“Semi-Blind” approaches to source separation: introduction to the special session

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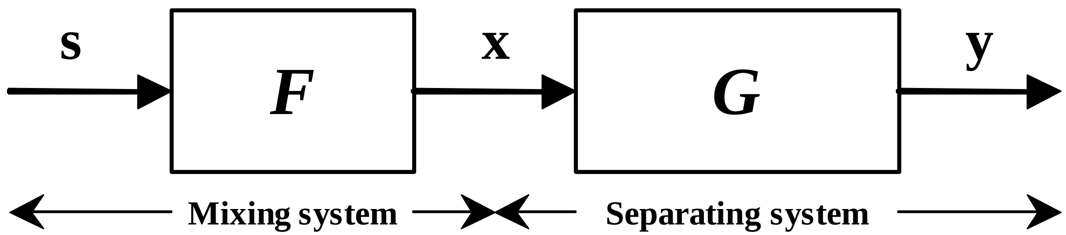
Outline

- Introduction to Blind Source Separation
- Relevance of "Semi-Blind" approaches (SBSS)
- A few examples
  - Temporal correlation
  - Non-Stationarity
  - Geometrical methods (bounded sources)
  - Discrete-valued sources
  - Sparsity of sources
  - Bayesian methods
  - Audio-Visual source separation
- Conclusions

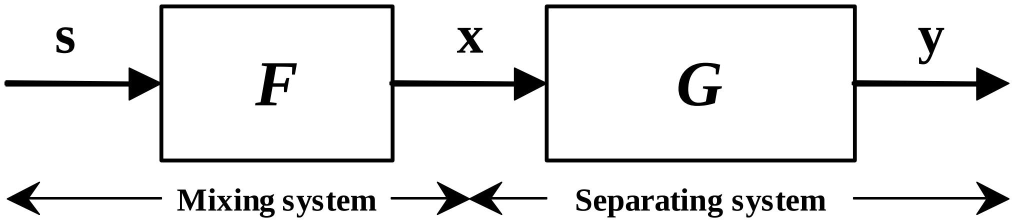
Blind Source Separation (BSS)

- Source signals $s_1, s_2, \ldots, s_N$
- Source vector: $\mathbf{s}=(s_1, s_2, \ldots, s_N)^T$
- Observation vector: $\mathbf{x}=(x_1, x_2, \ldots, x_M)^T$
- Mixing system $\rightarrow$ $\mathbf{x} = F(\mathbf{s})$



- Goal $\rightarrow$ Finding a separating system $\mathbf{y} = G(\mathbf{x})$

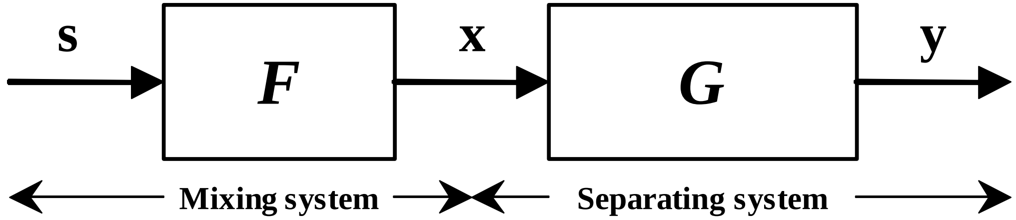
Blind Source Separation (*cont.*)



- Totally Blind:
  - No information about source signals
  - No information about mixing system

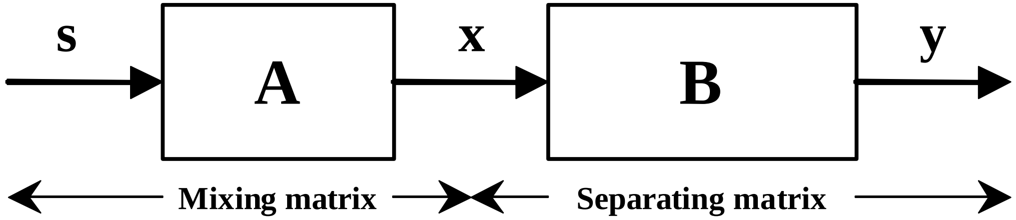
- Simply Impossible!

