A BLIND SOURCE SEPARATION METHOD FOR CONVOLVED MIXTURES BY NON-STATIONARY VIBRATION SIGNALS

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Abstract- A simple and feasible of BSS method to separate the convolution mixture of non-stationary vibration signals is present in this paper. The method is carried out by means of two iterative procedures: The first procedure is to estimate the coefficients of the filters. The independence criterion is used and the unknown filters are obtained by a back propagation procedure by means of simplifying the coefficients of filters. The next procedure is to estimate the source vibration signals. The coupled vibration signals are obtained by means of the filters gotten from the former procedure and the estimation sources are obtained through decoupled procedure. Simulation and experiment results show that the method is effective. This improved method can be used to separate convolutive mixtures with non-stationary mechanical vibrations.

Index terms: Mechanical Vibration, Blind Source Separation, Convolutive Mixture, Non-stationary.

I.   INTRODUCTION

Non-stationary vibration signals appear in the process of startup and shutdown of rotating machinery. As a failure occurs, the rotating machinery in operation will produce non-stationary vibration signals. The vibration signals recorded by the sensors fixed on each machine can be interfered by other machine vibration. As various effects on the vibration source signal such as the effects of mechanical structure on the vibration transmission path and vibration source signals coupling each other, so the vibration observation signals are the convolutive mixture of the machine nature vibrations, other machinery vibration and noises [1].The signals which reflect the condition of machine are dirty and can not be used directly. Blind source separation (BSS) can separate the source signals from a finite number of observations without any prior knowledge, which make it an attractive method in machinery condition monitoring and fault diagnosis [2-6]. Many algorithms for blind source separation have been introduced in the past few years. Several methods developed explicitly for nonstationary source with instantaneous mixtures [7-10].In many applications, such as separation of speech signals [11] or mechanical vibration signals, the sources may undergo convolutive mixing, and more complex BSS algorithms are presented to achieve better source separation. Some of BSS methods for non-stationary signals are blocked-based methods in time domain requiring somewhat sophisticated and expensive processing. The signals in the time domain are separated into a relatively stable block, and then the signal blocks are processed by an instantaneous BSS method for stationary process [12-15]. The effectiveness of such approach depended on the stationary status of non-stationary signal block. The performance of the algorithm on non-stationary block easily is poor. Some of BSS methods for non-stationary signals with convolutive mixtures are sub-band decomposition method in the frequency domain [16-19]. As the amplitude and the order of signals separated from mixtures are not certain, the method requires additional exact reconstruction process in the whole frequency band [20]. Such frequency-domain blind source separation method requires a sophisticate post-processing procedure [21]. In this paper, a simple and feasible BSS method is presented to separate the convolution mixture of non-stationary vibration signals. So that in the case of more machine, we can obtain pure mechanical vibration signal to improve the accuracy of fault diagnosis of machinery.

The organization of the paper is as follows. After a general introduction of the effect of non-stationary vibration signals on the machinery, the necessity to separate the nature source vibration signals from the observations is presented. The convolutive model is discussed in section II. The method to separate the source vibration signals from the convolutive model in stationary signals has been discussed in section III. In section IV, a new algorithm for separating non-stationary vibration source signals with operating principle and design details have been presented. The analysis and simulation results of new algorithm have been presented in section V. The analysis and experimental results of new algorithm have been presented in section VI. The lecture has been concluded in section VII. And section VIII is the acknowledgement.

II.   CONVOLUTION MIXTURE MODEL

Different mechanical vibration signal can be considered as independent signal, their transmission paths are equivalent to linear filters [1]. The observations can formulate as:

$$\mathbf{x}(t) = \mathbf{A}(t) * \mathbf{s}(t) + \mathbf{b}(t) \tag{1}$$

where $\mathbf{s}(t)$ is k unknown independent source signals, which are denoted as useful vibration signals and interference; $\mathbf{x}(t)$ are measurements from m sensor array, which are superposition of unknown vibration sources filtered by the unknown filters; $\mathbf{A}(t)$ is an unknown matrix of linear filters, characterized the transmission from the source to the sensor; $\mathbf{b}(t)$ is additive noise; $*$ is convolution operator.

