SURVEY PAPER *Special Section on Digital Signal Processing*

Blind Separation of Sources: Methods, Assumptions and Applications

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SUMMARY The blind separation of sources is a recent and important problem in signal processing. Since 1984 [1], it has been studied by many authors whilst many algorithms have been proposed. In this paper, the description of the problem, its assumptions, its currently applications and some algorithms and ideas are discussed.
key words: independent component analysis (ICA), contrast function, Kullback-Leibner divergence, prediction error, subspace methods, decorrelation, high order statistics, whitening, Mutual-Information, likelihood maximization, conjoint diagonalization.

1. Introduction

The blind separation of sources problem consists in retrieving unknown sources from only observing a mixture of them. In general case, authors assume that the sources are non-Gaussian signals and statistically independent of one another.
The blind separation of sources was initially proposed† by Hérault *et al.* [3], [4] to study some biological phenomena [1], [5] (Biological sensors are sensitive to many sources, therefore the central nervous system processes typically multidimensional signals, each component of which is an unknown mixture of unknown sources, assumed independent [6]). Later on, this problem has been a very known and important signal processing problem. In fact, we can find this problem in many situations: radio-communication (in mobile-phone as SDMA (Spatial Division Multiple Access) and free-hand phone), speech enhancement [7], separation of seismic signals [8], [9], sources separation method applied to nuclear reactor monitoring [10], airport surveillance [11], noise removal from biomedical signals [12], [13], *etc.*

2. Models & Assumptions

The blind separation of sources problem consists in retrieving the p unknown sources from the q mixture signals, obtained by q sensors.
Let $S(t) = (s_1(t), \cdots, s_p(t))^T$ denotes the $p \times 1$ source vector, $Y(t) = (y_1(t), \cdots, y_q(t))^T$ the observation signals, and X^T the transpose of X. As shown in Fig. 1, the channel effect can be modeled as:

$$Y(t) = H[S(t), \ldots, S(t-M)], \tag{1}$$

where H is an unknown function which depends only on the channel and the sensors parameters. The separation consists on the estimation of a system G that its outputs signals $X(t) = G[H(S)]$ are the estimation of the sources.

2.1 Linear Mixtures

In the general case, $H[\ ]$, in Eq. (1) is non-linear vectorial function†† which depends on the present and the past of the source signals.
Until now, there is no general solution or algorithm for non-linear mixtures. However, a few authors proposed some algorithms for specifics mixture functions [14]–[18]. In the following, we assume that the channel is linear. In this case, Eq. (1) can be rewritten as:

$$y_j(t) = \sum_{i=1}^{p} h_{ji}(t) * s_i(t), \qquad 1 \leqq j \leqq q \tag{2}$$

where $*$ is the convolutive product and $h_{ji}(t)$ is a linear filter which presents the effect of the ith source on the jth observation signal. In this case, the mixture is said to be a convolutive mixture (i.e. the channel has some memory effect). Thus, one can write:

$$Y(n) = [\mathbf{H}(z)]S(n) = \sum_l \mathbf{H}(l)S(n-l), \tag{3}$$

where n denotes discrete time. Using the z-transform,

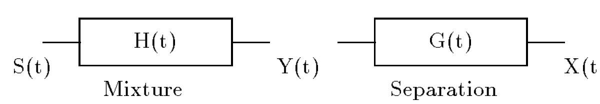

Fig. 1 General structure.

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†We must mention that Barness [2] proposed a similar algorithm to Jutten-Hérault's solution.

††A vectorial function $H(X_i)$ is an application in $\mathbb{R}^m$ of a space vector $X \in \mathbb{R}^n$. It can be considered as a vector of functions where each of its components can be written as function of the input vectors.

Eq. (3) can be rewritten as:

$$Y(z) = \mathbf{H}(z)S(z), \tag{4}$$

and in this case the convolution becomes a simple matrix multiplication.
Finally, many authors are involved in the separation of instantaneous mixture (or memoryless mixture). In this case, one can consider that the channel has no memory, thus matrix $\mathbf{H}(z)$ can be rewritten simply as a real matrix $\mathbf{H}$. In this case, we can write:

$$Y(n) = \mathbf{H}S(n). \tag{5}$$

2.2 Assumptions

The *blindness* in separating sources has been questioned in [19]. Aside this fact, it is widely used the following assumptions:

- **Assumption 1**: The sources are statistically independent of one another. This assumption is very important and a common one for all the algorithms of blind separation.
- **Assumption 2**: The channel can be instantaneous or convolutive and the matrix $\mathbf{H}$ is assumed to be invertible. Authors generally assume that $p = q$ or $q > p$ (this is a fundamental assumption for the sub-space approaches), but some works have been carried out for the case of $p > q$ for particular sources (as BPSK and MSK sources [20]).
- **Assumption 3**: The sources have a non-Gaussian distribution, or more precisely, at most one of them can be a Gaussian signal.

In the next section, we discuss the necessity of these assumptions.

