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SEPARABILITY OF CONVOLUTIVE MIXTURES BASED ON WIENER FILTERING AND MUTUAL INFORMATION CRITERION

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ABSTRACT

In this paper, we focus on convolutive mixtures, expressed in the time-domain. We present a method based on the minimization of the mutual information and using wiener filtering. Separation is known to be obtained by testing the independence between delayed outputs. This criterion can be much simplified and we prove that testing the independence between the contributions of all sources on the same sensor at same time index also leads to separability. We recover the contribution by using Wiener filtering (or Minimal Distortion Principal) which is included in the separation procedure. The independence is tested here with the mutual information. It is minimized only for non-delayed outputs of the Wiener filters. The test is easier and shows good results on simulation.

1. INTRODUCTION

Blind source separation (BSS) is a method for recovering a set of unknown source signals from the observation of their mixtures. Among open issues, recovering the sources from their linear convolutive mixtures remains a challenging problem. Many solutions have been addressed in the frequency-domain, particularly for the separation of non-stationary audio signals. In the BSS of stationary signals, two problems remain open in the time-domain. It has been proved [1] that convolutive mixtures are separable, that is, the independence of the outputs insures the separation of the sources, up to a few indeterminacies. However, the meaning of the independence is not the same in convolutive and instantaneous contexts. In the convolutive context, the outputs have to be independent in the sense of stochastic processes [2] which requires the independence of the random variables $y_i(n)$ and $y_j(n-m)$ for all discrete times n and m. The independence criteria are therefore more complicated and computationally expensive. Several ideas are given in [3, 4] to test the independence in function of time delays m, using the mutual information criterion. The second problem is coming from the inherent indeterminacy of the definition of a source in the BSS model. Indeed, any linear transform of a source can also be considered as a source and there is an infinity of separators that can extract sources. Some constraints can be added either on the source signals (they are usually supposed to be normalized) or on the separator system (Minimal Distortion Principal [5]). In [5], one proposition is to choose the separator which minimizes the quadratic error between sensors and outputs, also known as Wiener filter. In this paper, we deal with convolutive mixtures and express the model in the time-domain. In this paper, we consider an example of convolutive mixing model with p inputs and p outputs. We are only interested in the contribution of these p sources recorded on each sensor. These signals are uniquely defined, which removes the filter indeterminacy. It can also help to simplify the independence criterion and we prove in this paper that testing the independence between the contributions of all sources on the same sensor at same time index n also leads to separability. We recover these contributions $z_i(n)$ by using Wiener filters which are included in the separation procedure. The independence criterion is therefore less complicated as it requires only the independence between the outputs $z_i(n)$ and $z_j(n)$ (and no more $y_i(n)$ and $y_j(n-m)$). The mutual information is used here and shows good results on simulation.

2. MODELING THE OBSERVED SIGNALS

Let us consider the standard convolutive mixing model with M inputs and M outputs. Each sensor $x_j(n)$ $(j=1,\ldots,M)$ receives a linear convolution (noted $*$) of each source $s_i(n)$ $(i=1,\ldots,M)$ at discrete time n :

$$x_j(n) = \sum_{i=1}^{M} h_{ji} * s_i(n). \quad (1)$$

where h_{ij} represents the impulse response from source i to sensor j. The inverse of mixing filters are not necessarily causal, therefore the aim of BSS is to recover non-causal filters with impulse responses f_{ij} between sensor i and output j, such that the output vector $y(n)$ estimates the sources, up to a linear filter :

$$y_j(n) = \sum_{i=1}^{M} \sum_{k=-L}^{L} f_{ji}(k) x_i(n-k). \quad (2)$$

Any linear transform of a source can also be considered as a source and there is an infinity of separators f_{ij} that can extract sources. We focus here on the estimation of the signals $h_{ij} * s_i(n)$, coming from source i on sensor j. These signals are uniquely defined, which removes the filter indeterminacy. Let the model be a p sources, p sensors scheme . For sake of simplicity, we call here sources the p contributions on the first sensor. Therefore, $x_1(n)$ is equal to :

