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BSS 를 이용한 회전 기계 진단 신호 분석

Identification of fault signal for rotating machinery diagnosis using Blind Source Separation (BSS)

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Key words : Blind, BSS, Cumulant, detection, higher order, kurtosis, MBD, MIMO, mixing, separation, skewness, signal

ABSTRACT

This paper introduces multichannel blind source separation (BSS) and multichannel blind deconvolution (MBD) based on higher order statistics of signals from convolutive mixtures. In particular, we are concerned with the case that the number of inputs is the same as the number of outputs. Simulations for two input two output cases are carried out and their performances are assessed. One of the major applications of those sequential algorithms (BSS and MBD) is demonstrated through the fault signal detection from only a single measurement of rotating machine, which offers a certain degree of practicability in the engineering field such as machine health monitoring or condition monitoring.

1. INTRODUCTION

Multiple Input Multiple Output (MIMO) models arise frequently in signal processing (e.g., seismic exploration, digital communications, antenna array processing, biomedical signal processing, and multi-channel machine conditioning systems). The sensor signals from a p element array are a p-dimensional vector process representing the mixture of m different independent source signals. The propagation characteristics between m source signals and p sensor signals is often modeled as a linear (instantaneous or convolutive) MIMO system.

The Blind Source Separation (BSS) problem is a basic and difficult problem (e.g., [Bar-Ness et al, 1981]). Since then many solutions have been proposed, most of which are based on independence criteria which involve higher-order moments generated by non-linear functions [Jutten and Herault, 1991], cumulants [Lacoume and Ruiz, 1988; Cardoso, 1989; Comon, 1989] or contrast functions [Moreau and Macchi, 1993; Comon, 1994; Delfosse and Loubaton, 1995].

Most of these works are related to the separation of instantaneous linear mixtures of sources: the observation at any time t are a linear superposition (with real coefficients) of the sources at time t. For the linear instantaneous mixture model, source separation can be achieved by utilising the higher-order based joint diagonalisation of the observed signal matrix [Cardoso and Comon, 1990; Yellin and Weinstein, 1994; Cardoso, 1998a, 1998b; Lathauwer et al, 1999; Zhu et al, 1999]. A solution for this problem uses a time-based model in which the source separation is achieved through higher-order statistics and independency criteria. This approach utilises the joint-cumulant of output signals.

Multichannel blind deconvolution (MBD) is an extension of the single channel blind deconvolution which utilises an objective function maximisation based on the central limit theorem [Donoho, 1981]. For this, a variable norm deconvolution method is introduced [Gray, 1979]. This is a multichannel technique which iteratively estimates an inverse to the unknown system which when convolved with the measured signals yields the unknown impacting signals. This inverse is estimated such that the resulting output signals are as spiky and non-Gaussian as possible. The proposed method is derived from statistical theory and utilises the non-linear optimisation technique discussed in this paper.

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2. MODEL SELECTION AND PROBLEM FORMULATION

For more general case consideration, a two input two output system based on models of cross coupling referred to as doubly coupled (feed back) mixing system is selected.

2.1 General convolutive mixing system

The model of the convolutive mixture for multi-channel case is shown in the following figure;

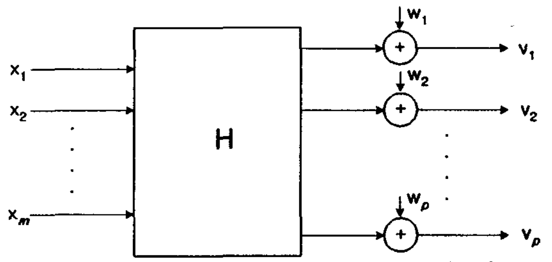


Figure 2.1 Multi-input multi-output system with unknown system H and independent input signals x, unknown white Gaussian noise w, and observed signal v.

In general situations, the observed signal v(k) at the sensor output is a p vector with components that result from the unknown m sources **x**(k) i.e.,

$$\mathbf{v}(k) = [v_1(k) \ldots v_p(k)]^T$$
$$\mathbf{x}(k) = [x_1(k) \ldots x_m(k)]^T \qquad (2.1)$$

and the input signals are assumed to be independent each other and at least one of the input signals is non-Gaussian. The system **H** is a ($p \times m$) matrix of impulse responses (in the time domain) or equivalently a ($p \times m$) matrix of transfer functions in the z-domain.