2.3 Indeterminacy

In blind source separation, one can obtain the sources, but there are some indeterminacies. In fact, Eq. (4) can be rewritten as:

$$Y(z) = \mathbf{H}(z)\mathbf{P}^T\mathbf{\Delta}^{-1}(\mathbf{\Delta}\mathbf{P}S(z)) = \breve{\mathbf{H}}(z)\breve{S}(z),$$

where $\breve{\mathbf{H}}(z) = \mathbf{H}(Z)\mathbf{P}^T\mathbf{\Delta}^{-1}$, $\breve{S}(z) = \mathbf{\Delta}\mathbf{P}S(z)$, $\mathbf{\Delta}$ is any full rank diagonal matrix and $\mathbf{P}$ is any permutation matrix. It is obvious that $\breve{S}(z)$ can be considered as the source vector (its component are statistically independent from each other). For this reason, the separation can be only achieved up to a permutation and a scalar filter (resp. coefficient) in the case of convolutive (resp. instantaneous) mixture.

3. Independence Properties

The first assumption is fundamental for the blind separation. To explain the necessity of this assumption, let us start by giving some important concepts.

By definition, two random variables u_i and u_j are said to be independent if their mutual probability density function (pdf) is the product of their marginal pdf [21], [22]:

$$p(u_i, u_j) = p(u_i)p(u_j). \tag{6}$$

For discrete random variables, Eq. (6) can be rewritten using a similar relationships.

4. Important Concepts

To use the independence property, one can choose between the following concepts:

- **Kullback-Leibner divergence**: Let u_i and u_j be two random variables with marginal pdf $p_{u_i}(v)$ and $p_{u_j}(v)$, the Kullback-Leibner divergence is defined as:

$$\delta(p_{u_i}, p_{u_j}) \stackrel{def}{=} \int p_{u_i}(v) \log \frac{p_{u_i}(v)}{p_{u_j}(v)} dv \geqq 0. \tag{7}$$

  where $\delta(p_{u_i}, p_{u_j}) = 0$ if and only if (iff) $p_{u_i}(v) = p_{u_j}(v)$ [23], [24].
- **Mutual Information**: It should be mentioned that some authors propose methods based on the mutual information $i(p_U)$ [25], [26]:

$$i(p_U) = \int p_U(V) \log \frac{p_U(V)}{\Pi_{i=1}^{N} p_{u_i}(v_i)} dV \tag{8}$$

  where U is a random vector and its components are u_i. If u_i are independent from each other then $i(p_U) = 0$.
- **Moments and cumulants**: Many proposed algorithms use indirectly the statistical independence by using the relationships among the moments or the cumulants. The moment and the cumulant are grounded on the definition of characteristic functions. The first characteristic function $\Phi_U(V)$, of p continuous random vector $U^T = (u_1, u_2, \ldots, u_p)^T$, is defined as [21], [22], [27]–[29] the expectation of the function $h(U) = \exp(jV^TU)$:

$$\Phi_U(V) \stackrel{\Delta}{=} E\exp(jV^TU) = \int \exp(jV^TU)dF(U), \tag{9}$$

  where $F(U)$ is the cumulative distribution function (cdf) of U. The second characteristic function $\Psi_U(V)$ is defined as:

$$\Psi_U(V) = \ln\{\Phi(V)\}. \tag{10}$$

  These two functions are very important for the definition of the moments and the cumulants. In fact, the qth order moment of U is given by [22], [27], [29], [30]:

$$Mom_q(u_1, u_2, \ldots, u_q) \triangleq E(u_1 u_2 \ldots u_q) = (-j)^q \frac{\partial^q \Phi_U(V)}{\partial v_1\ \partial v_2 \ldots\ \partial v_q}\Big|_{V=0}. \quad (11)$$

where EX is the expectation of X. The qth order cumulant of U is given by:

$$Cum_q(U) \triangleq Cum(u_1, u_2, \ldots, u_q) = (-j)^q \frac{\partial^q \Psi_U(V)}{\partial v_1\ \partial v_2 \ldots\ \partial v_q}\Big|_{V=0}. \quad (12)$$

Using Eq. (12), one can prove that the cumulant of U is equal to zero if at least one component of U is statistically independent from the others [30], [31]. In fact, let us suppose that the first r components of U are independent from the others. in this case the first characteristic function can be rewritten as:

$$\Phi_U(V) = E\exp(jV^T U) = E\exp(j\sum_{i=1}^{r} v_i u_i) E\exp(j\sum_{i=r+1}^{q} v_i u_i), \quad (13)$$

and one can write the second characteristic function as:

$$\begin{aligned}\Psi_U(V) &= \ln E\exp(jV^T U) \\ &= \ln(E\exp(j\sum_{i=1}^{r} v_i u_i) E\exp(j\sum_{i=r+1}^{q} v_i u_i)) \\ &= \ln(E\exp(j\sum_{i=1}^{r} v_i u_i)) + \ln(E\exp(j\sum_{i=r+1}^{q} v_i u_i)).\end{aligned}$$