Blind Source Separation (*cont.*)



- *prior* information for the so-called "Blind" case:
  - Statistical "Independence" of sources
  - "Structure" of the mixing system (linear, convolutive, PNL, …)
  - No. of sources?
- If F is invertible, then identification of F leads to source separation
- Main idea: Find "G" to obtain "independent" outputs ($\Rightarrow$ Independent Component Analysis=ICA)

BSS in linear (instantaneous) mixtures

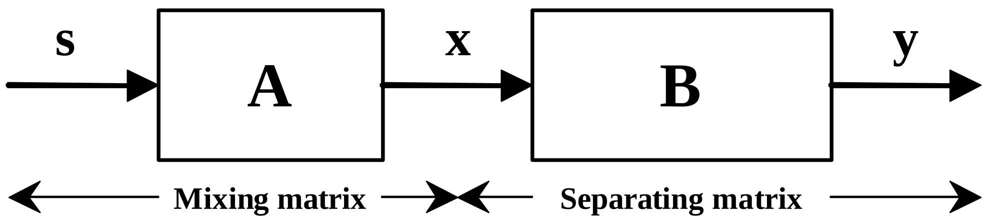


- Mixing system: **x=As (A** full rank**)**
- Separating system: **y=Bx**

Considering signals as random variables i.e. ignoring their temporal structure (iid assumption):

- Separability Theorem [Comon 1994,Darmois 1953]: If at most 1 source is Gaussian: statistical independence of outputs $\Rightarrow$ source separation ($\Rightarrow$ ICA: a method for BSS)
- Indeterminacies: permutation, scale
- Note: 2nd order independence (decorrelation) is not sufficient (Gaussian sources cannot be separated).

BSS in linear mixtures



Separation idea:

- Output Independence:
  - Non-linear decorrelation: E{ f(y1) g(y2) }=0
  - HOS: eg. Cancelling 4^{th} order cross-cumulant
  - Cancellation Outputs' Mutual Information
- Output Non-Gaussianity

Restrictions:

- Indeterminacies: scale, permutation
- Sources should be non-Gaussian (except possibly one)

Semi-Blind approaches

- There is more *a priori* information (but very weak) $\rightarrow$ Exploit it! $\rightarrow$ Semi-Blind

- Advantages:
  - Improving the separation performance
  - Providing simpler algorithms
  - Situations for which a Blind solution is difficult
    - More sources than sensors
    - Separating Gaussian sources

Gaussian mixtures and 2nd order methods

- SS not possible where sources are at the same time (Cardoso, ICA2001):
  - Gaussian
  - White (first “i” in “i.i.d”)
  - Stationary (“i.d.” in “i.i.d”)

- Any of these dropped ⇒ SS is possible
  - Dropping Gaussianity ⇒ iid non Gaussian : “Blind” (Gaussian signals - except one - cannot be separated)
  - Dropping stationarity or whiteness ⇒ Gaussian non iid: “Semi-Blind” (Gaussianity is not required, i.e. second-order statistics is enough, Gaussian signals can be separated)

Non-white (temporally correlated sources)

- Minimize cost function (joint diagonalization):

$$C(\mathbf{B}) = \sum_{l=1}^{L} w_l \,\text{off}(\hat{\mathbf{R}}_{\mathbf{y}}(\tau_l)) = \sum_{l=1}^{L} w_l \,\text{off}(\mathbf{B}\hat{\mathbf{R}}_{\mathbf{x}}(\tau_l)\mathbf{B}^T)$$

$$\text{where}: \hat{\mathbf{R}}_{\mathbf{x}}(\tau_l) = \hat{E}\{\mathbf{x}(t-\tau_l)\,\mathbf{x}(t)\}$$