$$x_1(n) = s_1(n) + s_2(n) + \ldots + s_p(n). \quad (3)$$

Let $y_1(n)$, $y_2(n)$,..., $y_p(n)$ be p outputs of the BSS :

$$y_j(n) = \sum_{i=1}^{p} \sum_{k=-L}^{L} g_{ji}(k) s_i(n-k). \quad (4)$$

where $g_{ij} = f_{ij} * h_{ij}$ represents the global filter.
If $y_j(n)$ is any linear filtering of only one source, than

the contribution of this source on the first sensor is calculated by an (eventually non causal) Wiener filter $W_j(z)$ such that the quadratic error between $x_1(n)$ and $y_j(n)$: $E\left\{\left|x_1(n) - w_j * y_j(n)\right|^2\right\}$ is minimized (1). The p contributions of the sources on the first sensor are so given by :

$$z_j(n) = \sum_{i=1}^{p} \sum_{k=-L}^{L} w_j(k) y_i(n-k). \tag{5}$$

where the Discrete Fourier Transforms (DFT) of the Wiener filters $w_j(k)$ are computed in function of the cross-spectra $\gamma_{YjX1}(f)$ of $x_1(n)$ and $y_j(n)$, and $\gamma_{Yj}(f)$ the spectra of $y_j(n)$:

$$\begin{aligned} W_1(f) &= \frac{\gamma_{Y1X1}(f)}{\gamma_{Y1}(f)} \\ W_2(f) &= \frac{\gamma_{Y2X1}(f)}{\gamma_{Y2}(f)} \\ W_3(f) &= \frac{\gamma_{Y3X1}(f)}{\gamma_{Y3}(f)} \\ &\vdots \\ W_p(f) &= \frac{\gamma_{YpX1}(f)}{\gamma_{Yp}(f)}. \end{aligned} \tag{6}$$

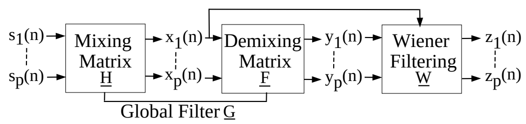

Figure 1: Demixing and separating system.

3. SEPARABILITY OF THE SOURCE CONTRIBUTIONS ON ONE SENSOR

In specific cases, testing the independence between $y_1(n), y_2(n), y_3(n), \ldots,$ and $y_p(n)$ is sufficient [7] to ensure the separation. For example, for i.i.d. normalized sources, the sum of fourth-order cumulants of the outputs is a contrast function [8] under a condition on separating filters [7]. For linear filtering of i.i.d. signals, the same result is obtained after a first step of whitening of the data. However, in a general case, delays must be introduced in the contrast function, the separability of convolutive mixtures is obtained only when the components of the output vector $y(n)$ are independent in the sense of stochastic variables : $y_1(n), y_2(n-m_1), y_3(n-m_2), \ldots, yp(n-m_{p-1})$ have to be independent for all discrete time delays $m_1, m_2, \ldots, m_{p-1}$. For example, a solution is to minimize the criterion J :

$$J = \sum_{m_1} \sum_{m_2} \cdots \sum_{m_{p-1}} I(y_1(n), y_2(n-m_1), \ldots, y_2(n-m_{p-1})). \tag{7}$$

where I represents the mutual information (8). I is nonnegative and equal to zero if and only if the components are statistically independent.

$$I(y) = \int_R p_y(y) \ln \left(\frac{p_y(y)}{\prod_{i=1}^{p} p_{yi}(y_i)} \right) dy. \tag{8}$$

