Blind Source Separation: From Basic Concepts to New Challenges

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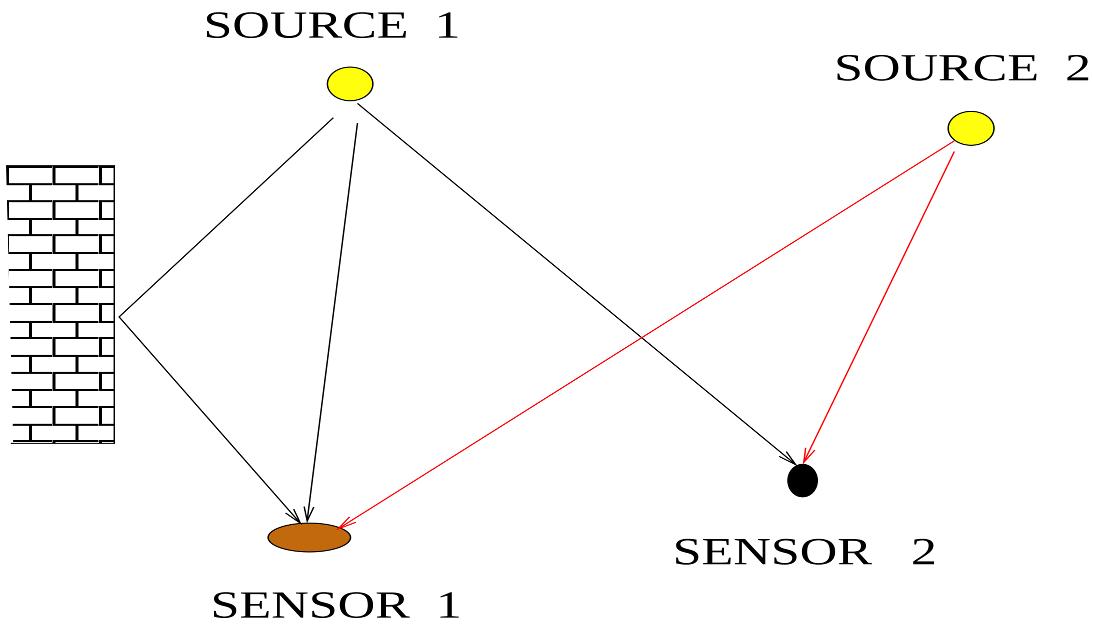
Outline

- Some Basic Concepts & Application Examples
- General ICA Principles
- Recent Works & New Challenges
- Concluding Remarks

The situation of interest



m different (possibly noisy) linear combinations of n independent source signals are observed at the sensors.

Instantaneous linear mixture model

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t)$$

- $\mathbf{x}(t)$: $m \times 1$ observation vector (array output),
- $\mathbf{s}(t)$: $n \times 1$ *unknown* source vector,
- $\mathbf{n}(t)$: $n \times 1$ additive noise vector assumed independent from the source signals,
- $\mathbf{A}$: $n \times m$ *unknown* mixing matrix assumed *in-structured*, i.e it cannot be expressed in terms of a simple parametric model.

Parametric versus Blind model

- **Parametric model**: The mixture is structured (e.g. $\mathbf{A} = \mathbf{A}(\theta)$ where θ are the sources DOA), in which case, the parameters of the mixture matrix are first estimated then the sources are evaluated as $\hat{\mathbf{s}}(t) = \mathbf{A}(\hat{\theta})^{\#}\mathbf{x}(t)$.

- **Blind model**: When the mixture matrix is unstructured (lack of array calibration, unknown propagation model, disturbance, ...) it is safer (more robust) to proceed in a blind way and estimate the mixture or the sources using statistical (or other) information.

Other BSS models

- **Convolutive mixture model**:

$$\mathbf{x}(t) = \sum_k \mathbf{A}_k \mathbf{s}(t-k) + \mathbf{n}(t)$$

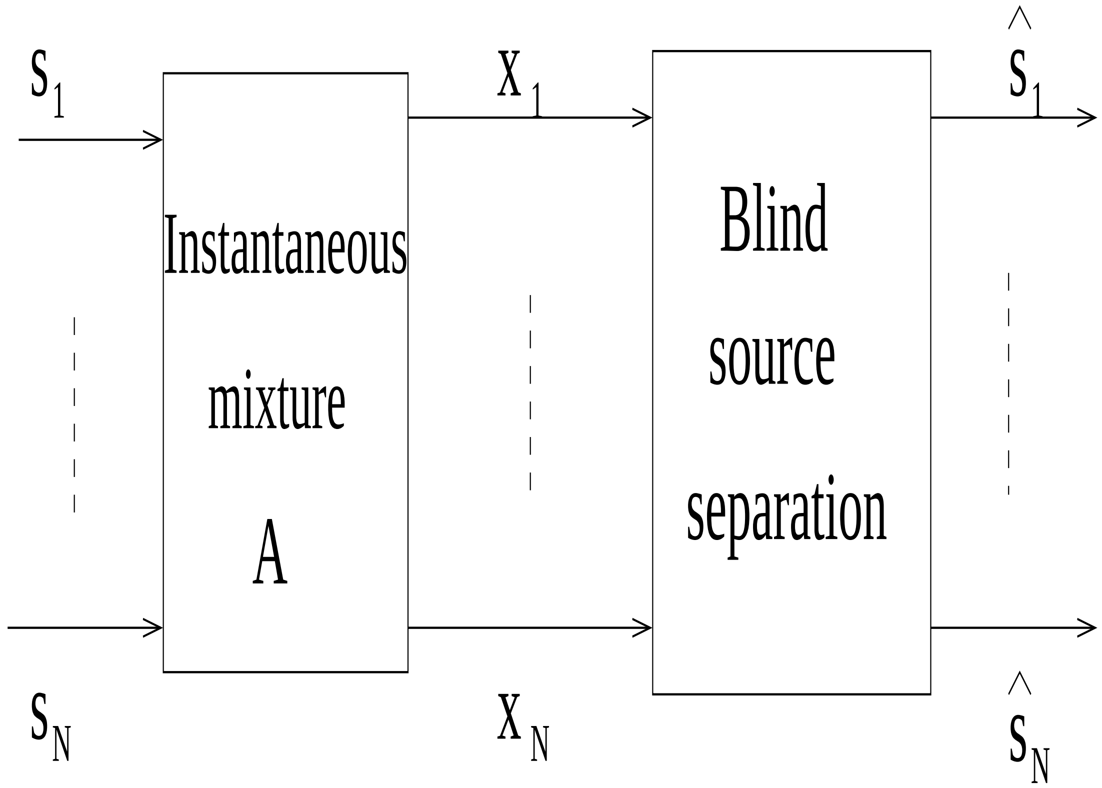
  This is, for example, the model for MIMO communication systems when the channel delay spread is larger than the symbol duration.