Finally, the qth order cumulant of U becomes:

$$\begin{aligned}Cum_q(U) = &\ (-j)^q \frac{\partial^q \ln(E\exp(j\sum_{i=1}^{r} v_i u_i))}{\partial v_1\ \partial v_2 \ldots\ \partial v_q}\Big|_{V=0} \\ + &\ (-j)^q \frac{\partial^q \ln(E\exp(j\sum_{i=r+1}^{q} v_i u_i))}{\partial v_1\ \partial v_2 \ldots\ \partial v_q}\Big|_{V=0} \\ &= 0 \end{aligned} \quad (14)$$

It is obvious that the first (resp. the second) part of the cumulant only depends on v_i, $1 \leqq i \leqq r < q$, (resp. $r \leqq i \leqq q$), and its derivative with respect to the vector V is zero.
Therefore the statistical independence of the signals means that the cross-cumulant of all the order should be equal to zero. However in practice, we can not cancel the cross-cumulant of all the order and in many cases authors use the cumulants up to the fourth order.

4.1 Separation Principles

Many researchers use the first assumption (see Sect. 2.2) in different ways:

1. Many algorithms use the minimization of criteria based on the cumulants.
2. Some algorithms use the direct definition of the independence and they minimize a criteria based on the maximization of the likelihood or the entropy (or the kullback-Leibner divergence).

As we mentioned in the previous sub-section, the statistical independence of the signals means that the cumulant of all the order should be equal to zero. However, the following question arises: what is the minimum order of the cumulant which can be used to achieve the separation? To answer this question, let us suppose that the sources are zero-mean signals and let us start our discussion with the second order statistics.

4.1.1 Second Order Statistics (SOS)

In the general case, where we only assume the three previous assumptions (see Sect. 2.2), the SOS are not enough to separate the sources. In fact, it is known that every matrix $\mathbf{H}$ have singular value decomposition (SVD) [34]:

$$\mathbf{H} = \mathbf{U}\mathbf{\Delta}^{1/2}\mathbf{V}, \quad (15)$$

where $\mathbf{\Delta}$ is a diagonal matrix and, $\mathbf{U}$ and $\mathbf{V}$ are orthogonal, i.e. $\mathbf{U}.\mathbf{U}^T = \mathbf{I}$ (or unitary for complex matrix, i.e. $\mathbf{U}\mathbf{U}^h = \mathbf{I}$), here $\mathbf{I}$ is the identity matrix and $\mathbf{U}^h$ is the hermitian transpose of $\mathbf{U}$. Without loss of generality, let us suppose that the sources are unite power. In this case the covariance matrix of the observation signal becomes:

$$\begin{aligned}\mathbf{\Gamma} = E(YY^h) &= E(\mathbf{U}\mathbf{\Delta}^{1/2}\mathbf{V}SS^h\mathbf{V}^h(\mathbf{\Delta}^{1/2})^h\mathbf{U}^h) \\ &= \mathbf{U}\mathbf{\Delta}^{1/2}\mathbf{V}E(SS^h)\mathbf{V}^h\mathbf{\Delta}^{1/2}\mathbf{U}^h \\ &= \mathbf{U}\mathbf{\Delta}^{1/2}\mathbf{V}\mathbf{V}^h\mathbf{\Delta}^{1/2}\mathbf{U}^h \\ &= \mathbf{U}\mathbf{\Delta}\mathbf{U}^h \end{aligned} \quad (16)$$

It is obvious that the covariance matrix $\mathbf{\Gamma}$ doesn't depend on the matrix $\mathbf{V}$. Thus, SOS alone is not enough to separate the sources.

4.1.2 Third Order Statistics (TOS)

When the sources have symmetric pdf the TOS are zero. This restriction can not be acceptable in many cases, thus TOS are not enough to achieve a blind separation of the sources.

4.1.3 Fourth Order Statistics (FOS)

Some authors denote the statistics of order higher than two by HOS or high order statistics: The FOS are enough to separate blindly the sources, and they are used in many algorithms [35]–[40]. In the case of two sources, it is was proved by algebraic method in [41]

that the separation can not be achieved by using SOS but it can be using the FOS.
We must mention that the cumulant of order higher than two are zero for Gaussian signal. Thus, the separation of Gaussian signals can not be carried out by using the HOS and one needs to add the third assumption (see subsection 2.2). Now, by using the same fact, one can separate the sources using the HOS in the case of additive Gaussian noise [42]. Finally, the fourth order cross-cumulants of zero-mean signal are given by [43]:

$$\begin{aligned} Cum_{13}(u_i, u_j) &= Eu_i u_j^3 - 3Eu_i^2 Eu_i u_j \\ Cum_{31}(u_i, u_j) &= Eu_i^3 u_j - 3Eu_j^2 Eu_i u_j \\ Cum_{22}(u_i, u_j) &= Eu_i^2 u_j^2 - Eu_i^2 Eu_j^2 - 2(Eu_i u_j)^2 \end{aligned}$$

5. Summary Of Principal Methods

The classification of the methods is very difficult because some of the algorithms use different aspects. In this section, we will try to subjectively classify the algorithms with respecting to their major aspect.