- off($\mathbf{M}$) $\rightarrow$ a measure of diagonality of **M**, eg.
  - $\text{off}(\mathbf{M}) = \sum_{i \neq j} m_{ij}^2$ (SOBI, TDSEP)
  - $\text{off}(\mathbf{M}) = D(\mathbf{M} \mid diag\mathbf{M}) = \sum_i \log m_{ii} - \log\left|\det \mathbf{M}\right|$ (Kawamoto et. al. 1997)

Non-stationary sources

- Minimize (Matsuoka et. al. 1995)

$$C(\mathbf{B}) = \sum_{l=1}^{L} w_l \,\mathrm{off}(\mathbf{B}\hat{\mathbf{R}}_l\mathbf{B}^T)$$

$$\hat{\mathbf{R}}_l = \hat{E}_l\{\mathbf{x}(t)\,\mathbf{x}^T(t)\} \rightarrow \text{Short} - \text{time covariance matrix}$$

- See also Pham, Cardoso (IEEE 2001)
- Similar criterion as for colored sources $\Rightarrow$ Joint diagonalization of variance-covariance matrices

Colored or Non-stationary sources

- A few advantages:
  - Only 2^{nd}-order statistics
  - Separating Gaussian sources
  - Fast iterative algorithms for jointly diagonalizing matrices (JADE, SOBI, TDSEP, algo. of Yeredor, Pham, etc.)

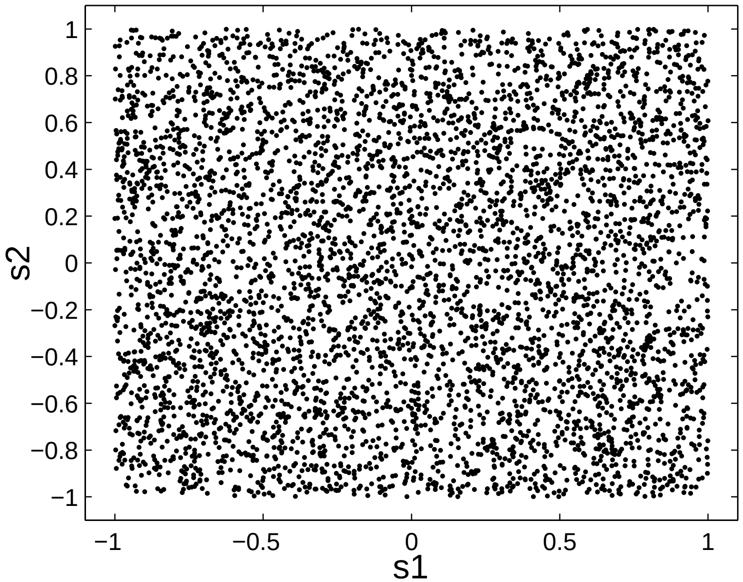
- Paper by Deville et al.

Some Semi-Blind approaches

- Geometrical approaches
  - Bounded sources (papers by Vrins and Pham, Lee et al.)
  - Discrete-valued sources
- Sparse sources (paper by Gribonval)
- Bayesian approaches (papers by Mohammad-Djafari and Bali et al.)
- Audio-Visual approaches
- Other prior: known source spectrum (paper by Igual et al.)