2.2 Two input two output systems and input-output relationship

The aim of this study focuses on the restoration of impacting signals from observed multichannel signals using both source separation and deconvolution.

We concentrate on a two input two output system based on models of cross coupling referred to as doubly coupled (feed back).

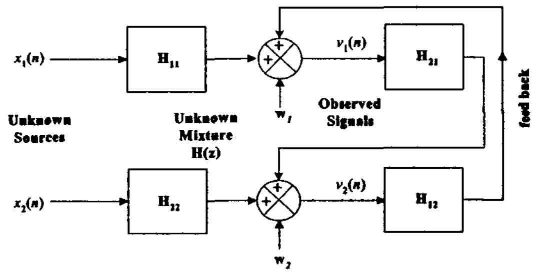


Figure 2.2 Two-input two-output system, (Double coupled mode)

When the observed signals are the result of 'feed back' as in Figure 2.2, they may be written as

$$v_i(n) = \sum_{k=0}^{L_{ii}-1} h_{ii}(k) x_i(n-k) + \sum_{k=0}^{L_{ij}-1} h_{ij}(k) x_j(n-k) + w_i(n) \qquad (2.2)$$

where $h_{ij}(k)$ is the kth coefficient of filter H_{ij} with $\forall i, j \in \{1,2\}$.

In contrast to the case of single coupling, this models the outputs of remote measurement points as affecting other outputs.

In the z-domain

$$V_1(z) = H_{11}(z)X_1(z) + H_{12}(z)V_2(z)$$
$$V_2(z) = H_{21}(z)V_1(z) + H_{22}(z)X_2(z) \qquad (2.3)$$

2.3 Blind Source Separation via joint-cumulant cancellation (nulling)

The structure of the source separation system is chosen as being of the form in Figure 2.3 [Yellin and Weistein, 1994].

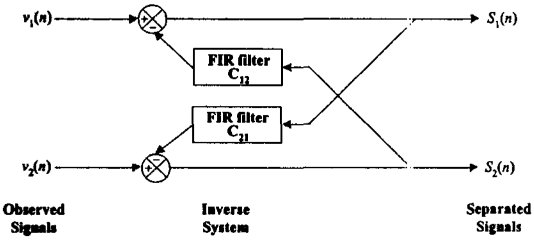


Figure 2.3 Recursive source separation structure

This is a recursive form [Jutten and Herault, 1991]. Using this recursive separation system based on the observed signals $v_1(n)$ and $v_2(n)$, the outputs $s_1(n)$ and $s_2(n)$ are calculated as

$$s_i(n) = v_i(n) - \sum_{k=0}^{L_{ij}} c_{ij}(k) s_j(n-k) \qquad (2.4)$$

in which the updating of the filter coefficients (of the filters c_{ij}) are iterated by using the fourth-order joint cumulants cancellation of above two outputs which takes the form of the steepest descent algorithm as (for example),

$$c_{ij}(q+1,k) = c_{ij}(q,k) + \mu_{ij} E\{s_i(n)^3 \cdot s_j(n-k)\} \quad , \quad i \neq j, \forall i, j \in \{1,2\} \qquad (2.5)$$

where q represents each iteration step.

The magnitude of adaptation gain should be in a range that can assure stable convergence and computational efficiency. In this study, this value commonly has been used as 0.01 arising from the adaptation gain μ_{ij} in the range [Thi and Jutten, 1995],

$$0.005 \le \mu_{ij} \le 0.05$$

and the threshold t_r for the iteration to stop is set to [Cardoso, 1998]

$$t_r = \frac{1}{100 \cdot \sqrt{N}}$$

where N is the total number of data points.

2.4 Blind deconvolution via multichannel objective function maximization

The structure of the multichannel deconvolution operator is similar to the single channel blind deconvolution operator [Seo, 2000]. However, unlike the source separation structure, this deconvolution operator uses a single inverse filter which shown below.