The delays $m_1, m_2, \ldots, m_{p-1}$ can be taken in an a priori set $[-K, \ldots, K]$, which depends on the degree of the filters corresponding to the whole mixing-separating system. The criterion (7) is computationally expensive. In [3], a gradient-based algorithm minimizes (7) : at each time iteration, a random value of delay $m_1, m_2, \ldots, m_{p-1}$ is chosen and $I(y_1(n), y_2(n-m_1), y_3(n-m_2), \ldots, y_p(n-m_{p-1}))$ is used as the current separation criterion.
We propose to study here the separability of $z_1(n), z_2(n), \ldots,$ and $z_p(n)$ (5) versus $y_1(n), y_2(n), \ldots,$ and $y_p(n)$ where $z_j(n)$ is linked to $y_j(n)$ by wiener filtering (5)(6).
We will show that it is simpler and that no time delay $(n-m)$ with $m = i, \ldots, p-1$ is needed. Suppose now any outputs $y_1(n), y_2(n), \ldots,$and $y_p(n)$. To ensure the separation, it is necessary (but not sufficient) that the mutual information $I(y_1(n), y_2(n), \ldots, y_p(n))$ is zero. Then two cases can happen. If each output $y_j(n)$ only depends on one different source, the outputs $(y_1(n), y_2(n), \ldots, y_p(n))$ are also independent in the sense of stochastic processes (the separation has been effected) and so are for $z_1(n), z_2(n), \ldots,$ and $z_p(n)$. In that case, we have $I(y_1(n), y_2(n), \ldots, y_p(n)) = 0$, $I(z_1(n), z_2(n), \ldots, z_p(n)) = 0$ and the separation is obtained.
In the second case, the outputs $y_j(n)$ can be independent $(I(y_1(n), y_2(n), \ldots, y_p(n)) = 0$ at time delay 0) but remain mixtures of sources. For example, in the case of i.i.d sources, the p following outputs $y_j(n)$ are independent (9):

$$\begin{aligned} y_1(n) &= s_1(n) + s_2(n) + \ldots + s_p(n) \\ y_2(n) &= s_1(n-1) + s_2(n-1) + \ldots + s_p(n-1) \\ &\vdots \\ y_p(n) &= s_1(n-(p-1)) + s_2(n-(p-1)) + \ldots + \\ &\quad s_p(n-(p-1)). \end{aligned} \tag{9}$$

It occurs (typically for i.i.d. sources) when one source is common in the p outputs but with two different time index $(n-n_0)$ and $(n-n_1)$. In that case, $y_j(n)$ are independent but surely not the components of $z_j(n) = W_i(z) y_j(n)$, as common time index can appear after linear filtering. It can be seen intuitively, since Wiener filtering aims at the maximization of the correlation between $z_1(n)$ and $x_1(n)$ (respectively $z_2(n)$ and $x_1(n), \ldots, z_p(n)$ and $x_1(n)$). We will prove theoretically that indeed $z_1(n), z_2(n), \ldots, z_p(n)$ cannot be independent in that case and that $I(y_1(n), y_2(n), \ldots, y_p(n))$ is not equal to zero. The separation is not achieved in that second case.
As a consequence, the only solution to perform BSS is to test the cancellation of both $I(y_1(n), y_2(n), \ldots, y_p(n))$ and $I(z_1(n), z_2(n), \ldots, z_p(n))$ at same time index n.
To describe the second case, we suppose that $y_1(n), y_2(n), \ldots, y_p(n)$ are mixtures of sources and that $I(y_1(n), y_2(n), \ldots, y_p(n)) = 0$. $z_1(n), z_2(n), \ldots,$ and $z_p(n)$ are deduced from $y_1(n), y_2(n), \ldots, y_p(n)$ by Wiener filtering (figure 1) and are also mixtures of sources. Let be $Z_1(f), Z_2(f), \ldots,$ and $Z_p(f)$, their DFT's :

$$\begin{aligned} Z_1(f) &= W_1(f) Y_1(f) \\ Z_2(f) &= W_2(f) Y_2(f) \\ &\vdots \\ Z_P(f) &= W_P(f) Y_P(f). \end{aligned} \tag{10}$$

They are of the form (10)(12) where the transfer functions $W_1(f), W_2(f), \ldots,$ and $W_p(f)$ of the Wiener filters are expressed in function of the DFT of filters $g_{ij}(k), G_{ji}(f)$, and the source spectra (11) :