Assuming linear filter is L-order reversible causal filter, equation (1) is transformed by z transformation, we can obtain

$$\mathbf{x}(z) = \mathbf{A}(z)\mathbf{s}(z) + \mathbf{b}(z) \tag{2}$$

where $\mathbf{A}(z)$ is propagation matrix, and its elements are

$$\mathbf{A}(z) = \begin{bmatrix} A_{11}(z) & \cdots & A_{1m}(z) \\ \vdots & \ddots & \vdots \\ A_{k1}(z) & \cdots & A_{km}(z) \end{bmatrix} \tag{3}$$

where

$$A_{ij}(z) = \sum_{\tau=0}^{L} a_{ij}(\tau) \cdot z^{-\tau} \tag{4}$$

Assuming no noise in channel, $m = k = 2$, and the sensors are close to sources as far as possible, equation (2) is simplified as

$$\mathbf{x}(z) = \mathbf{A}(z)\mathbf{s}(z) \tag{5}$$

where

$$\mathbf{A}(z) = \begin{bmatrix} 1 & A_{12}(z) \\ A_{21}(z) & 1 \end{bmatrix} \tag{6}$$

III. SEPARATION FOR CONVOLUTION MIXTURE

The aim of the blind source separation method is to obtain the estimate of the source signals with a linear filter on observations:

$$\hat{\mathbf{s}}(z) = \mathbf{B}(z)\mathbf{x}(z) = \mathbf{B}(z)\mathbf{A}(z)\mathbf{s}(z) \tag{7}$$

where $\mathbf{B}(z)$ is the filter matrix.

If $\mathbf{A}(z)$ is unknown, $\mathbf{B}(z)$ can not be obtained. When the convolutive mixing process is modeled as a FIR filter, the coefficient of filter $\mathbf{C}$ and the source signals can be estimated by the method of back propagation learning. The process of the method with back propagation learning is shown in figure1.
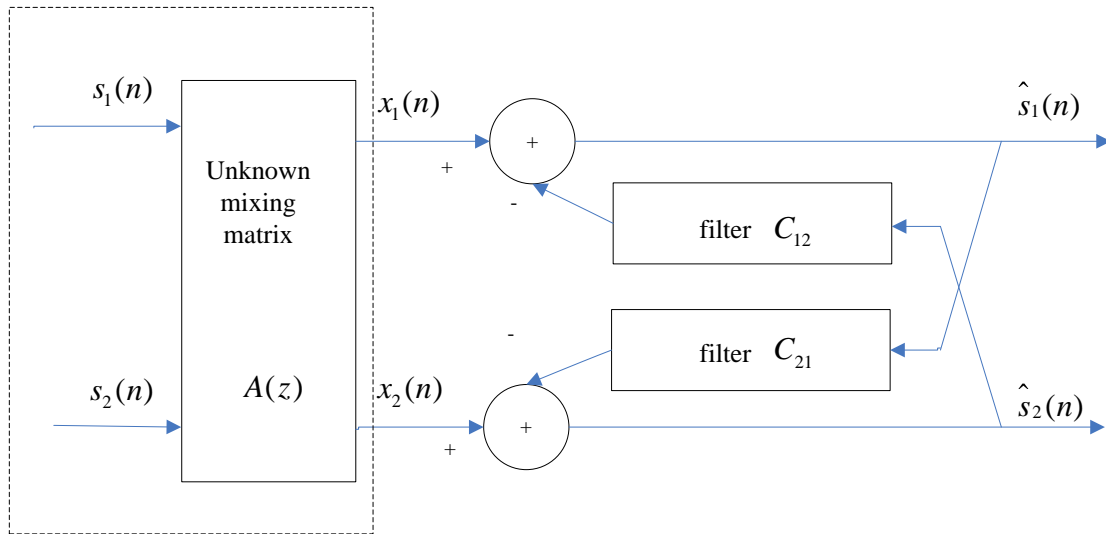

Figure 1. BSS process with back propagation learning

The output of the system is

$$s_i(n) = x_i(n) - \sum_{i \neq j} C_{ij}(n) * s_j(n) \tag{8}$$

In the case of two sources,

$$s_i(n) = x_i(n) - \sum_{k=0}^{L} C_{ij}(n,k) \cdot s_j(n-k), i, j \in (1 \ 2), i \neq j \tag{9}$$

where $C_{ij}(n,k)$ is k element of the filter matrix at point n, and $C_{ii}(z) = 0$.