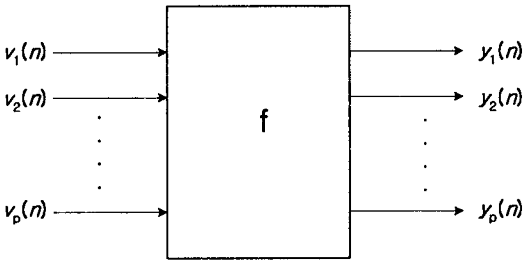


***Figure 2.4** Multichannel blind deconvolution operator*

Since the deconvolution operator is commonly applied to the input signal to produce the output signal, the number of input signals (denoted by p) to the inverse system, which is the same as the number of output signals. The output signal coming from each channel (j=1~p) is expressed as

$$y_j(n) = \sum_{k=0}^{L-1} v_j(n-k) \cdot f(k) \qquad (2.6)$$

For the restoration of an impacting signal, we introduce a multichannel objective function as

$$O(\mathbf{y}, r) = \sum_{j=1}^{p} \frac{\frac{1}{N}\sum_{n=0}^{N-1} |y_j(n)|^r}{\left[\frac{1}{N}\sum_{n=0}^{N-1} |y_j(n)|^2\right]^{r/2}} \qquad (2.7)$$

where $\mathbf{y}$ is the output p-vector of the inverse filter and the parameter r governs the relative weightings of the nature of an impulsive signal [Claerbout, 1973], which is similar to the single channel case. This parameter r is adjusted depending on the characteristics of input impacting signals concerned, defining 'variable norm deconvolution' [Gray, 1979].

The impacting signal reconstruction is achieved by maximising the objective function (the summation of normalised variable higher order moments or cumulants of each output signal) with respect to the filter coefficients.

The final equation of the multichannel inverse filter (deconvolution operator) is expressed as

$$\sum_{l=0}^{L-1}\left[\sum_{j=1}^{p}\frac{1}{u_{2j}}\sum_{n=0}^{N-1} v_j(n-l)\cdot v_j(n-k)\right]\bullet f(l) = \sum_{j=1}^{p}\left[\frac{1}{u_{1j}}\sum_{n=0}^{N-1}|y_j(n)|^{r-1}\cdot \mathrm{sgn}(y_j(n))\cdot v_j(n-l)\cdot v_j(n-k)\right]$$
$$k = 0, 1, \ldots, L-1 \qquad (2.8)$$

where

$$u_{1j} = \frac{1}{N}\sum_{n=0}^{N-1} |v_j(n)|^r$$

$$u_{2j} = \frac{1}{N}\sum_{n=0}^{N-1} y_j(n)^2$$

$v_j(n)$: n-th sample of the signal recorded on channel j (N samples per channel and p channels)

$f(l)$: l-th sample of an inverse filter having L length

$y_j(n)$: n-th sample of the output of the inverse filter coming from channel j (N samples per channel and p channels)

The inverse filter equation (2.8) can be expressed in matrix from

$$\mathbf{R} \cdot \mathbf{f} = \mathbf{g} \qquad (2.9)$$

where $\mathbf{R}$ is the autocorrelation matrix of observed signals, $\mathbf{f}$ is the inverse filter coefficient vector, and $\mathbf{g}$ denotes the cross-correlation of the observed signals and the output of the inverse filter.

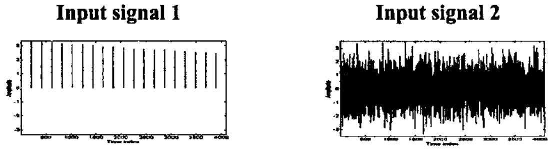
3. SIMULATIONS OF SOURCE SEPARATION AND DECONVOLUTION FOR IMPACTING SIGNAL RECONSTRUCTION

The objective of this sub-section is to restore an impacting signal from the measured (observed) signals through source separation and blind deconvolution.

3.1 Signals and systems for simulations

The two input signals consist of an impacting signal and a Gaussian signal (normal operating excitation) are shown in Figure 3.1. For each input signal, N represents the number of samples, γ_3 and γ_4 are the skewness and kurtosis of the signal, respectively.

Input signal 1 **Input signal 2**



N=4096, γ_3 =14.73, γ_4 =219.4 **N=4096, γ_3 =0.053, γ_4 =2.99**

***Figure 3.1** Input signals*

Using these input signals, examples of the blind source separation from observed signals and restoration of the impacting signal procedures are demonstrated.