(To simplify the equations, we replace $G_{ij}(f)$ by G_{ij}, $\gamma_{si}(f)$ by γ_{si}, and $\gamma_{Yi}(f)$ by γ_{Yi}).

$$\begin{aligned} W_1(f) &= \frac{\bar{G}_{11}\gamma_{s1} + \bar{G}_{12}\gamma_{s2} + \ldots + \bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}} \\ W_2(f) &= \frac{\bar{G}_{21}\gamma_{s1} + \bar{G}_{22}\gamma_{s2} + \ldots + \bar{G}_{2p}\gamma_{sp}}{\gamma_{Y2}} \\ &\vdots \\ W_p(f) &= \frac{\bar{G}_{p1}\gamma_{s1} + \bar{G}_{p2}\gamma_{s2} + \ldots + \bar{G}_{pp}\gamma_{sp}}{\gamma_{Yp}}. \end{aligned} \tag{11}$$

$$\begin{aligned} Z_1(f) = &\frac{|G_{11}|^2\gamma_{s1} + G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}} S_1(f) \\ &+ \frac{G_{12}\bar{G}_{11}\gamma_{s1} + |G_{12}|^2\gamma_{s2} + \ldots + G_{12}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}} S_2(f) \\ &\vdots \\ &+ \frac{G_{1p}\bar{G}_{11}\gamma_{s1} + \bar{G}_{12}G_{1p}\gamma_{s2} + \ldots + |G_{1p}|^2\gamma_{sp}}{\gamma_{Y1}} S_p(f) \\ Z_2(f) = &\frac{|G_{21}|^2\gamma_{s1} + G_{21}\bar{G}_{22}\gamma_{s2} + \ldots + G_{21}\bar{G}_{2p}\gamma_{sp}}{\gamma_{Y2}} S_1(f) \\ &+ \frac{G_{22}\bar{G}_{21}\gamma_{s1} + |G_{22}|^2\gamma_{s2} + \ldots + G_{22}\bar{G}_{2p}\gamma_{sp}}{\gamma_{Y2}} S_2(f) \\ &\vdots \\ &+ \frac{G_{2p}\bar{G}_{21}\gamma_{s1} + G_{2p}\bar{G}_{22}\gamma_{s2} + \ldots + |G_{2p}|^2\gamma_{sp}}{\gamma_{Y2}} S_p(f) \\ &\vdots \\ &\vdots \\ Z_p(f) = &\frac{|G_{p1}|^2\gamma_{s1} + G_{p1}\bar{G}_{p2}\gamma_{s2} + \ldots + G_{p1}\bar{G}_{pp}\gamma_{sp}}{\gamma_{Yp}} S_1(f) \\ &+ \frac{G_{p2}\bar{G}_{p1}\gamma_{s1} + |G_{p2}|^2\gamma_{s2} + \ldots + G_{p2}\bar{G}_{pp}\gamma_{sp}}{\gamma_{Yp}} S_2(f) \\ &\vdots \\ &+ \frac{G_{pp}\bar{G}_{p1}\gamma_{s1} + G_{pp}\bar{G}_{p2}\gamma_{s2} + \ldots + |G_{pp}|^2\gamma_{sp}}{\gamma_{Yp}} S_p(f). \end{aligned} \tag{12}$$

$z_j(n)$ is a linear filtering of $s_1(n), s_2(n), \ldots,$ and $s_p(n)$ as $y_1(n), y_2(n), \ldots,$ and $y_p(n)$. Call $u_{ij}(k)$, the new mixing filters between the sources $s_i(n)$ and the signals $z_j(n)$: $u_{ij}(k) = [w_j * g_{ij}](k)$ where $*$ stands for the linear convolution. $z_j(n)$ are expressed as :

$$z_j(n) = \sum_{i=1}^{p}\sum_{k=-L}^{L} u_{ij}(k)s_i(n-k). \tag{13}$$

The p signals $z_1(n), z_2(n), \ldots,$ and $z_p(n)$ cannot be independent ($I(z_1(n), z_2(n), \ldots, z_p(n))$ is not zero) if it exists non zero coefficients $u_{11}(k), u_{12}(k), \ldots,$ and $u_{1p}(k)$ for common time delays k. And, at least, we prove that one coefficient, $u_{ij}(k)(0)$, is non zero. Suppose that the DFT is computed on N time samples :