Geometric: Bounded Sources

- Independence $\Leftrightarrow p_{s1s2}(s_1,s_2)=p_{s1}(s_1)\,p_{s2}(s_2)$
- Bounded support for p_{s1} and p_{s2} $\Rightarrow$ rectangular support for p_{s1s2}
- $\Rightarrow$ scatter plot of sources forms a rectangle

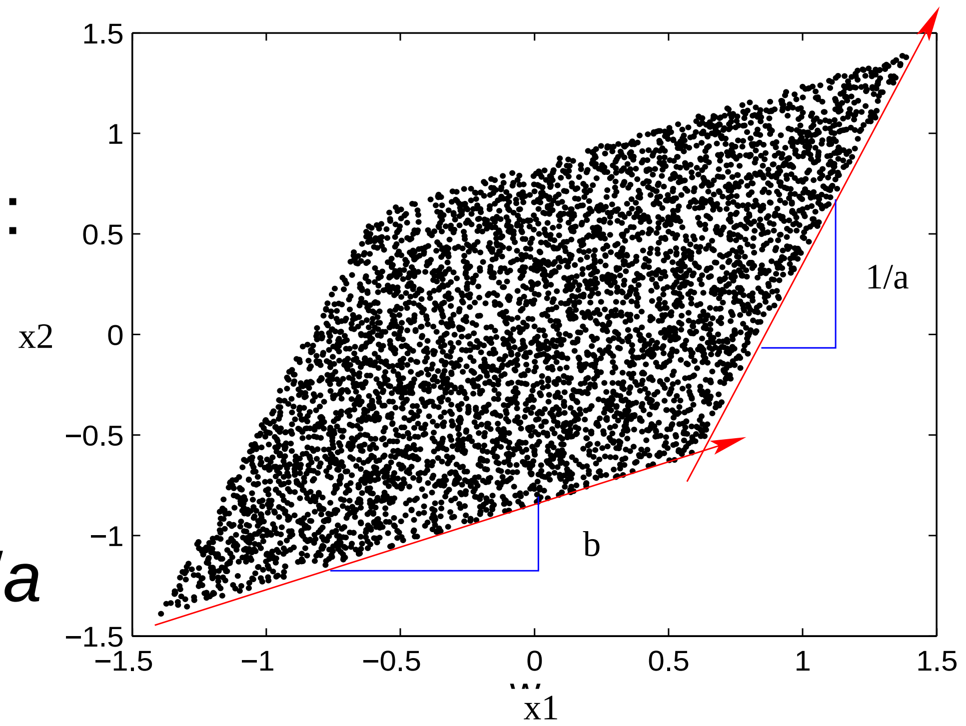


Bounded Sources (*cont.*)

- **x = As** transforms this rectangle to a parallelogram
- Mixing matrix assumed:

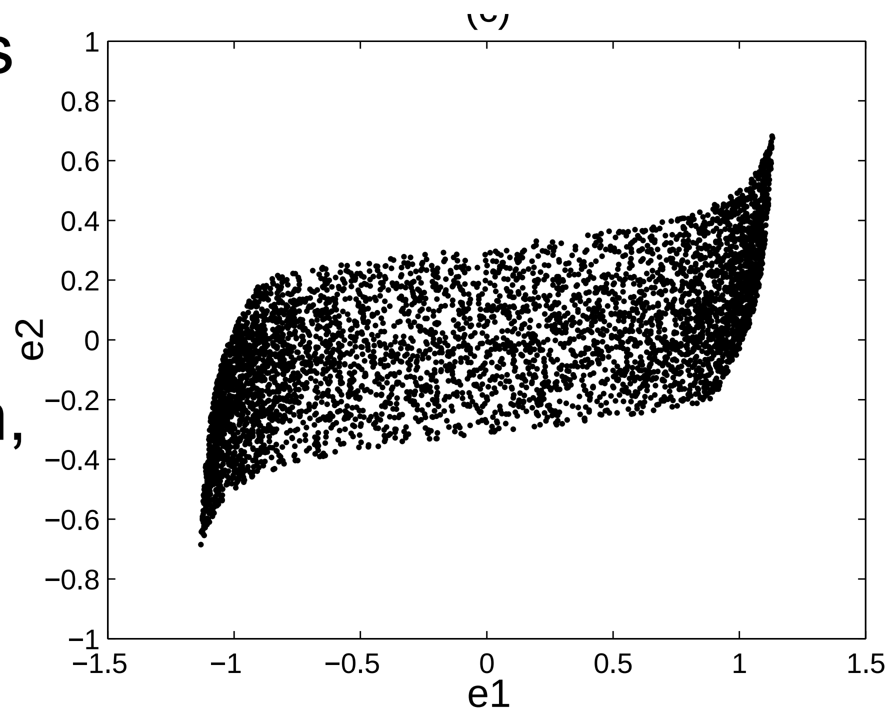
$$\mathbf{A} = \begin{bmatrix} 1 & a \\ b & 1 \end{bmatrix}$$