- **Post non-linear mixture model**:

$$\mathbf{x}(t) = f(\mathbf{A}\mathbf{s}(t)) + \mathbf{n}(t)$$

  where f is a non-linear function. Other linear-quadratic models have also been considered in the literature.

Blind source separation problem



Objectives:

1. *Signal synthesis*: Identify the mixture matrix and/or recover the input signals from the observed signal by exploiting the *statistical independence* or other features of the sources.

2. *Signal analysis*: Analyse a multi-variate signal by decomposing it into a set of independent components (independent component analysis ICA).

ICA versus PCA

- **Principal component analysis**: seeks directions in feature space that best represent the data in *least squares* sense.

- **Independent component analysis**: seeks directions in feature space that are most *independent* from one another.

Inherent ambiguities

The observation is unchanged by exchanging a scalar factor between the k-th source signal and its corresponding column vector of $\mathbf{A}$:

$$x(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) = \sum_{k=1}^{n} \frac{\mathbf{a}_k}{\alpha_k} \alpha_k s_k(t) + \mathbf{n}(t)$$

The labeling of the source signals being arbitrary, the identification of the columns of the mixing matrix A is possible only up to a diagonal *factor* and a *permutation* matrix.

Application of BSS: Cocktail Party Problem

We need to separate several speakers from their mixtures recorded by an array of microphones: Cocktail Party Problem

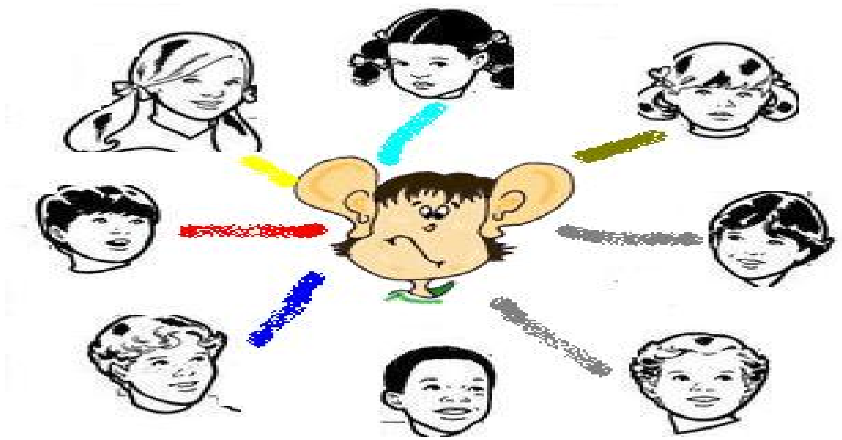


Figure 1: Speech signal separation.

Application of BSS: Romeo Project

Romeo is a humanoid robot from Aldebaran Robotics which is intended to be a genuine personal assistant and companion. Its hearing system is formed of an array of 16 microphones which uses BSS technique to extract the desired (master's) signal in order to allow speech recognition.

Robot ROMEO

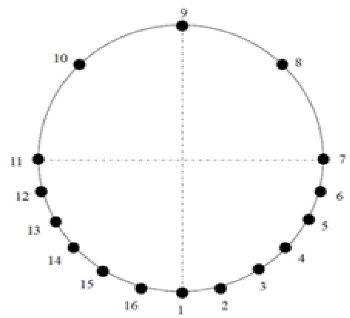
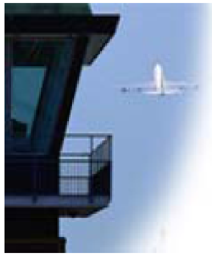
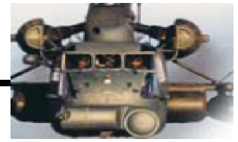


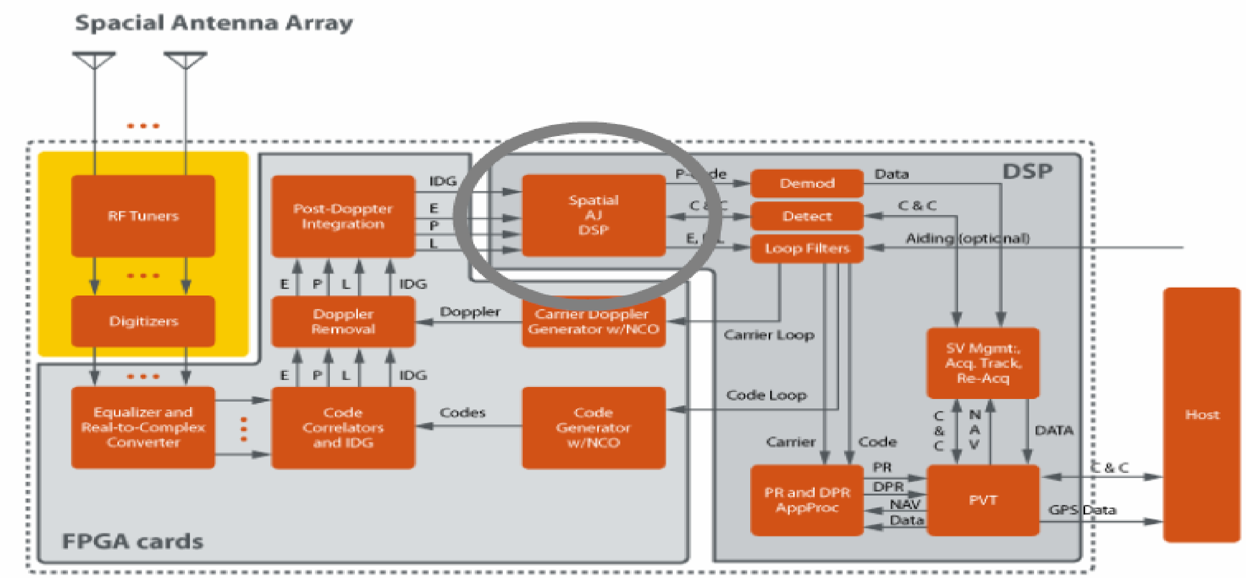
Figure 2: Speech signal separation for humanoid robot 'ROMEO'