$$u_{11}(0) = \sum_{f=0}^{N-1} \frac{|G_{11}|^2\gamma_{s1} + G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}}. \tag{14}$$

$$\begin{aligned} |u_{11}(0)|^2 = &\left(\sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}}\right)^2 \\ &+ \left|\sum_f \frac{G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}}\right|^2 \\ &+ \sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}} \left(\sum_f \frac{\bar{G}_{11}G_{12}\gamma_{s2} + \ldots + \bar{G}_{11}G_{1p}\gamma_{sp}}{\gamma_{Y1}}\right) \\ &+ \sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}} \left(\sum_f \frac{G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}}\right). \end{aligned} \tag{15}$$

If the third term and the fourth term of the sum are positive or null, then $u_{11}(0)$ cannot be null. If they are negative, $(u_{11}(0))^2$ is always superior to a strictly positive value (16). Similar computations can be done with $u_{12}(0), \ldots, u_{1p}(0), u_{21}(0), \ldots, u_{2p}(0), \ldots,$ and $u_{p1}(0), \ldots, u_{pp}(0)$.

$$\begin{aligned} |u_{11}(0)|^2 \geq &\left(\sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}}\right)^2 \\ &+ \left|\sum_f \frac{G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}}\right|^2 \\ &- \sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}} \left(\left|\sum_f \frac{\bar{G}_{11}G_{12}\gamma_{s2} + \ldots + \bar{G}_{11}G_{1p}\gamma_{sp}}{\gamma_{Y1}}\right|\right) \\ &- \sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}} \left(\left|\sum_f \frac{G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}}\right|\right). \\ |u_{11}(0)|^2 \geq &\left|\sum_f |G_{11}|^2 \frac{\gamma_{s1}}{\gamma_{Y1}} - \left|\sum_f \frac{G_{11}\bar{G}_{12}\gamma_{s2} + \ldots + G_{11}\bar{G}_{1p}\gamma_{sp}}{\gamma_{Y1}}\right|\right|^2. \end{aligned} \tag{16}$$

Therefore, for any outputs $(y_j(n))_{j=1,\ldots,p}$ which verify $I(y_1(n), y_2(n), \ldots, y_p(n)) = 0$, then after Wiener filtering projected on the same sensor (here the first one) $I(z_1(n), z_2(n), \ldots, z_p(n))$ is non zero. The only exception concerns the outputs $y_j(n)$ which depend on one source and it means that the separation has been achieved. As a consequence, testing $I(y_1(n), y_2(n), \ldots, y_p(n)) = 0$ and $I(z_1(n), z_2(n), \ldots, z_p(n)) = 0$, ensures the separability. The criterion is much more easier to test than the mutual information of delayed outputs as it can be verified in an iterative way. Moreover the outputs are directly the contribution of the sources on the processed sensor.

4. SEPARATING ALGORITHM AND SIMULATIONS

Let us consider a convolutive mixing model with two inputs and two outputs. The final separating algorithm for convolutive mixtures is based here on the minimization of the mutual information using the score function which is the gradient of the mutual information [3] but the previous proof of separability could be exploited with another independence test.

Initialization : $y(n) = x(n)$
Repeat until convergence :

- Estimate the score function difference between $y_1(n)$ and

$y_2(n) : \beta(y_1(n), y_2(n))$

- Update: $y(n) \leftarrow y(n) - \mu\beta(y_1(n), y_2(n))$
- Compute the Wiener filters $W_i(z)$, and the contributions : $z_j(n) = W_i(z)y_j(n)$
- Replace : $y(n) \leftarrow z(n)$