5.1 Instantaneous Mixtures

5.1.1 Moments or Cumulants Based Algorithms

The first algorithm was proposed by Jutten *et al.* [6], [47], [48], for recursive architecture†. That algorithm consists on updating the separation matrix $\mathbf{C} = (c_{ij})$ by using:

$$c_{ij}(t+1) = c_{ij}(t) + \alpha f[\hat{x}_i(t)] g[\hat{x}_j(t)], \tag{17}$$

where f and g are two odd non-linear functions. Jutten and Herault algorithm was a heuristic proposal, but it was proved in [49] that it works for symmetric pdf. To generalize that approach, Jutten *et al.* [47], [50] proposed another criterion based on the cross-cumulant $Cum_{31}(x_i, x_j)$.
Independently from the previous work, Lacoume and Ruiz [51] proposed another heuristic two step algorithm. Using the SVD decomposition of the matrix $\mathbf{H}$, $\mathbf{H} = \mathbf{U}\mathbf{\Delta}^{\frac{1}{2}}\mathbf{V}$, they proved that the matrices $\mathbf{U}$ and $\mathbf{\Delta}$ (see Eq. (16)) can be estimated by a simple decorrelation, and the matrix $\mathbf{V}$ can be estimated by maximization of the following function:

$$F(\theta, X) = \frac{1}{(Cum_{13}(X))^2 + (Cum_{31}(X))^2 + (Cum_{22}(X))^2}$$

where θ is a rotation angle, the matrix $\mathbf{V}$ is replaced by a Givens rotation matrix.
Finally, Mansour *et al.* proposed in [40], [52], using the Levenberg-Marquardt algorithm [53], the minimization of a criterion based only on the cross-cumulant (2x2).

†In this case, the separation matrix is denoted by $\mathbf{C}$ and has a zero on its principal diagonal. With respecting to our notation, one can find that the separation matrix $\mathbf{G} = (\mathbf{I} + \mathbf{C})^{-1}$.

5.1.2 Algebraic Approaches

Comon Approach: His approach is based on the fact that a square matrix can be decomposed as:

$$\mathbf{H} = \mathbf{L}\mathbf{Q}\mathbf{\Delta}, \tag{18}$$

where $\mathbf{L}$ is an lower triangular matrix with positive components on its principal diagonal, $\mathbf{Q}$ is a rotation matrix, and $\mathbf{\Delta}$ is a signature matrix††. Comon [54], [55] proposed a direct algebraic method to separate the instantaneous mixture of two sources. In fact, to separate the sources up to a permutation $\mathbf{P}$ and a scale factor (i.e. diagonal matrix $\mathbf{\Delta}$), one can compute a matrix $\mathbf{F}$ such that:

$$\mathbf{F}\mathbf{H} = \mathbf{\Delta}\mathbf{P}. \tag{19}$$

or more simply, $\mathbf{F} = \mathbf{Q}^h \mathbf{L}^{-1}$. Comon proved that one can estimate $\mathbf{L}$ by using a simple Cholesky factorization [34] of the covariance matrix of the observed signals. Now, the estimation of $\mathbf{Q}$ can be obtained by the product of p^2 plans rotations (i.e. Givens rotations). Finally, the different Givens angles can be obtained as the solution of second order polynomial equations based on the fourth order cumulants. In [38], Comon generalized his approach for three sources. Finally, Cardoso et Comon [56] proposed a direct solution using tensorial notation.
Garat method: Garat [57] proposed an algebraic method which consists on resolving a non-linear equation system based on the cumulants. He proved that the column of the mixture matrix can be estimated up to a permutation and a scaling factor from the solutions of quadratic and homogeneous equations based on the fourth order cumulants. He also presents an adaptive version of his method using an ad-hoc algorithm applied on a couple of signals at the same time.
Mansour-Jutten approach. This approach [41] is limited to the case of two sources and it consists on finding an algebraic solution to a non-linear equation system based on the statistics of the observed signals.

5.1.3 Contrast Function

A contrast function J [58]–[60] is an application in $\mathbb{R}$ of a space random vector $X \in \mathbb{R}^n$. It only depends on the pdf of X and has the following properties:

- $J(X)$ is symmetric with respect to the components x_i of X (i.e. for any permutation matrix $\mathbf{P}$, we have $J(X) = J(\mathbf{P}X)$).

††A signature matrix is a diagonal one which has ± 1 as components on its principal diagonal.

- $J(X)$ is invariant by any scale change (i.e. for any full rank diagonal matrix $\mathbf{\Delta}$, we have $J(\mathbf{\Delta}X) = J(X)$).
- $J(X)$ is maximum if the components of X are mutually independent, i.e., for any full rank matrix $\mathbf{H}$, we have $J(\mathbf{H}X) \leqq J(X)$.
- if the components of X are independent among them, then $J(\mathbf{H}X) = J(X)$ iff $\mathbf{H} = \mathbf{P\Delta}$ ($\mathbf{P}$ is a permutation matrix and $\mathbf{\Delta}$ is a full rank diagonal one).