Application of BSS: Anti-Jamming Receiver



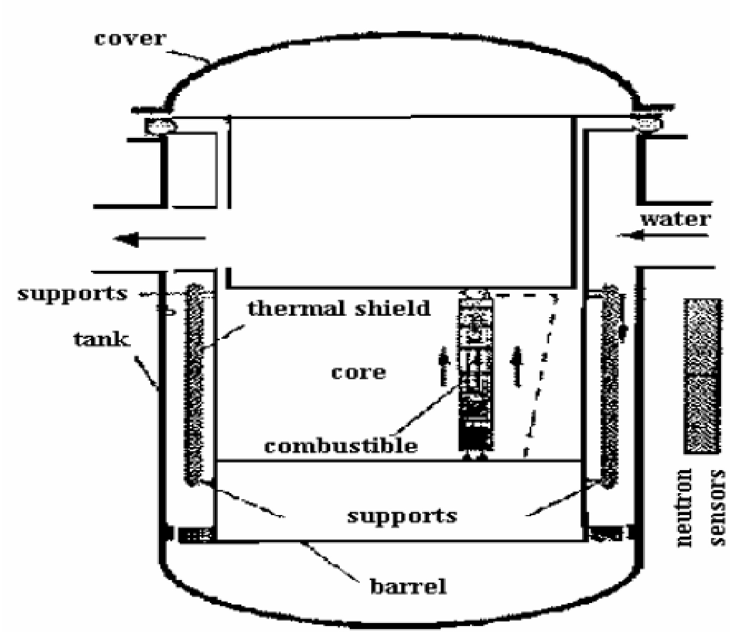


BEAMSTAR GPS Anti-Jam Receiver
Block Diagram

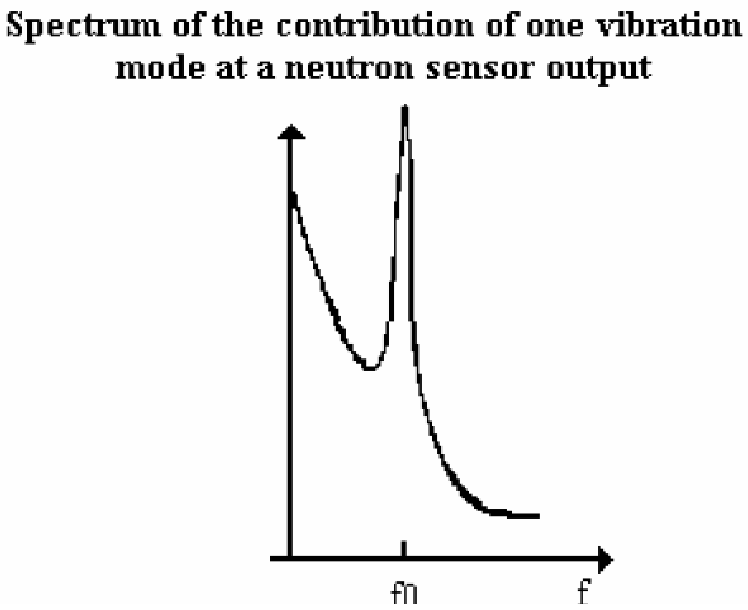


Application of BSS: Nuclear Reactor Monitoring

- **Nuclear reactor diagram**

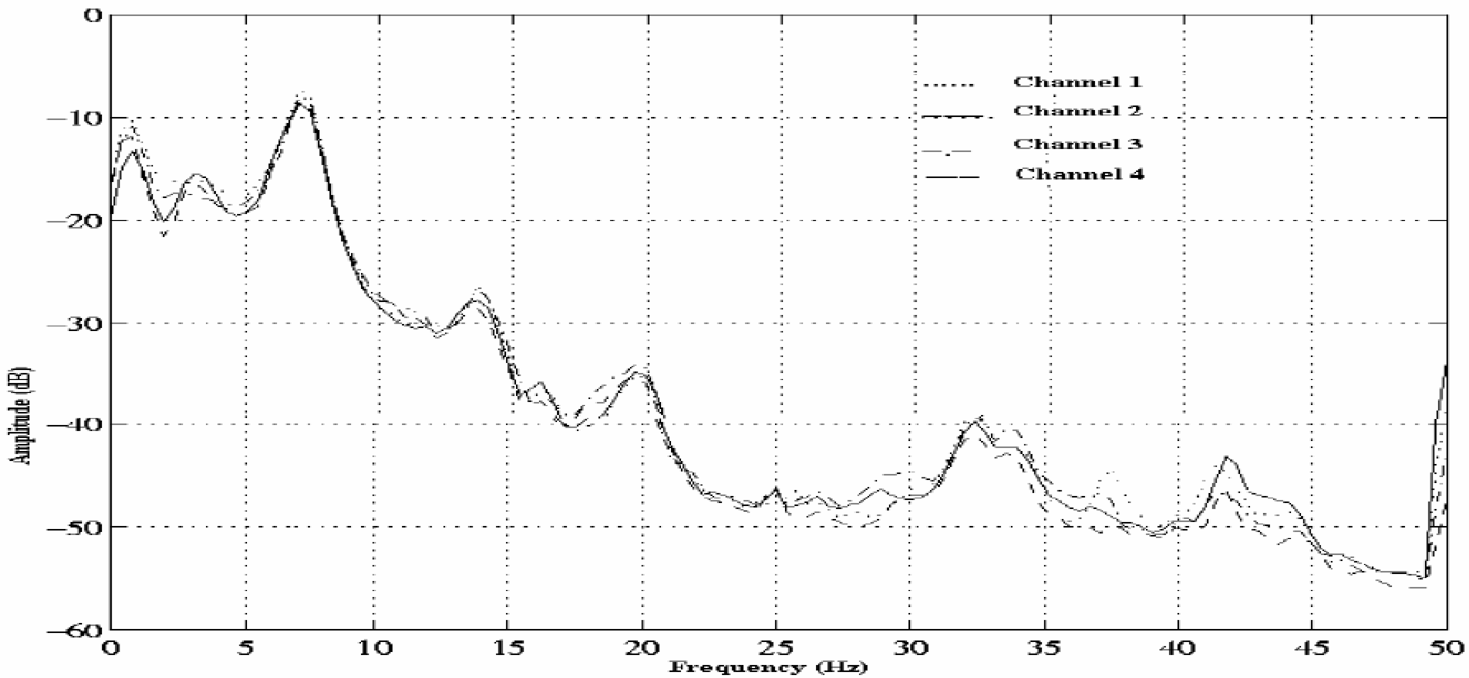


- **Theoretical spectrum of one source**



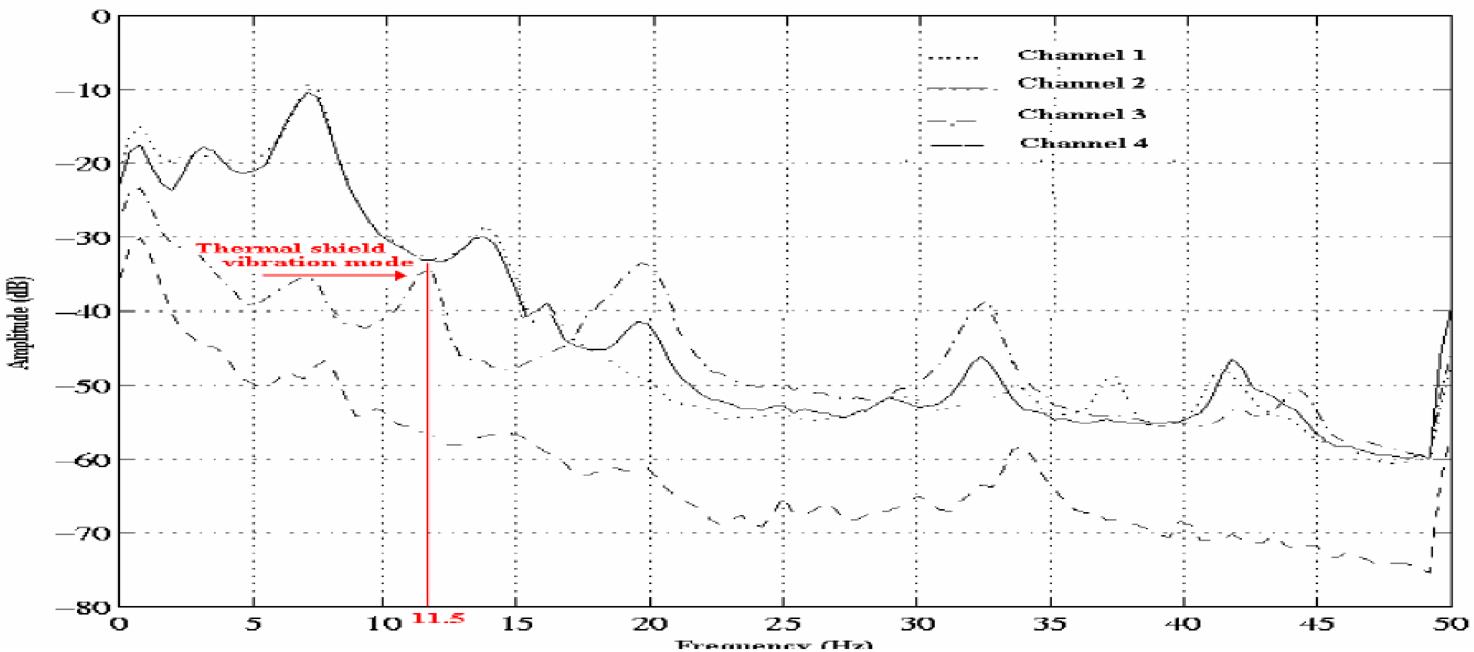
Application of BSS: Nuclear Reactor Monitoring

✓ Spectral densities of the recorded data (D'Urso, 1995)



Application of BSS: Nuclear Reactor Monitoring

✓ Spectral densities of the separated data using SOBI (a SOS method) (Belouchrani, 1995)



Application of BSS: SAR Imaging (Radar)

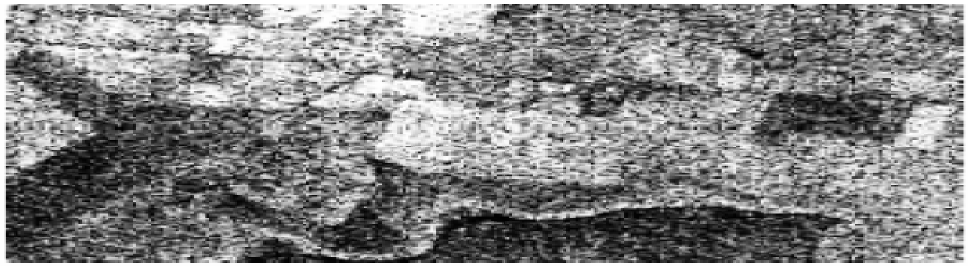


Fig. 1. ERS-2 SAR image, April 24, 1998.