- Slopes of borders → 1/*a* and *b* → mixing matrix



Bounded Sources (*cont.*)

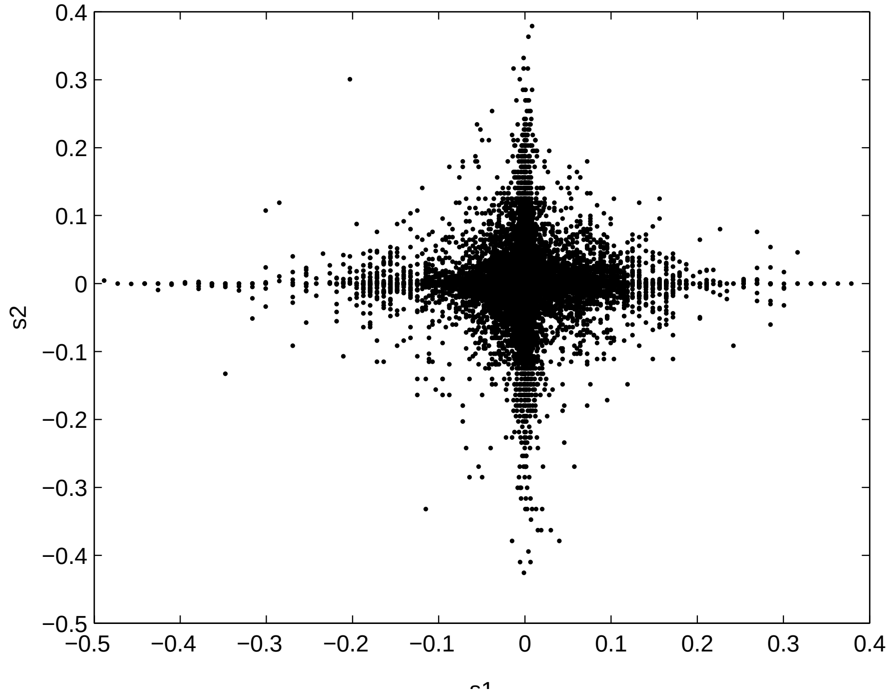
- Post Non-Linear (PNL) mixtures: linear mixtures but non-linear sensors
- Geometric: Transform again to a parallelogram, and then separate