Contrast functions in blind source separation were introduced at first by Comon in [58], as:

$$J(x) = \sum_i |Cum_4(x_i)|^2. \tag{20}$$

Using a likelihood estimator, this function was also independently introduced by Gaeta [61].
Moreau and Macchi [62] proposed an algorithm based on the minimization of that contrast function with respect to the separation matrix and they suggest that separation can be carried out easily by using another contrast function:

$$J(x) = \sum_i |Cum_4(x_i)|. \tag{21}$$

This new contrast function [62] can separate the sources that have the same sign of kurtosis (the normalized fourth order cumulant [63], [64]). In addition, it needs a whitening pre-processing step (see subsection 5.1.6). In [65], [66], Macchi and Moreau proposed another contrast function which doesn't need a whitening pre-processing step:

$$J(X) = \sum_i^p \frac{|Cum_4(x_i)|}{(Ex_i^2)^2} - \beta \sum_{i<j=1}^p \frac{|Cum(x_i^2 x_j^2)|}{Ex_i^2 Ex_j^2} - \gamma \sum_{i \neq j=1}^p \frac{|Cum(y_i y_j^3)}{\sqrt{Ey_i^2 (Ey_j^2)^3}}$$

They proved that the last function [60] is a contrast function for X, if $\beta \geqq 1,\ \gamma \geqq 0$.

5.1.4 Deflation

For the sources with the same sign of kurtosis [63], [64], Delfosse and Loubaton [69] proposed a deflation method (i.e. at each iteration, one can get one source). Their method was inspired by the one proposed by Shalvi and Weinstein [70]. After a whitening pre-processing step (see the subsection 5.1.6), they separate the sources by minimizing a contrast function (with respecting to a separation vector $G(n)$):

$$K(G) = \frac{E(G(n)Y(n))^4}{4}.$$

In fact, they proved that when $G(n)$ corresponds to a minimum of K then one can obtain the estimation of one source by $x_i(n) = G(n)Y(n)$. After that, one can reduce the number of sources to separate the remaining $p-1$ ones. They proved [71] that this algorithm don't have any spurious solutions and that this approach can be applied to the general case where the sources can have different sign of kurtosis [71]. Finally, using the ordinary differential equation (ODE, see [72]), they found that variance of the asymptotic error is [73]:

$$\Xi = -\frac{E(x_i^6)}{2Cum_4(x_i)}\mathbf{I},$$

where $\mathbf{I}$ is the identity matrix and $Cum_4(x)$ is the fourth order cumulant of x.

5.1.5 Kullback-Leibner & Mutual Information

Lacoume *et al.* proved [23], [74] that the mutual information is a contrast function. The mutual information comes from the definition of the Kullback-Leibner divergence (7) by:

$$i(p_x) = \int p_x(u) \log \frac{p_x(u)}{\Pi_{i=1}^N p_{x_i}(u_i)} du$$

Bell and Sejnowski proposed on [25] an information-maximization approach to blind separation and blind deconvolution problem. In addition, Pham [24] proposed an independent component analysis (ICA) algorithm based on Kullback-Leibner divergence.

5.1.6 Whitening & Rotation

Many authors [51], [55], [75] proposed algorithms to run in two steps: The first is a whitening pre-processing, where they only use the SOS. The second step is the estimation of a rotation matrix which is estimated generally by using the HOS.
Among many algorithms, we will mention the algorithm of Cardoso and Laheld. This algorithm was subject of many papers and research studies:
For the sources with the same sign of kurtosis, Laheld *et al.* [75]–[77] proposed two versions of that algorithms: PFS "parameter free separation" (named later as EASI "equivariant adaptive separation via independence" [77]) and the SPFS (Stabilized PFS†). In [75], [77], a performance study and some simulations can be founded.
The main idea of that algorithm consists on the decomposition of the separation matrix $\mathbf{G}$ as the product of two matrices $\mathbf{G} = \mathbf{WU}$, where $\mathbf{W}$ is a spatial decorrelation matrix and $\mathbf{U}$ is an unitary one such that the sum of the kurtosis of the output signals is maximum. Therefore, the separation matrix can be updated by:

†An IBSS (Iterative Blind Source Separation) algorithm, which is similar to the EASI and the SPFS, can be founded in [78]

$$\mathbf{G}(t+1) = (\mathbf{I} + \mu\mathbf{J}(\mathbf{T}(t)S(t)))\mathbf{G}(t), \tag{22}$$

where $\mathbf{J}(\mathbf{T}(t)S(t))$ is a criterion of $\mathbf{G}$ ($\mathbf{T}$ is the total matrix $\mathbf{T} = \mathbf{HG}$). From (22), they prove that the total matrix is updated by [75]:

$$\mathbf{T}(t+1) = \{\mathbf{I} - \mu\mathbf{J}(\mathbf{T}(t)S(t))\}\mathbf{T}(t). \tag{23}$$

The last equation means that the performances of this algorithm are independent from the mixture matrix $\mathbf{H}$. In [79], Cardoso *et al.* proposed a batch version NPFS (Newton PFS) which is an approximation using a Newton matrix. In their work, they introduce the relative Gradient algorithm. The last algorithm was independently introduced by Amari *et al.* [80],[81] as the Natural Gradient.