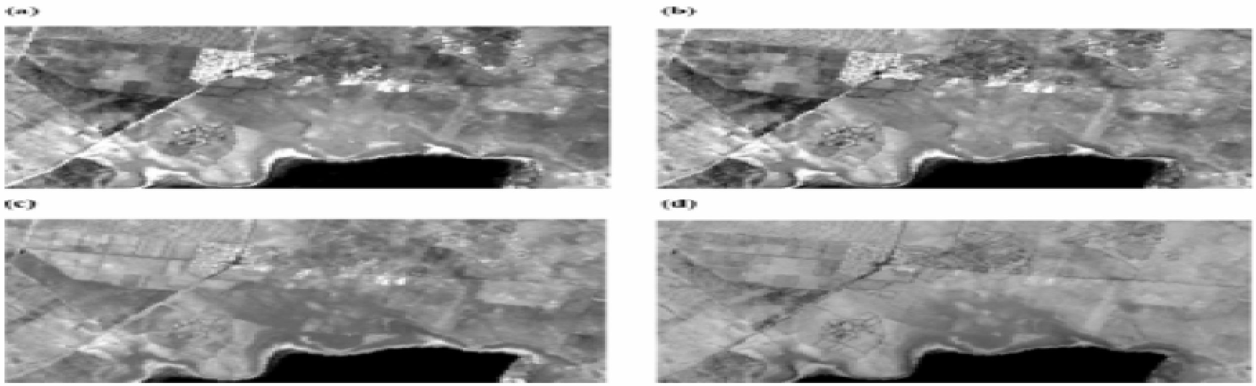


Fig. 2. HRV-XS image of SPOT-4, May 31, 1998. (a) Band 1(XS1). (b) Band 2 (XS2). (c) Band 3 (XS3). (d) Band 4 (XS4).

M.S. Naceur, M.A. Loghmari and M.R. Boussema,"The contribution of the sources separation method in the decomposition of mixed pixels", IEEE Trans. on Geoscience and Remote Sensing, Vol.42, No, 11, Nov. 2004, pp:2642 - 2653

Application of BSS: SAR Imaging (Radar)

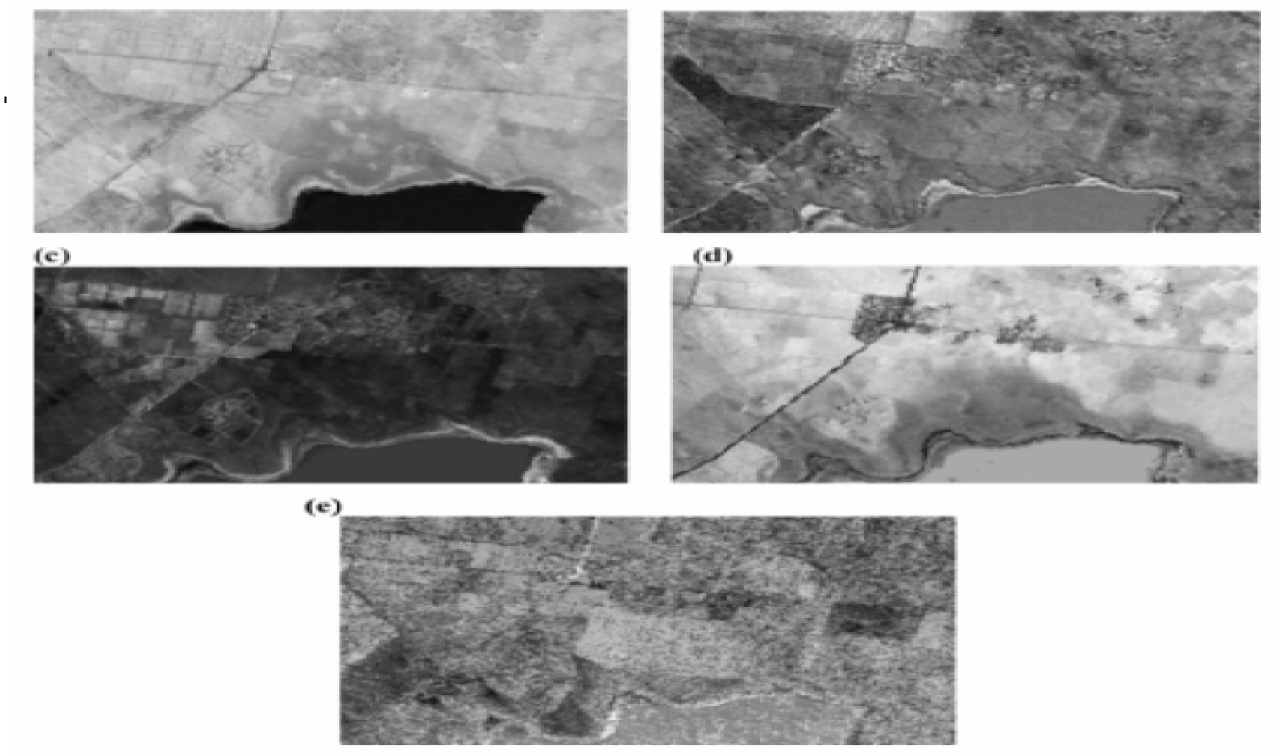


Fig. 5. Source images extracted from the SOBI algorithm. (a) Source image 1. (b) Source image 2. (c) Source image 3. (d) Source image 4. (e) Source image 5.

Application of BSS: Image Separation

Example: BSS applied to EEG signal analysis

- Several work on the application of BSS to EEG data have been presented in the literature, e.g. Gorodnitsky et al, 2001.
- Herein, an example of such application is presented (http://www.tsi.enst.fr/~cardoso). In this example, the EEG data contains brain and ocular sources, which contain horizontal eye movement (subject moves his eyes in predetermined pattern) and vertical eye movement (eye blink).
- BSS attempts to separate the contribution of these different sources.