The observed signal includes feed back of system outputs as in Figure 2.2 and illustrated as a simulation model in the following figure;

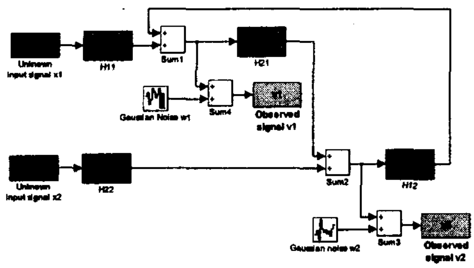


***Figure 3.2** Simulation model*

We assume that $H_{11}(z) \neq H_{22}(z) \neq 0$, $H_{12}(z)$ and $H_{21}(z)$ have finite impulse responses and that we assume noises are zero. The unknown system MA(6) is modelled as

$$H(z)=\begin{bmatrix} 0.2+0.8z^{-1}+0.4z^{-2} & 0.5-0.3z^{-1} \\ 0.3z^{-1}-0.6z^{-2} & -0.21z^{-1}-0.5z^{-2}+0.72z^{-3}+0.36z^{-4}+0.12z^{-6} \end{bmatrix} \quad (3.1)$$

The input signals used in this simulation case are already shown in Figure 3.1. The system's pole-zero maps and impulse response function shapes with their output signals are shown in the following figure;

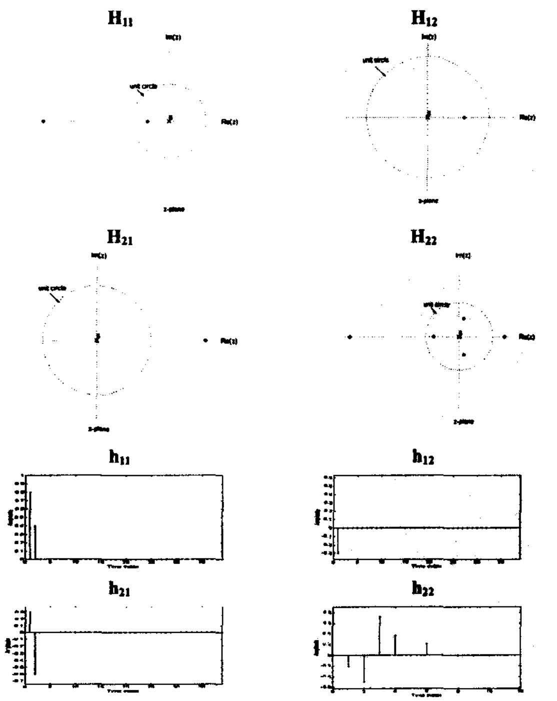
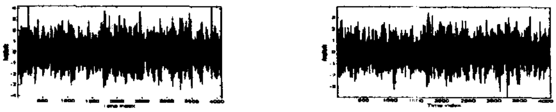


***Figure 3.3** Characteristics of the unknown systems*

The outputs of this system are shown below;



γ_3 =0.069, γ_4 =2.911, α -coefficient=2.1 | γ_3 =0.016, γ_4 =2.784, α -coefficient=2.25

***Figure 3.4** Two channel observed signal from simulation*

Using two observed signals in each simulation case, we tried to identify the impacting signal through Blind Source Separation (BSS) and Multichannel Blind Deconvolution (MBD).

The results are shown in subsequent section with the shapes of the separated/restored signals and their statistical parameters summarised in table.

3.2 Results of impacting signal identification

The impacting signal is restored from both the BSS and MBD process in this simulation.

Results of identified impacting signal and the performance of each method is compared.

