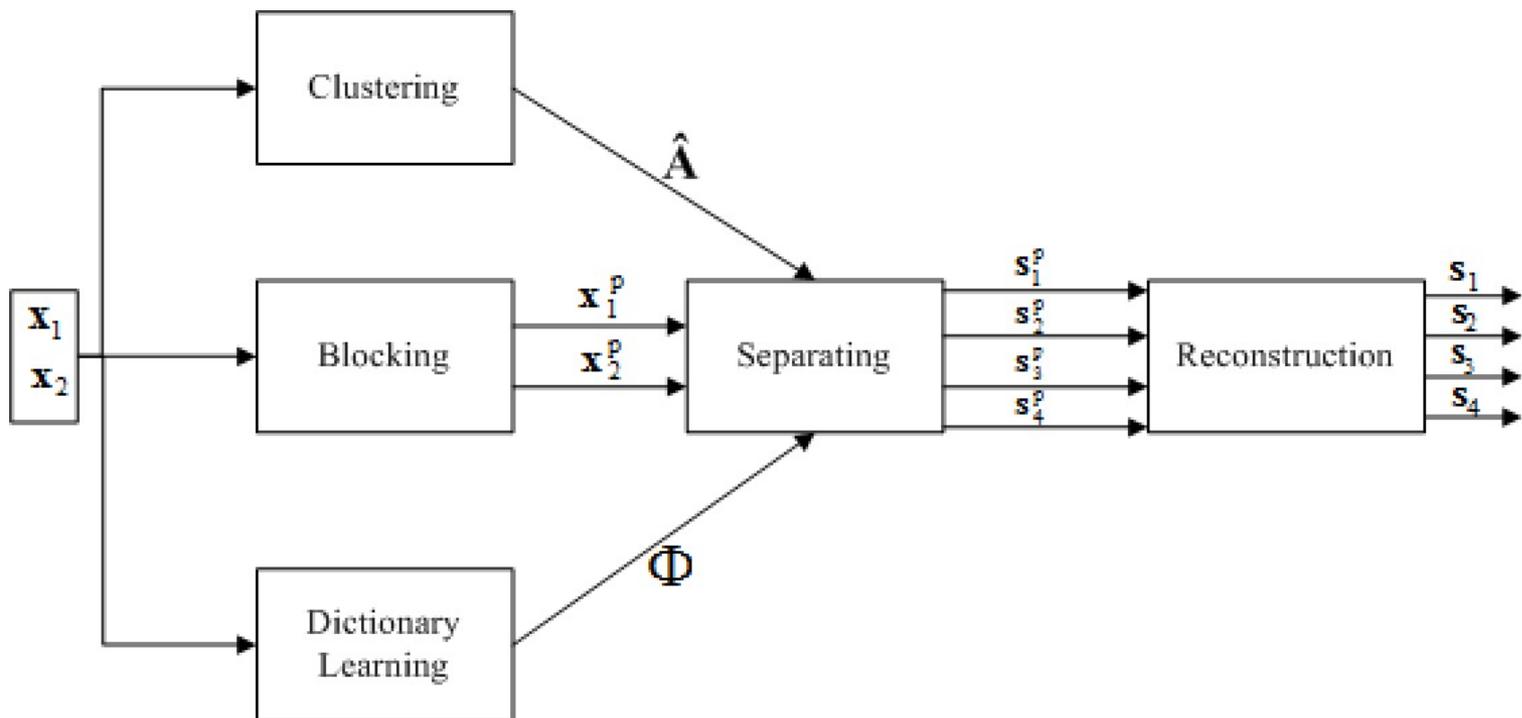


Representative algorithms:

- MOD and its extensions (Engan, 1999, 2007)
- K-SVD and its extensions (Aharon and Elad, 2006, 2009)
- GAD (Maria and Plumbley, 2010)
- ...

Dictionary learning for underdetermined source separation

Separation system for the case of $M = 2$ and $N = 4$:



Sound demo for underdetermined source separation



s1



s2



s3



s4



x1



x2



es1



es2



es3



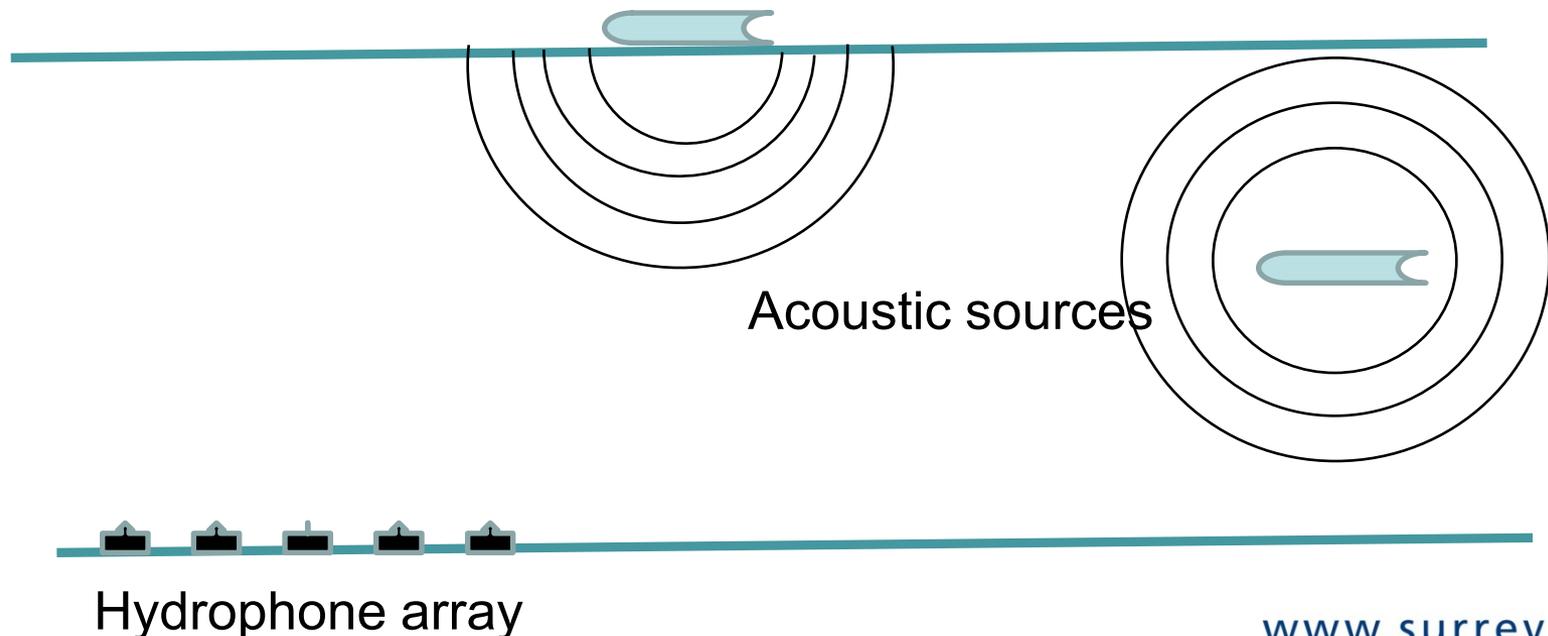
es4



T. Xu, W. Wang, and W. Dai, Compressed sensing with adaptive dictionary learning for underdetermined blind speech separation, *Speech Communication*, vol. 55, pp. 432-450, 2013.

Convolutional source separation for underwater acoustic sources

- Separation and de-noising of underwater acoustic signals
- Applications include tracking surface and underwater acoustic sources, underwater communications, geology and biology
- Measurements using hydrophone arrays



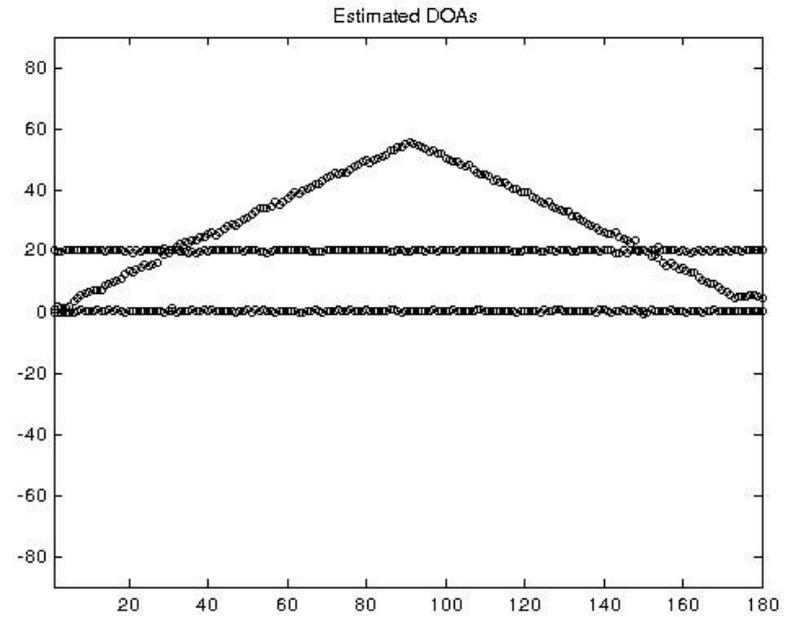
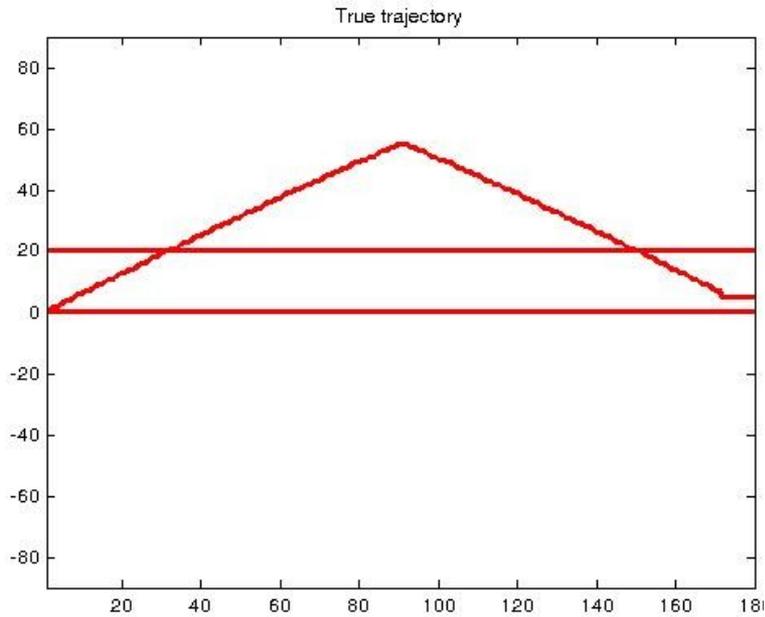
Sequential sparse Bayesian methods