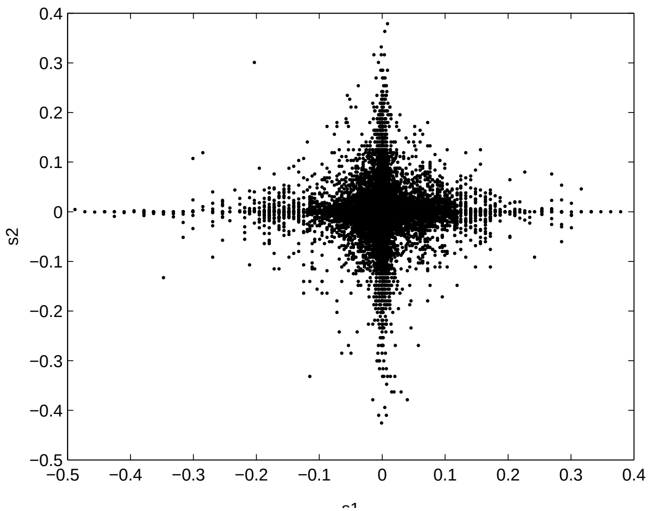
Sparse sources

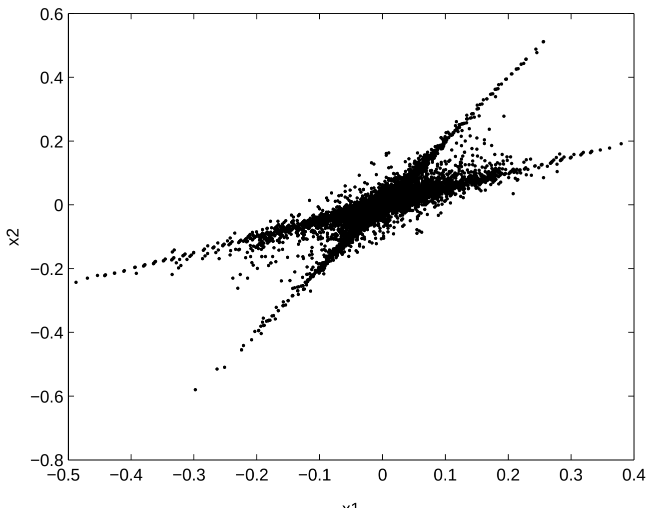
Like speech, ECG, EEG,...

- The rectangle is not well filled (requires lot of data sample).
- Source PDF's are concentrated about zero.
- Probability of having a point on the border of parallelogram is too low.



