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

- Goal $\rightarrow$ Finding a separating system $y = G(x)$
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 (⇒ Independent Component Analysis=ICA)
BSS in linear (instantaneous) mixtures

- Mixing system: \( x = A s \) (\( A \) full rank)
- Separating system: \( y = B x \)

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 4th 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) → Exploit it! → 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):

\[ C(B) = \sum_{l=1}^{L} w_l \text{off}(\hat{R}_y(\tau_l)) = \sum_{l=1}^{L} w_l \text{off}(B\hat{R}_x(\tau_l)B^T) \]

where: \( \hat{R}_x(\tau_l) = \hat{E}\{x(t-\tau_l)x(t)\} \)

- \( \text{off}(M) \to \) a measure of diagonality of \( M \), eg.
  - \( \text{off}(M) = \sum_{i \neq j} m_{ij}^2 \) (SOBI, TDSEP)
  - \( \text{off}(M) = D(M \mid \text{diag}M) = \sum_i \log m_{ii} - \log|\det M| \) (Kawamoto et. al. 1997)
Non-stationary sources

- Minimize (Matsuoka et. al. 1995)

\[ C(B) = \sum_{l=1}^{L} w_l \text{off}(BR_lB^T) \]

\[ \hat{R}_l = \hat{E}_l \{ x(t)x^T(t) \} \rightarrow \text{Short – time covariance matrix} \]

- 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\textsuperscript{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 ⇔ \( p_{s_1s_2}(s_1, s_2) = p_{s_1}(s_1) p_{s_2}(s_2) \)
- Bounded support for \( p_{s_1} \) and \( p_{s_2} \) ⇒ rectangular support for \( p_{s_1s_2} \)
- ⇒ scatter plot of sources forms a rectangle
Bounded Sources (cont.)

- $\mathbf{x} = \mathbf{A}\mathbf{s}$ transforms this rectangle to a parallelogram.
- Mixing matrix assumed:
  $$\mathbf{A} = \begin{bmatrix} 1 & a \\ b & 1 \end{bmatrix}$$
- Slopes of borders $\rightarrow 1/a$ and $b \rightarrow$ 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 \( \neq \) 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 \( \Rightarrow p(\text{spectrum/video, audio}) \) \( \Rightarrow \) B estimated by ML
A, B \( \Rightarrow \) Voice activity detector \( \Rightarrow \) 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