Example: BSS applied to EEG signal analysis

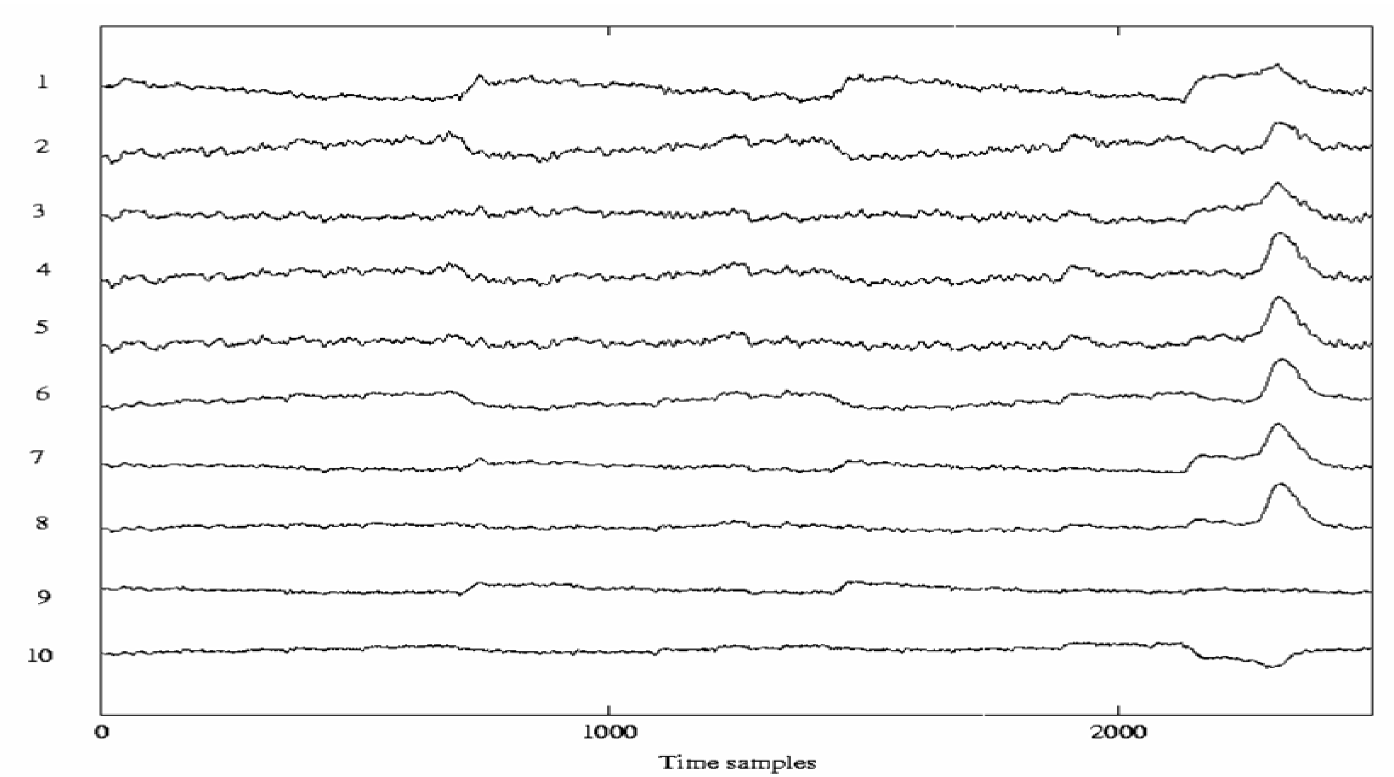


Figure 3: Recorded EEG data.

Example: BSS applied to EEG signal analysis

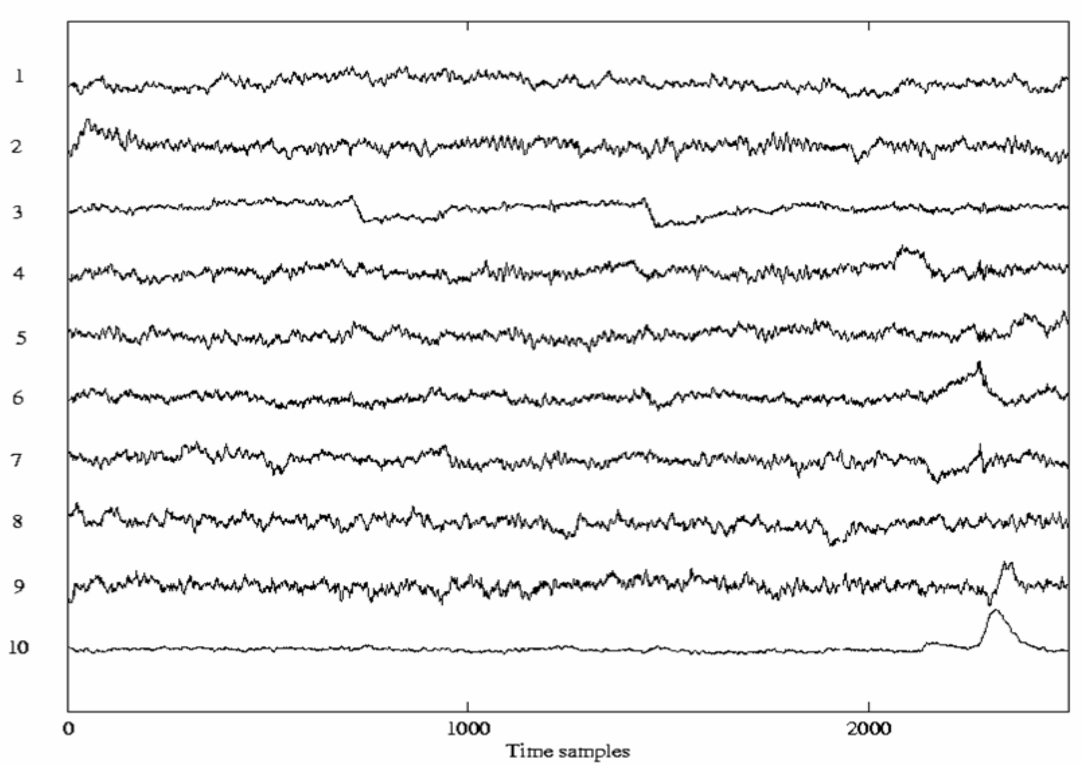
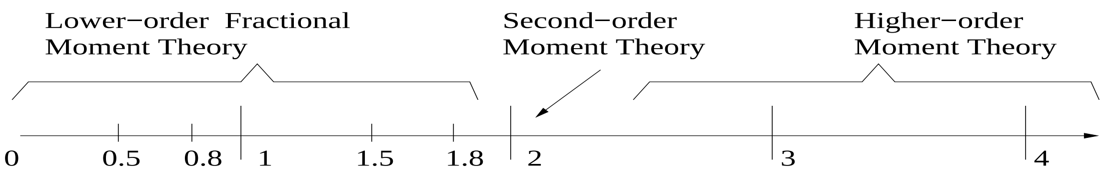


Figure 4: EEG data processed by JADE an HOS-based BSS method.