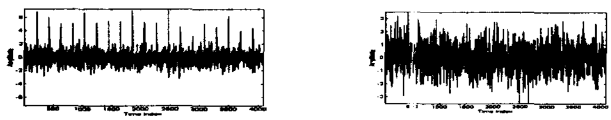
Separated signal from BSS ($\mu = 0.01$)

Output 1 | **Output 2**

γ_3 =0.345, γ_4 =3.808 | γ_3 =-0.023, γ_4 =2.874

Restored signals from MBD (L=6)

Output 1 | **Output 2**

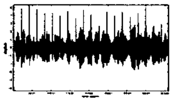
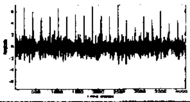


γ_3 =1.532, γ_4 =9.548 | γ_3 =0.092, γ_4 =3.243

***Figure 3.4** Separated and restored signals of simulation*

Overall comparison for impacting signal restoration from both BSS and MBD process is given by the following table, in which there summarises the statistical performances and features of each signal to compare the impacting signal restoration through the BSS and MBD process.

Table 3.1 Comparison of impacting signal restoration results from BSS and MBD process

	BSS (μ =0.01, t_r=2.6e-3)	MBD (L=6)
skewness	0.345	1.532
kurtosis	3.808	9.548
Restored impact signal		

3.3 Discussions

Discussion for source separation process (iteration stopping criteria)

Restoration of the impacting signal from observed signals through BSS is based on the statistical independency of the input signal. Hence, the independency criteria represented by the higher order sense are inspected and used as stopping criteria for iterative calculation of filter coefficients in equation (2.5). The various independency measures (higher order joint cumulants) are applied and compared in the following table.

Table 3.2 Comparison of impacting signal separation results

Simulation condition : L=6, μ=0.01, t_r=0.0026							
	J_1	J_2	J_3	J_4	J_5	J_6	J_7
Iteration	183	126	36	209	62	58	458
Skewness	0.345	0.352	0.230	0.342	0.322	0.398	0.101
Kurtosis	3.808	3.814	3.48	3.835	3.731	3.647	3.003

The various higher order joint cumulants expressed in Table 3.2 are defined below (Cum_{ij} , $i+j=4$ denotes cross cumulants);

$\mathbf{J_1}$: $\left|Cum_{22}\{s_1(n), s_2(n)\}\right|$

$\mathbf{J_2}$: $\left|Cum_{31}\{s_1(n), s_2(n)\}\right|$

$\mathbf{J_3}$: $\left|Cum_{31}\{s_2(n), s_1(n)\}\right|$

$\mathbf{J_4}$: $E\{Cum_{22}\{s_1(n), s_2(n-k)\}\}$ for $k = 0,1,\ldots,L-1$ and takes minimum value

$\mathbf{J_5}$: $E\{Cum_{22}\{s_2(n), s_1(n-k)\}\}$ for $k = 0,1,\ldots,L-1$ and takes minimum value

$\mathbf{J_6}$: $E\{Cum_{31}\{s_1(n), s_2(n-k)\}\}$ for $k = 0,1,\ldots,L-1$ and takes absolute minimum value

$\mathbf{J_7}$: $E\{Cum_{31}\{s_2(n), s_1(n-k)\}\}$ for $k = 0,1,\ldots,L-1$ and takes absolute minimum value

As a result, with the given adaptation gain μ commonly selected as 0.01, and each threshold values t_r, it has been turned out that the criterion $\mathbf{J_1}$ ($\left|Cum_{22}\{s_1(n), s_2(n)\}\right|$) can yield consistent identification.

The variable norm parameter selection for the multichannel blind deconvolution process

As expressed in equation (2.7), the multichannel objective function contains the variable norm value which can be any real value *r* (*r*>2). From two different simulations, we observed the kurtosis of the restored impacting signal for each *r* value selection.

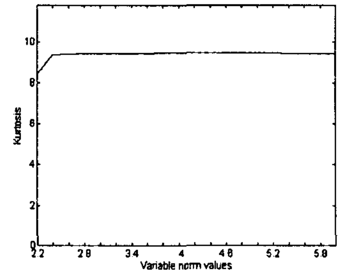


Figure 3.5 The effect of variable norm value on the impacting signal restoration through MBD process

For example, when *r* takes the value 4, the multichannel objective function corresponds *kurtosis* and the algorithm becomes the multichannel 'Minimum Entropy Deconvolution (MED)' [Wiggins, 1977].

The kurtosis of the restored impacting signal are consistent results for *r*>2.4.