5.1.7 Likelihood Maximization

It is known that the likelihood estimator is efficient and non-biased estimator [83],[84]. Gaeta and Lacoume [85],[86] proposed an approach based on the likelihood maximization. That approach consists on the modeling of the source pdf by a fourth order Gram-Charlier expansion (or Edgeworth expansion) [43] and the estimation of the different parameters using likelihood estimators. In [87]–[89], Harroy and Lacoume study the performances of the Gaeta-Lacoume algorithm and they founded that that algorithm can reach the Cramer-Rao bound [83].

Independently Pham *et al.* [90] proposed an algorithm based on the likelihood maximization. At first, by assuming that the sources are independent and identically distributed (iid) signals, they found, using the maximum of likelihood, the best estimator of the mixing matrix $\mathbf{H}$. After that, they used the found parameters to estimate the mixing matrix in case of non-iid signals. Garat [57] presents two versions of that algorithm: the QMV-I (Quasi-Maximum likelihood) for iid signals; and QMV-II for the sources correlated in time but not in space and the last algorithm is only using the SOS.

In digital communications, the sources pdf can be known, Belouchrani [78],[91] proposed an likelihood maximization algorithm for separate iid sources with some additive Gaussian noise. The likelihood maximization is carried out according to EM algorithm [92],[93]. He developed two versions of his approach: MLS (Maximum Likelihood Separation) and the SMLS (Stochastic Maximum Likelihood Separation).

5.1.8 Second Order Statistics

In many cases, the sources can be considered as correlated in time. In these cases, one can simplify the criteria and used only the SOS. The principal idea of this algorithm consists on the separation using the covariance matrix at different instants. *In all these methods, one must also assume that the correlation functions of the sources are differents* [94]. For stationary correlated in time sources (but independent from each other), one can find a $\tau \neq 0$ such:

$$ES(t)S^T(t-\tau) = \mathbf{C}(\tau), \tag{24}$$

where E is the expectation and the matrix $\mathbf{C}(\tau)$ is a non-zero diagonal matrix. Féty [95] proposed an algorithm which consists on the diagonalization of different covariance matrices of the observed signals:

$$\mathbf{\Gamma}(\tau) = \mathbf{HC}(\tau)\mathbf{H}^T, \tag{25}$$

That idea was improved by Tong [96], then by Comon [97]. This algorithm (which is similar to AMUSE the Tong's algorithm [98]) can be found in details in [23], [99]: Comon suggested the construction of two matrices using two sets of parameters α_τ and β_τ:

$$\mathbf{\Gamma}_1 = \sum_\tau \alpha_\tau \mathbf{\Gamma}(\tau) \tag{26}$$

$$\mathbf{\Gamma}_2 = \sum_\tau \beta_\tau \mathbf{\Gamma}(\tau). \tag{27}$$

Now, using a factorization algorithm, one can find two other matrices $\mathbf{R}$ and $\mathbf{U}$ such that

$$\mathbf{\Gamma}_1 = \mathbf{R}\mathbf{R}^h\mathbf{R}^{-1}\mathbf{\Gamma}_2\mathbf{R}^{-h} = \mathbf{U}\mathbf{\Lambda}^2\mathbf{U}^h. \tag{28}$$

$\mathbf{U}$ is the matrix of the eigen-vectors and $\mathbf{\Lambda}$ is a diagonal matrix of the eigen-values. One can freely choose the parameters α_τ and β_τ with the condition that we have a maximum distance among the eigen-vectors corresponding to $\mathbf{\Lambda}$ (one should mention that the choice of these parameters, to respect that condition, is not clear). Finally the matrix $\mathbf{H}$ is estimated up to a permutation and a full rank diagonal matrix by $\mathbf{H} = \mathbf{RU}$.

Belouchrani [78],[100],[101] proposed another method based also on the approximatively conjoint diagonalization [35],[36]. The conjoint diagonalization of k matrices $\mathbf{M}_l$, here $l = 1, \ldots, K$ is the matrix $\mathbf{V}$ which minimize the following criterion:

$$C(\mathbf{V}) = -\sum_{l,i} |V_i^h \mathbf{M}_l V_i|^2, \tag{29}$$

where V_i is the ith column of $\mathbf{V}$. We should mention also that Amari *et al.* proposed an algorithm to separate temporally correlated signals [81],[102].

Finally, Pham and Garat [57],[94] proved, using the likelihood maximization method, the existence of optimum filters to separate the sources. Their likelihood function L_τ is found using the asymptotic convergence of the discrete Fourier transform (DFT) $d_S(n)$ of the independent sources to Gaussian ones. In fact, the vector $d_S(n)$ $(n = 0, ..., \tau/2)$ are asymptotically independent zero-mean Gaussian vectors, with a diagonal covariance matrix $\mathbf{D}_g(n/\tau) = diag(g_1(n/\tau), \cdots, g_p(n/\tau))$. In addition, the function L_τ can be determined by the logarithm of conjoint pdf $d_Y(n)|_{n=0}^{\tau/2}$:

$$L_\tau = -\frac{1}{2}\sum_{i=1}^{p}\sum_{n=0}^{\tau/2}\frac{|e_i^T \mathbf{H}^{-1} d_S(n)|^2}{g_i(n/\tau)} - Tln|\det\{\mathbf{H}\}|$$

here e_i^T is the ith raw of an identity matrix and $d_Y(n)$ is the DFT of the vector $Y(t)$:

$$d_Y(n) = \frac{1}{\sqrt{\tau}}\sum_{t=0}\tau - 1e^{-j2\pi nt/\tau}Y(t). \tag{30}$$