The performance for two sources and two observations are shown in figures 2 and 3 with simulations results. Each source (of 1500 samples) is constituted of the sum of a uniform random signal and a sinusoid. They are mixed with filters :

$$H(z) = \begin{bmatrix} 1+0.2z^{-1}+0.1z^{-1} & 0.5+0.3z^{-1}+0.1z^{-1} \\ 0.5+0.3z^{-1}+0.1z^{-1} & 1+0.2z^{-1}+0.1z^{-1} \end{bmatrix}$$

The mutual information (between $z_1(n)$ and $z_2(n)$) and the quadratic error between $z_1(n)$ and the exact contribution are plotted in fig.2 and 3 with marks, for each iteration. They are averaged on 50 realizations of the sources. It shows good results for the convergence speed and the residual quadratic error. The results can still be improved by adding some constraints. Indeed, four contributions must be computed in this scheme by projecting $y_1(n)$ (respectively $y_2(n)$) on the two sensors: $z_{11}(n), z_{21}(n)$ (respectively $z_{12}(n), z_{22}(n)$). The convergence speed is increasing by adding the mutual information between the projections on the second sensor $I(z_{21}(n), z_{22}(n))$ to $I(z_{11}(n), z_{12}(n))$ (as previously) in the minimization. The results are displayed in figures 2 and 3 in solid line and show the increasing of the convergence.

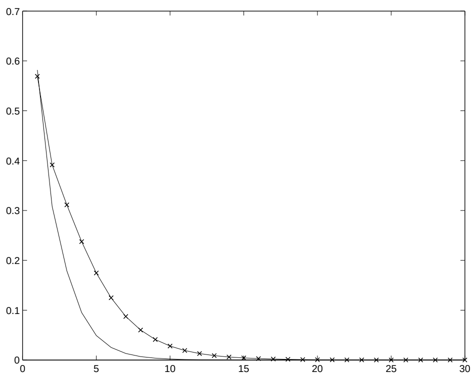

Figure 2: Mutual information versus iterations.

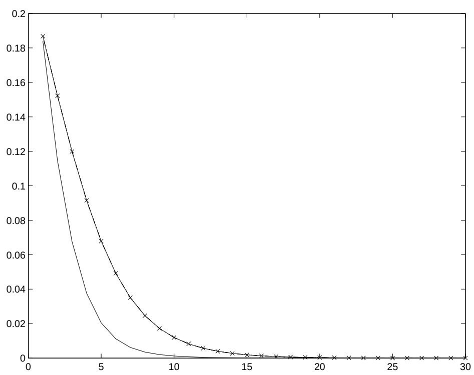

Figure 3: Quadratic error between the contribution of one source on the first sensor and its estimate, versus iterations.

Therefore, the new algorithm is:

Initialization : $y(n) = x(n)$
Repeat until convergence :

- Estimate the score function difference between $\beta(z_{11}(n), z_{12}(n)), \beta(z_{21}(n), z_{22}(n))$
- Update: $y(n) \leftarrow y(n) - \mu\,[\beta(z_{21}(n), z_{22}(n)) + \beta(z_{11}(n)z_{12}(n))]$
- Compute the Wiener filters $W_{ij}(z)$, and the contributions: $z_{ij}(n) = W_{ij}(z)y_j(n)$
- Replace : $y(n) \leftarrow [z_{11}(n), z_{12}(n)]$

5. CONCLUSION

In this paper, we focus on the separability of convolutive mixtures, expressed in the time-domain. In the convolutive context, the outputs $y_i(n)$ have to be independent in the sense of stochastic processes which requires the independence of $y_i(n)$ and $y_i(n-m)$ for all discrete times n and m. The independence criteria are therefore complicated and computationally expensive. The criterion has been simplified as we recover only the contribution of all sources on all sensors, by using Wiener filtering (or Minimal Distortion Principal). It has been proved that testing the independence between these contributions on the same sensor also leads to separability, without testing an independence test of delayed outputs. The criterion is easier to test and is implemented here by minimizing the mutual information of the outputs after Wiener filtering. The experiments show its efficiency, it shows good results on simulation and experimental signals for the separation of piston slap and combustion in diesel engine [6].

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