The effect of these *r* values become less significant when the observed signals are close to Gaussian and possess an α-coefficient over 2 (see Figure 3.4). This means that for the problem of impacting signal reconstruction with severe noise corrupted observed signals, *r* can be selected to be greater than 4 (for more detailed information about variable *r* deconvolution, refer to Gray's thesis [Gray, 1979]). In this study, we selected the *r* as 4.

3.4 Application of BSS for a rotating motor health monitoring

One of the major applications of BSS and source identification (blind deconvolution) has been applied for the monitoring of small rotating motors in its operation.

The discrete steps for the BSS and source identification process are as follows;

Step 1 : (First column from the left)

The time history of measured signal is given.

Step 2 : (column 2)

From the measured signal, the separation of signal is carried out using BSS.

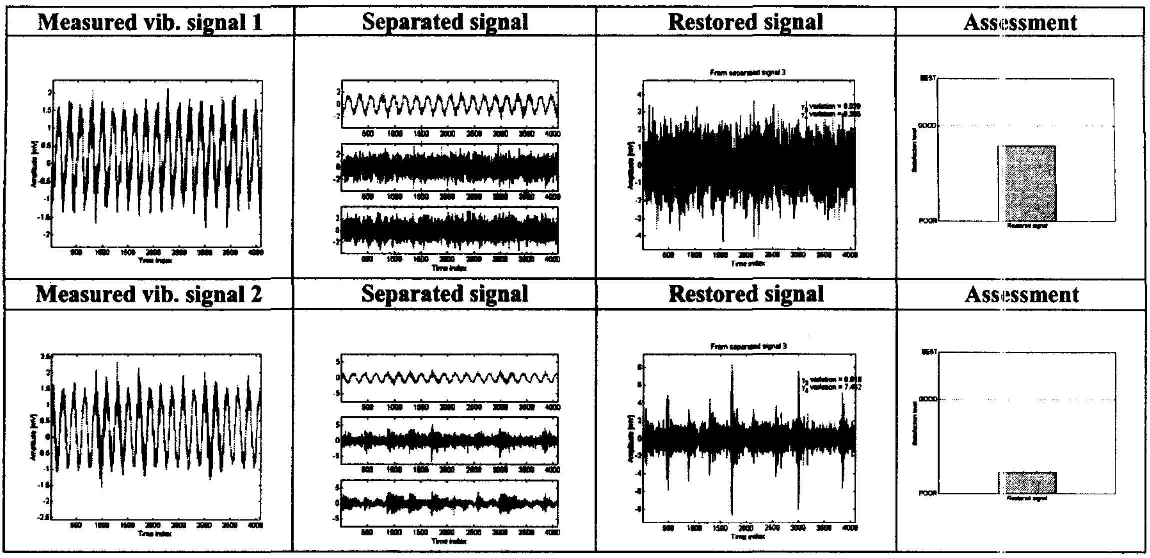
This signal separation is performed by dividing the single measured signal into multi channel (three) signals, which are created from the one sample delays of the original signal [Seo, 2000].

Thus, we can have hypothetical multi-channel signals from which the blindly separated signals are plotted in the second column.

Step 3 : (column 3)

From those separated signals, only one signal is used in the BD (Blind Deconvolution) process, which has an α-coefficient near to 2 (Gaussian, refer to [Seo, 2000]).

The selected signal to be deconvolved is the measured signal whose sinusoidal component is suppressed and any irrelevant extreme event (single spike which is thought as a measurement error) is eliminated. Thus, in the fourth column, the time history of the restored (deconvolved) signal through BD process (with FIR inverse filter, length=15, fourth order) is given. The difference of third- and fourth-order normalised cumulants (i.e., skewness and kurtosis, respectively) between the selected signal and restored signal are plotted to monitor the status of the measured signal.