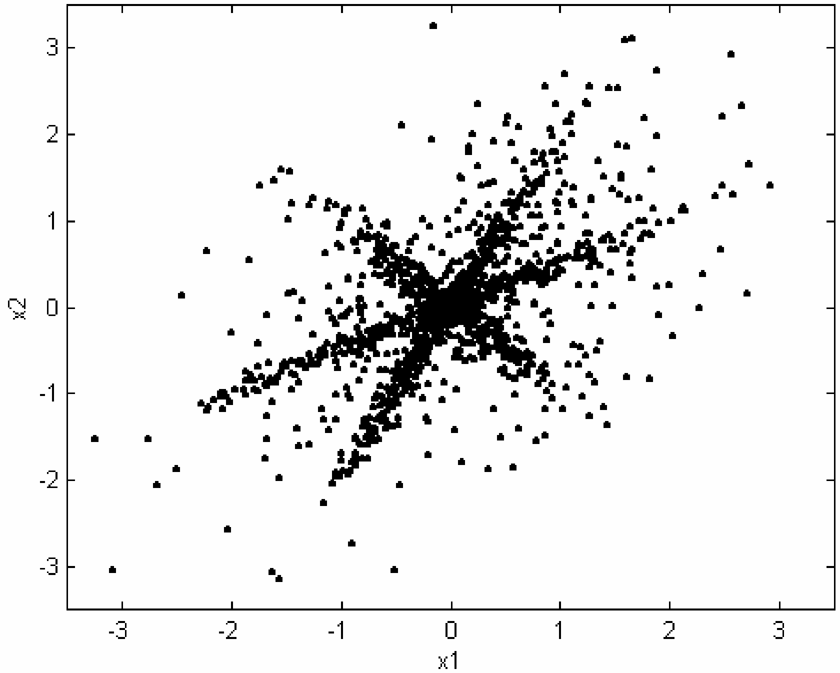
Sparse sources





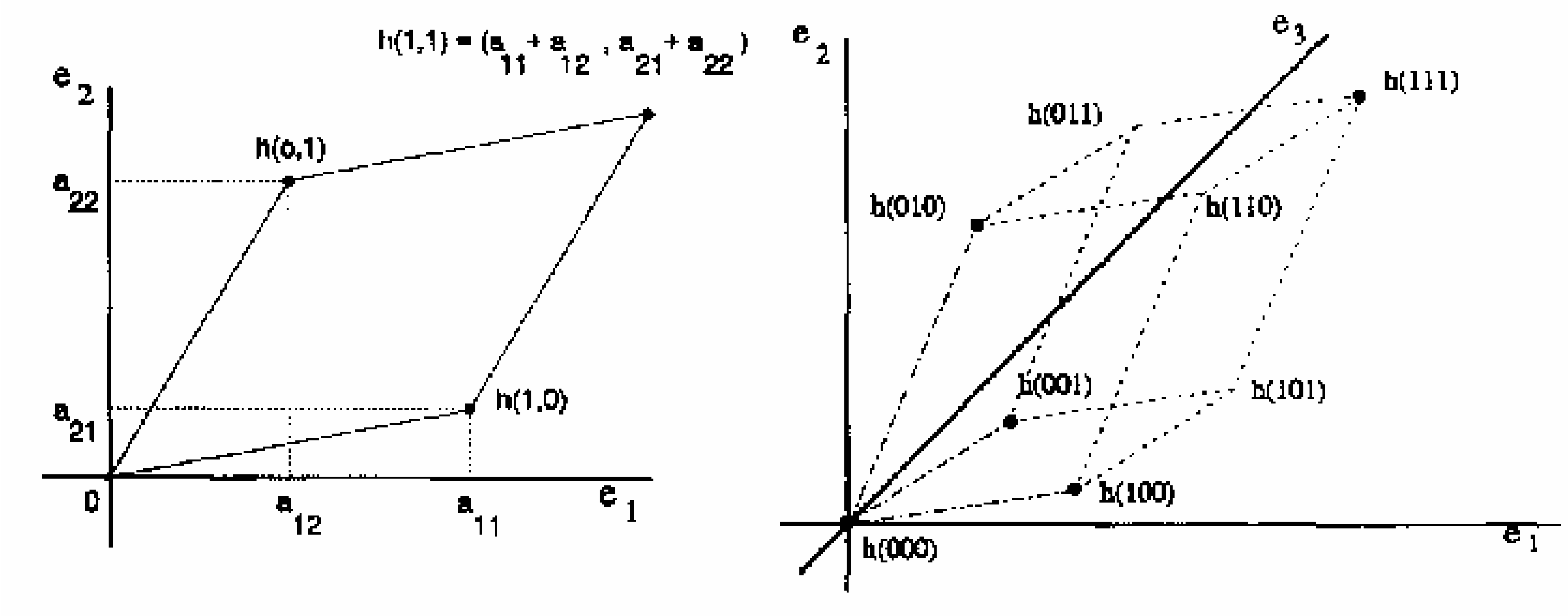
- Geometrical approach: Using “axes” instead of “borders”

Sparse Sources



- Possibility to separate more sources than sensors
- Identification of mixtures ≠ source separation
- Review paper, and a demo by Dr. Rémi Gribonval