5.1.9 Non Stationary Source Separation

Matsuoka *et al.* [103], [104] were the first to propose an algorithm to separate the nonstationary sources, where they assumed that the power ratio of two sources $Es_i^2(t)/Es_j^2(t)$ is a function of time and not constant. It is known that the covariance matrix is a positive definite matrix [34], and that Hadamard inequality [105] of an arbitrary positive semidefinite matrix $\mathbf{R} = (r_{ij})$ is given by:

$$\prod_{i=1}^{p} r_{ii} \geqq \det\{\mathbf{R}\}, \tag{31}$$

where the equality is hold iff the matrix $\mathbf{R}$ is a diagonal matrix. Using Eq. (31), it is easy to prove that:

$$\sum_{i=1}^{p}\log r_{ii} - \log\det\{\mathbf{R}\} \geqq 0. \tag{32}$$

Using this nice property and a stochastic Gradient algorithm, the authors separate the sources by minimizing the following criterion:

$$Q(\mathbf{G}, \mathbf{R}(t)) = \frac{1}{2}\{\sum_{i=1}^{N}\log(Ex_i^2(t) - \log|EX(t)X^T(t)|\}$$

where $\mathbf{R}(t)$ is the covariance matrix of the estimated sources. Recently, the authors generalized their criterion to separate convolutive mixtures [106], and applied it in real world speech separation [107]. In [108], [109], Mansour and Ohnishi proved that the separation of non-stationary sources is possible by only using the SOS.

5.1.10 Geometrical Approach

In [110], [111] the authors proposed an original idea to separate the sources. That idea is based on the information obtained from the geometrical representation of the observed signals in the observed signal space. In [112], the authors propose a theoretical study of their approach and a simple algorithm to separate two sources can be found. Recently, the authors proposed a modified version of their algorithm [113], [114] for any number of sources.

5.2 Convolutive Mixtures

In some applications as telecommunications (radio-mobiles, GSM) or real world speech processing, one can not approximate the convolutive mixture by an instantaneous one, except for narrow band signals (in this case the convolutive mixture becomes an instantaneous one with a complex mixing matrix). Since 1990, few methods of source separation have been proposed in the case of convolutive mixtures. These methods were generally based on high order statistics [116]–[120].

5.2.1 High order Statistics

The first algorithm for convolutive mixture using HOS was proposed by Jutten *et al.* [116]. That algorithm deals with two sensors, two sources and the channel are considered as finite impulse response (FIR) filters [121]. To estimate the parameters of the channel filter, the authors generalize their previous criterion, which dealt with instantaneous mixture [6]. In fact, they use the cancellation of the cross-moments but at different instants:

$$E(f(x_i(n)g(s_j(n_k))) = 0 \tag{33}$$

It was proved later that this algorithm can be improved by using the cross-cumulants instead of moments [7], [117]). Charkani [122] improved the same algorithm by searching the optimal functions f and g.

5.2.2 Frequency Approaches

At first view, it seems from (3) that the convolutive mixture of real signals problem can be transformed to an instantaneous mixture of complex problem using Fourier transformation:

$$\mathbf{Y}(z) = \mathbf{H}(z)\mathbf{X}(z), \tag{34}$$

The last equation is similar to the instantaneous model (5). Unfortunately, the problem is not so easy due to the permutation indeterminacy. In the instantaneous mixture, the permutation shall not be regarded as a great problem, but in the convolutive case that means the sources cannot be obtained by simply adding the separated band of frequency (the frequency band separated at the same output can be for different signals). Once we separate the mixture using Fourier transformation and narrow band filter, we must perform a post-separation processing algorithm [123].

To solve this problem, Capdevielle [123], [124] found the separated frequency band corresponded to each sources by using the correlation properties estimated over a slippery window of the output sources.

For the separation of seismic signals, Thirion *et al.* [9], [125] proposed another approach using the phases information and a likelihood criterion [87]. Concerning

the permutation problem, they suggest that the separated frequency band of the same signal can be obtained by minimizing the fluctuation phases in the frequency domain.
For the same problem, Charkani and Hérault [126] prove that the separation of the convolutive mixture can be realized using a criterion of fourth order cross-cumulants which should be applied in the frequency domain.