Other BSS Applications

- *Airport surveillance* (Chaumette et al.,1993): separate the aircraft responses that fall in the same beam of the radar,
- *Astronomical Image* separation (Cardoso et al 2002): Extracting the cosmic microwave backgroud (a fossil electromagnetic radiation) from images corrupted by intra-galactic dust, extra-galactic SZ effect, etc.
- *Financial data* (Back et al., 1997): extraction of structure from stock returns,
- *Radio and mobile communication* (MIMO system deconvolution),

BSS (statistical) approaches



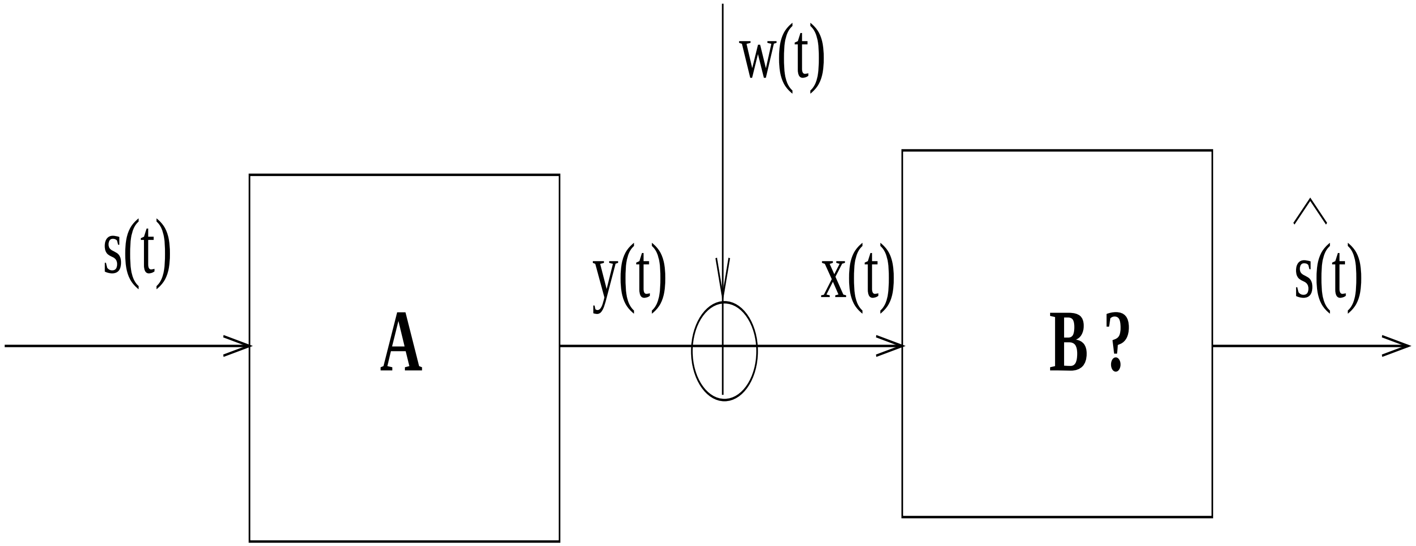
- HOS-based methods: Exploit the observations higher order statistics of non-gaussian sources either explicitly by processing their higher order cumulants or implicitly through the optimization of non-linear functions given by information-theoretic criteria.
- SOS-based methods: When the sources are 'temporally colored', one can achieve BSS using signal decorrelation.
- FLOM-based methods: Dedicated to the separation of impulsive signals, e.g. alpha-stable signals (these signals have infinite 2nd and higher order moments).

BSS approaches: General case

Property Restoral Principle: The separation of the sources is achieved in general by restoring a strong property of the sources that is 'destroyed' by the mixture and 'restored' by the BSS technique.

- *Statistical Independence*: Source separation by restoration of the source independence.
- *Sparsity*: Source separation by restoration of the source sparsity.
- *Disjointness*:Source separation by restoration of the source disjointness in certain transform domain.

Information theoretic principles



Matrix **B** is computed such that its outputs are most independent from one another.

Information theoretic principles

- By minimizing the mutual information between the components of $\hat{\mathbf{s}}(t)$.

- By minimizing the Kullbak-Leibler distance in between the pdf of $\hat{\mathbf{s}}(t)$ and the product of its components pdfs, i.e.

$$KL(p(\hat{\mathbf{s}}(t)), \prod_k p_k(\hat{s}_k(t)).$$

- My maximizing the nongaussianity of $\hat{\mathbf{s}}(t)$ (measures of nongaussianity include the Kurtosis -fourth order cumulant- and the Negentropy -differential entropy-).

BSS/ICA Algorithms

- If signals pdfs are available, BSS can be achieved via the previously mentioned criteria (MI, Kullback, ML, ...). However, using criteria for 'partial independence' is often enough for source separation (thanks to the particular structure of the observed signal).
- For coherent sources, BSS can be achieved by (2nd order) decorrelation: e.g. SOBI algorithm (Belouchrani et al)
- For non-gaussian white sources, BSS can be achieved by (4th order) decorrelation: e.g. JADE algorithm (Cardoso et al)
- BSS can be achieved by exploiting other signal properties: cyclostationarity, finite alphabet, constant modulus, etc.

SOME RECENT WORKS AND

NEW CHALLENGES

BSS of Non Linear Mixtures

Mainly two non-linear models have been deeply investigated:

- **The linear-quadratic model**: where the observations are of the form

$$x_i(t) = \sum_j a_{ij} s_j(t) + \sum_{j,k} b_{i,jk} s_j(t) s_k(t)$$

$\{a_{ij}\}$ and $b_{i,jk}$ are unknown mixture coefficients.

- **Post non-linear model**: where the observations are of the form

$$x_i(t) = f\left(\sum_j a_{ij} s_j(t)\right)$$

where f is a (partially) known non-linear function and $\{a_{ij}\}$ are unknown mixture coefficients.