Discrete-Valued Sources

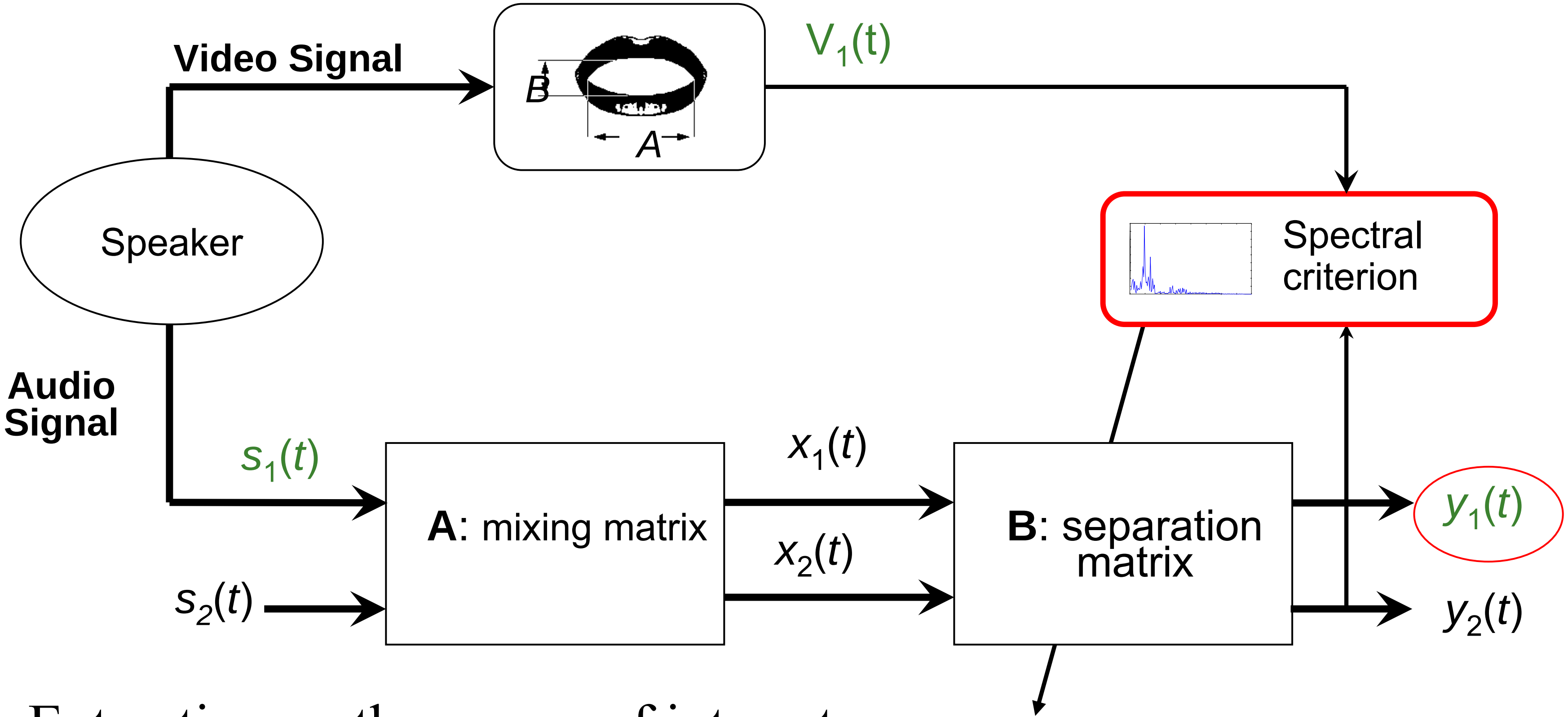


- (Belouchrani and Cardoso, 1994; Puntonet et. al., 1995; Taleb and Jutten, 1999; Grellier and Comon, 1998)
- Other example of sparsity. Usual in digital communications
- Possibility to separate more sources than sensors

Bayesian approaches

- Provide a general framework for modeling prior information :
  - source distribution,
  - time correlation,
  - additive noise,
  - …
- Can process more sources than sensors, and additive noise
- Review paper, by Dr. Ali Mohammad-Djafari

Audio-visual source extraction



Extraction on the source of interest

A, B, audio ⇒ p(spectrum/video, audio) ⇒ B estimated by ML

A,B ⇒ Voice activity detector ⇒ cancel permut. in convol. mixt.

Conclusion

- Semi-Blind methods, i.e. using priors
  - simpler and more efficient methods
  - can process problems that Blind methods cannot (Gaussian sources, more sources than sensors)
  - Disadvantage: more priors, less general
- This review is completed by
  - Bayesian Source Separation, by Dr. A. Mohammad-Djafari
  - A survey of Sparse Component analysis for BSS, by Dr. R. Gribonval and S. Lesage (+A Demo with music separation)
- Other papers in the special session give new examples of semi-blind approaches

Thank you very much for your attention