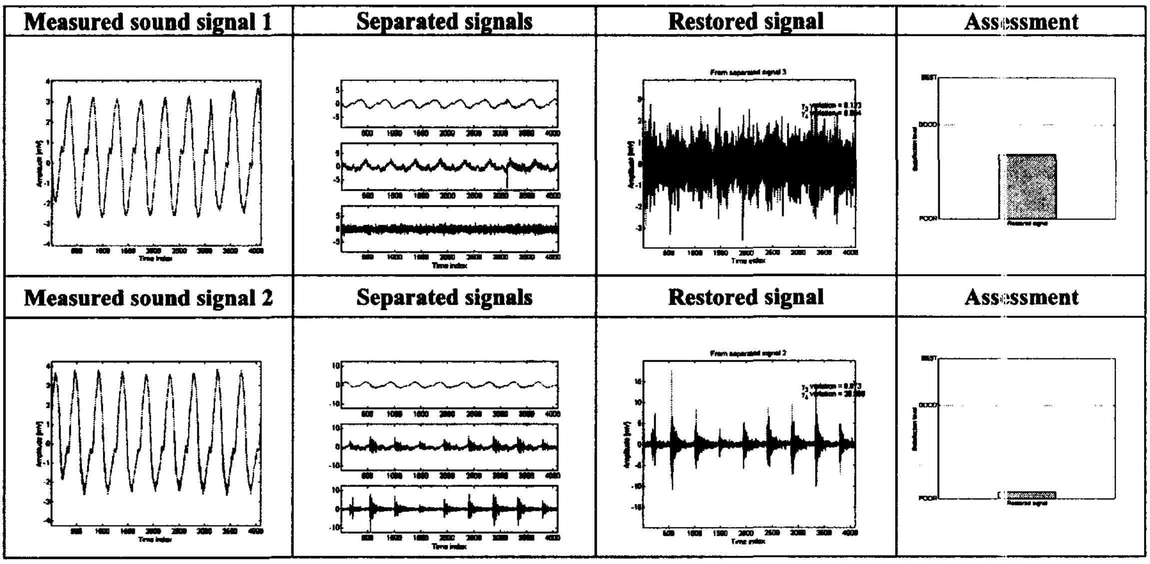


Figure 3.6 Applications for rotating machine health monitoring through the BSS algorithm from single measurement split into three channel signals (used signals are from vibration and sound pressure measurement for each motor)

Also, the visual inspection of the shape of the restored signal can support the results of numerical assessments.

Step 4 : (column 4)

Finally, the status of signal (in kurtosis) is given through the diagram in which the dotted line represents the threshold of acceptable level (kurtosis change up to 50%). From this diagram, we can assess the quality of products with reference to the dotted line and level ('POOR', 'GOOD', 'BEST').

4. SUMMARY AND CONCLUSION

In this paper, we have addressed the problem of the blind source separation and deconvolution of sources for convolutive mixtures for the reconstruction of an impacting signal among a set of observed signals. A theoretical derivations and numerical simulations have been carried out assuming that one of the sources are non-Gaussian (impacting signal) and the other signals are Gaussian and are independent of each other.

We showed that the cancellation of fourth-order output joint-cumulants leads to a satisfactory condition for the source separation and non-Gaussian impacting signal reconstruction. Three different types of joint-cumulants have been $Cum_{22}\{s_i(n), s_j(n-k)\}$, $Cum_{31}\{s_i(n), s_j(n-k)\}$, and $Cum_{13}\{s_i(n), s_j(n-k)\}$. In fact, the selection of these output joint-cumulants possibly depends on the nature of the unknown signals and is not known a priori. Nevertheless, focusing on the highly impulsive signal dealt in this study, the $Cum_{31}\{s_i(n), s_j(n-k)\}$ is considered to be the most effective cost function (updating function), and is thus employed here. To check the degree of independency of the separated signal, the criterion has been selected as $\left|Cum_{22}\{s_1(n), s_2(n)\}\right|$. This factor has shown consistency of convergence from numerous simulation results (refer **Table 3.2**).

The multichannel blind deconvolution process which utilises variable norm values as a multichannel objective function is introduced.

For a complicated system having multi-coupling or heavy noise interference, the multichannel blind deconvolution approach turns out to be a more effective method (see **Table**).

The selection of the variable norm values (r) depending on the status of each input and output signal of the inverse system remains to be studied further.

From extensive experiments for the practical application of BSS algorithm focusing on the underlying machine health monitoring problems, those results in section 3.4 with rather simple rotating motors even can offer a certain degree of practicability in the engineering field which of course shall be assisted from other relevant statistical methods such ad Independent Component Analysis (ICA) [Lathauwer et al 1999], for which some technical explanation will be presented in short coming future.

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