Assuming that $(\mathbf{I} + \mathbf{C}(z))^{-1}$ exists in z domain, equation (9) is transformed by z transformation, we get

$$\mathbf{s}(z) = (\mathbf{I} + \mathbf{C}(z))^{-1} \mathbf{x}(z) \tag{10}$$

In the case of two sources, by equation (7) and equation (10), we get

$$\mathbf{B}(z) = (\mathbf{I} + \mathbf{C}(z))^{-1} = \frac{1}{1 - C_{12}(z)C_{21}(z)} \begin{bmatrix} 1 & -C_{12}(z) \\ -C_{21}(z) & 1 \end{bmatrix} \tag{11}$$

So

$$(\mathbf{I} + \mathbf{C}(z))^{-1} \mathbf{A}(z) = \frac{1}{1 - C_{12}(z)C_{21}(z)} \times \begin{bmatrix} 1 - C_{12}(z)A_{21}(z) & A_{12}(z) - C_{12}(z) \\ A_{21}(z) - C_{21}(z) & 1 - C_{21}(z)A_{12}(z) \end{bmatrix} \tag{12}$$

The FIR filter solution is

$$C_{ij}(z) = A_{ij}(z) \tag{13}$$

Output signals are estimated as

$$\hat{s}_i = s_i \tag{14}$$

IV.   ADAPTIVE NON-STATIONARY SIGNAL SEPARATION ALGORITHM

On the basis of the separation process of convolutive mixtures, non-stationary signal sources are estimated by an adaptive algorithm.

When the coefficients of system filter are unknown, each filter coefficient is updated by the cost function. In the case of separating the stationary signals with instantaneous mixing model, Jutten update the filter coefficients by the cost function based on independence criteria, and extend it to the case of convolution mixture model [22]:

$$\Phi_{ij}(n,k) = \frac{\mathrm{d} C_{ij}(n,k)}{dt} = E\{ f(s_i(n)) g(s_j(n-k)) \} \tag{15}$$

In this case, the filter coefficients are calculated by equation (16).

$$C_{ij}(n+1,k) = C_{ij}(n,k) + \mu f(s_i(n)) g(s_j(n-k)), k \in [0, L] \tag{16}$$

where μ is the learning rate.

When the two output signals are independent, then filter coefficients will convergence. We extend this rule to the separation method of non-stationary signals. For calculation simplicity, in the algorithm, nonlinear function is set as

$$f = (\cdot)^3, \quad g = (\cdot) \tag{17a, b}$$

The effect of other source signals to mixtures is eliminated by the estimated filter, and the estimates of non-stationary source signals are obtained. But as the coupling between the signals at the same time point, each simultaneous output equations are used to further eliminate the coupling between the signals, and each point of non-stationary signals are estimated.

In the case of two sources, from equation (9), we can obtain

$$s_i(n) = x_i(n) - C_{ij}(n,0) \cdot s_j(n) - \sum_{k=1}^{L} C_{ij}(n,k) \cdot s_j(n-k), i, j \in (1\ 2), i \neq j \tag{18}$$

From equations (18), we can get $s_1(n)$ and $s_2(n)$, then

$$\begin{bmatrix} 1 & C_{12}(n,0) \\ C_{21}(n,0) & 1 \end{bmatrix} \begin{bmatrix} s_1(n) \\ s_2(n) \end{bmatrix} = \begin{bmatrix} x_1(n) \\ x_2(n) \end{bmatrix} - \begin{bmatrix} \sum_{k=1}^{L} C_{12}(n,k) \cdot s_2(n-k) \\ \sum_{k=1}^{L} C_{21}(n,k) \cdot s_1(n-k) \end{bmatrix} \tag{19}$$

Thus the output of the system is available.

$$\begin{bmatrix} s_1(n) \\ s_2(n) \end{bmatrix} = \begin{bmatrix} 1 & C_{12}(n,0) \\ C_{21}(n,0) & 1 \end{bmatrix}^{-1} \times \left(\begin{bmatrix} x_1(n) \\ x_2(n) \end{bmatrix} - \begin{bmatrix} \sum_{k=1}^{L} C_{12}(n,k) \cdot s_2(n-k) \\ \sum_{k=1}^{L} C_{21}(n,k) \cdot s_1(n-k) \end{bmatrix} \right) \tag{20}$$

So we can get the program flow of the algorithm, which is shown in figure 2.