5.2.3 Second Order Statistics

For the separation of convolutive mixture by only using the SOS, one can find two different strategies of research:

- It was proved in [127],[128] that the separation of *FIR strictly causal* channel can be carried out using the SOS applied to different instants.
- When the *number of sources are strictly less than the number of sensors*, $p < q$, one can used a subspace approach. The subspace approach leads generally to very elegant algorithms from theoretical point of view, but in general case, their convergence is relatively slow due to the minimization of large size matrices. We can find two different types of subspace methods:
  - The subspace approach is quite new in solving the blind identification problem [129]–[132]. Using similar approach, it is proved [133]–[136] that the separation of convolutive mixture can be realized by only using the SOS and some adding assumptions [137],[138] on the channel $\mathbf{H}$. In the general case, It was proved [137],[139]–[141] that by only using second-order statistics, we can reduce the convolutive mixture problem to an instantaneous mixture; then in the second step, we should only separate sources consisting of a simple instantaneous mixture (typically, most of the instantaneous mixture algorithms are based on fourth-order statistics).
    When the columns of the mixing matrix $\mathbf{H}(z)$ have different degrees[†], the separation of a convolutive mixture can be achieved by only using SOS [134],[135].
  - Using a subspace representation, Delfosse and Loubaton [142] proved that the separation of a convolutive mixture can be reduced to an instantaneous mixture by minimizing a linear prediction error (SOS); then in the second step, they use HOS to separate the residual instantaneous mixture. To this purpose, they assume that the filter $\mathbf{H}(z)$ is a causal, rational and full rank filter, $\forall z$. In other words, they prove that the innovations signals of the sources are the normalized innovation signals of the observed signals. In addition, they prove that these innovations can be obtained by only using SOS up to an orthogonal non-polynomial matrix $\mathbf{U}$. For the identification of $\mathbf{U}$, one must use HOS [73].

[†]The degree of a column is defined as the highest degree of the filters in this column.

5.3 Applications

As we mentioned in the introduction of this paper, blind separation of sources is an interesting problem because one can find it in many different situations and applications [143]:

1. In [45], the authors use ICA to separate electrocardiographic signals: the sources are assumed to be the heartbeat of a mother and the heartbeat of her foetus.
2. In [12],[13], the authors are interested as well in the separation of EEG signals.
3. The ICA also used to study other bio-medical signals as in [144].
4. Some authors use this problem to speech enhancement [145].
5. Desodt *et al.* [146] apply complex independent components analysis to the separation of radar signals. In addition, in [11] it was used for airport surveillance.
6. One can also find the blind separation in radio-communication field, especially for mobile-phones (SDMA, Spatial Division Multiple Access), or free-hand phone application [122].
7. Thirion *et al.* [8],[125] try to separate a seismic signals.
8. In [147] the authors try to separate the vibrations of rotating-machines, to control these machines. Recently, Rotating machine vibration analysis with second-order independent component analysis, was proposed by Ypma and Pajunen [148].
9. D'Urso and Cai [10] use sources separation method applied to nuclear reactor monitoring.
10. This model was used also to improved multi-tag radio-frequency identification systems based on new source separation neural networks [149]–[152].
11. Blind source separation of real world signals [153], [154].
12. This model was used to achieve an adaptive separation of mixed brod-band sound sources with delays by using a beamforming Hérault-Jutten network [155].
13. In [156], the authors propose a solution for discrim-

inate several optical sources by means of modified optical tracker and blind separaion of sources algorithms.

14. The ICA was used [157] to improve the on-line performance of information-maximization-based blind signal separation.
15. To extract the independent component of natural images, the authors of [158] used fourth-order cumulants algorithms.
16. The ICA was used also in some visual image communication systems [159].
17. To separate mixing images, Cichoski *et al.* [160] propsed a multi-layer neural networks with a local adaptive learning rule for blind separation of source signals.
18. Some algorithms were implemented using digital circuits [161],[162] or VLSI [163].

6. Conclusion

In this paper, we presented a survey of source separation problem, applications and the major methods and approaches. To conclude our paper, we must stress that in most studies three assumptions are fundamentals: The first two assumptions concern the sources: they should not be Gaussian signals (or at most one) and should be statistically independent from each others. The third is about the transmission channel: whether it is linear or not, memoryless, convolutive, with more sensors than sources, *etc.*

Most of the algorithm used higher order statistics. Moreover, the major problem consisted on the estimation of the HOS. To estimate the cumulant and the moments, most authors use the Leonov-Shiryayev formulas, see [43],[164]–[168].

We must also mention that batch algorithms to blind separation are generally faster than the adaptive ones, although the last ones are more robust against additive noise or estimation error (some stability studies were presented in [169]–[176]). Some author prefer to use the Nonlinear PCA criterion and maximum likelihood in independent component analysis [67].

To finish this paper, we would like to mention a part of the preface of the 1999 ICA proceedings [177]:"15 Years of research: The case of simple instantaneous mixtures now is well understood, but dealing, with convolutive mixtures is still challenging and the issue of non-linear mixtures has hardly been addressed. Regarding applications, a lot remain to be done to turn the ideas of source separation into a broadly accepted methodology addressing real world signal processing and data analysis problem." Cardoso, Jutten & Loubaton.

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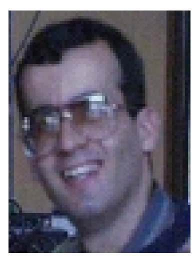

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