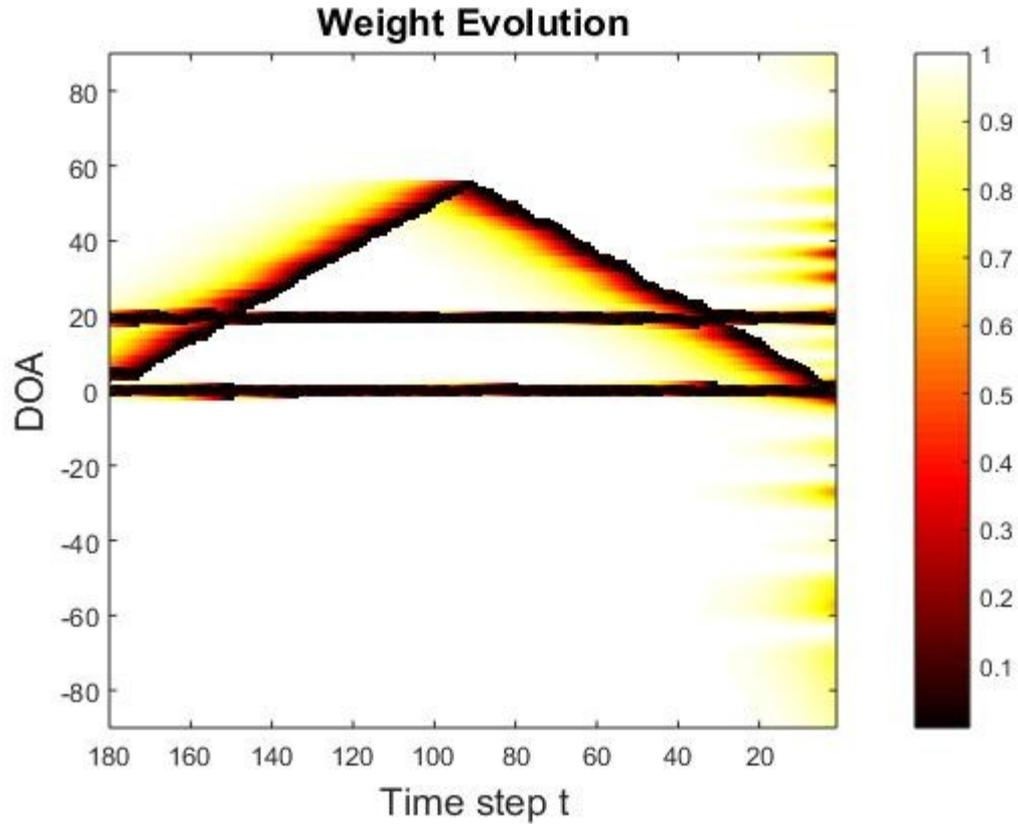
- Extends the classic Bayesian approach to a sequential maximum a posterior (MAP) estimation of the signal over time.
- Sparsity constraint is enforced with a Laplacian like prior at each time step.
- An adaptive LASSO cost function is minimised at each time step

C. Mecklenbrucker, P. Gerstoft, A. Panahi, M. Viberg, "Sequential Bayesian Sparse Signal Reconstruction using Array Data," *IEEE Transactions on Signal Processing*, vol. 61, no. 24, pp. 6344 - 6354, 2013.

An example for underwater source



Simulation results



Summary & future work



We have covered the following:

- ❑ Concept of convolutive source separation
- ❑ Methods for performing convolutive source separation, such as
 - Convolutive ICA and frequency domain ICA (permutation/scaling ambiguities)
 - Time-frequency masking (CASA, IBM, IRM, etc)
 - Integrating ICA/IBM
 - Music noise problem & mitigation
 - Model-based convolutive stereo source separation (ILD/IPD, MV, etc.)
- ❑ Underwater acoustic source localisation/separation
- ❑ Future work include improving source separation performance in highly noisy environment, and/or missing data scenarios.

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... and finally

Thank you for your attention!



Q & A

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