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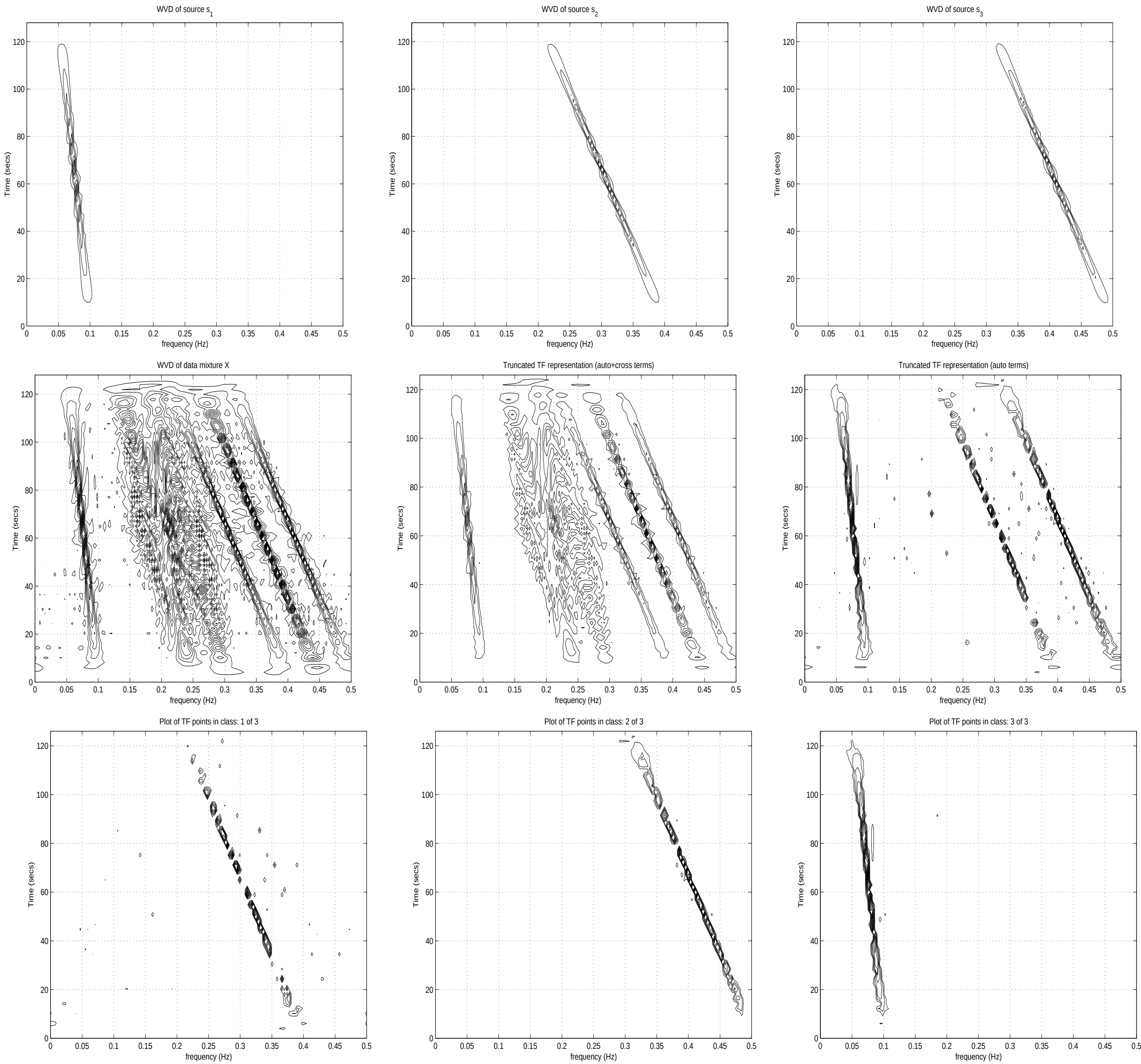
BSS of Underdetermined Mixtures

In that case, one have more sources than sensors and hence (even if $\mathbf{A}$ is known) the system is not invertible (infinite number of solutions)!

Sparsity based solution: To solve this problem one relies on sources sparsity in a given representation domain (time, frequency, time-frequency or wavelet transform domains).

One can distinguish two classes of UBSS methods:

- **UBSS with known dictionary**: This is the main approach for mono-sensor BSS, using for example 'Matching Pursuit' technique for signal separation.
- **UBSS with clustering**: based for example on 'space direction' in the multi-sensor case.


WVD of source s_1
WVD of source s_2
WVD of source s_3
WVD of data mixture X
Truncated TF representation (auto+cross terms)
Truncated TF representation (auto terms)
Plot of TF points in class: 1 of 3
Plot of TF points in class: 2 of 3
Plot of TF points in class: 3 of 3
Time (secs)
frequency (Hz)

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- A. Aissa-Elbey, N. Linh-Trung, K. Abed-Meraim, A. Belouchrani and Y. Grenier, ”Underdetermined Blind Separation of Nondisjoint Sources in the Time-Frequency Domain”, IEEE Transactions on Signal Processing, 2006.

BSS of Dependent Sources

BSS has been closely linked to the ICA concept. However, in many applications, sources can show certain statistical dependency but are still 'separable' thanks to a strong signal structure (or side information), e.g.:

- Sources sparsity
- sources boundedness or sources finite alphabet
- Auto-regressive sources or more generally sources with ARMA models
- Known sources joint copula function
- $\vdots$

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Informed Source Separation

'BLINDNESS' IS OVER!

We have now information through pre-processing, learning, pilots, priors (bayesian), etc.

There are two main research directions:

- **How to exploit** the priors and side information to achieve source separation

- **How to quantify, model and design** the needed information for a target separation quality

... Roughly, a virgin research field!

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CONCLUDING REMARKS

Summary

- BSS is achieved via the restoration of a strong property of the sources (independence, sparsity, disjointness, ...).
- For coherent sources, BSS is achieved by (2nd order) decorrelation which can be done in different domains: time, frequency, or time-frequency domain.
- Underdetermined BSS problem can be solved if the sources are sparse and disjoint in a given transform domain or by using side information
- Several new and difficult challenges are still unsolved ... Good opportunities for research and collaborations!!

THANK YOU FOR
YOUR ATTENTION