The main steps of the algorithm are as follows:

Step 1: Initialize the filter coefficients and the learning rate;

Step 2: Starting from point 2, calculate the source signal value of point n;

Step 3: According to the previous value, calculate the gain of the filter coefficients;

Step 4: Calculate filter coefficients;

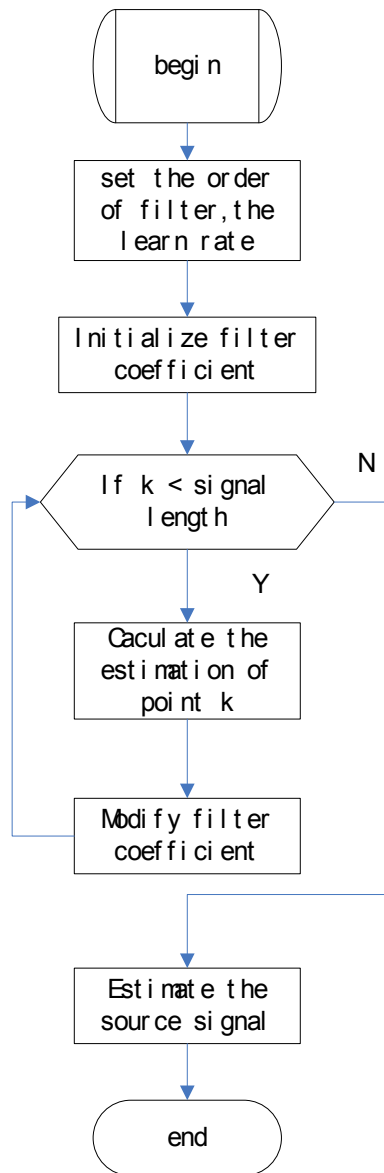Step 5: if k <signal length, return to step 2.

Figure 2. Program flow of the algorithm

V.   SIMULATIONS

This section uses mechanical vibration simulation signals as non-stationary signal sources; the separation performance of the blind source separation algorithm for convolution mixture of non-stationary signals is researched.

Three signals are used to test the algorithm. s1 is a FM sine signals. s2 is a non-stationary source signals with the frequency mutations in the signal. s3 is a sine signal.

$$s1 = \sin(500\pi t + 5\sin(6\pi t))$$

$$s2 = \begin{cases} \sin(74\pi t), & 0 \le t \le t_1 \\ \sin(40\pi t), & t_1 < t \le t_2 \end{cases} \tag{21}$$

$$s3 = \sin(240\pi t)$$

They are mixed by equation (3), in which the filter coefficients are

$$A_{12} = [\text{-0.0464} \ \text{-0.4099} \ \text{-0.1922} \ \text{-0.1166} \ \ 0.0725 \ ]^T$$

$$A_{13} = [\text{-0.2709} \ \ 0.1981 \ \ \text{-0.1720} \ \ 0.4294 \ \text{-0.2702} \ ]^T$$

$$A_{21} = [\text{-0.4079} \ \ 0.0543 \ \ \text{-0.3843} \ \ 0.2910 \ \text{-0.2804} \ ]^T \tag{22}$$

$$A_{23} = [\text{-0.3221} \ \text{-0.1987} \ \ \text{-0.0426} \ \text{-0.3498} \ \text{-0.0382} \ ]^T$$

$$A_{31} = [0.1424 \ \ \ 0.3732 \ \ \text{-0.1940} \ \ 0.1063 \ \text{-0.2582} \ ]^T$$

$$A_{32} = [0.2023 \ \ \ \text{-0.4758} \ \ \ 0.4293 \ \text{-0.0237} \ \text{-0.0284}]^T$$

The waveforms of source signals, mixed signals and separated signals in the time domain are shown in figure 3. Sampling length is 4096. s1, s2, s3 are source signals. x1, x2, x3 are mixtures. ss1, ss2, ss3 are the separated signals. The waveform between 2.3 seconds and 2.85 seconds is shown in figure 3, which covers the point of the frequency mutation in the signal s2. It can be seen that the separated signal waveforms are very similar with the source signal waveforms.

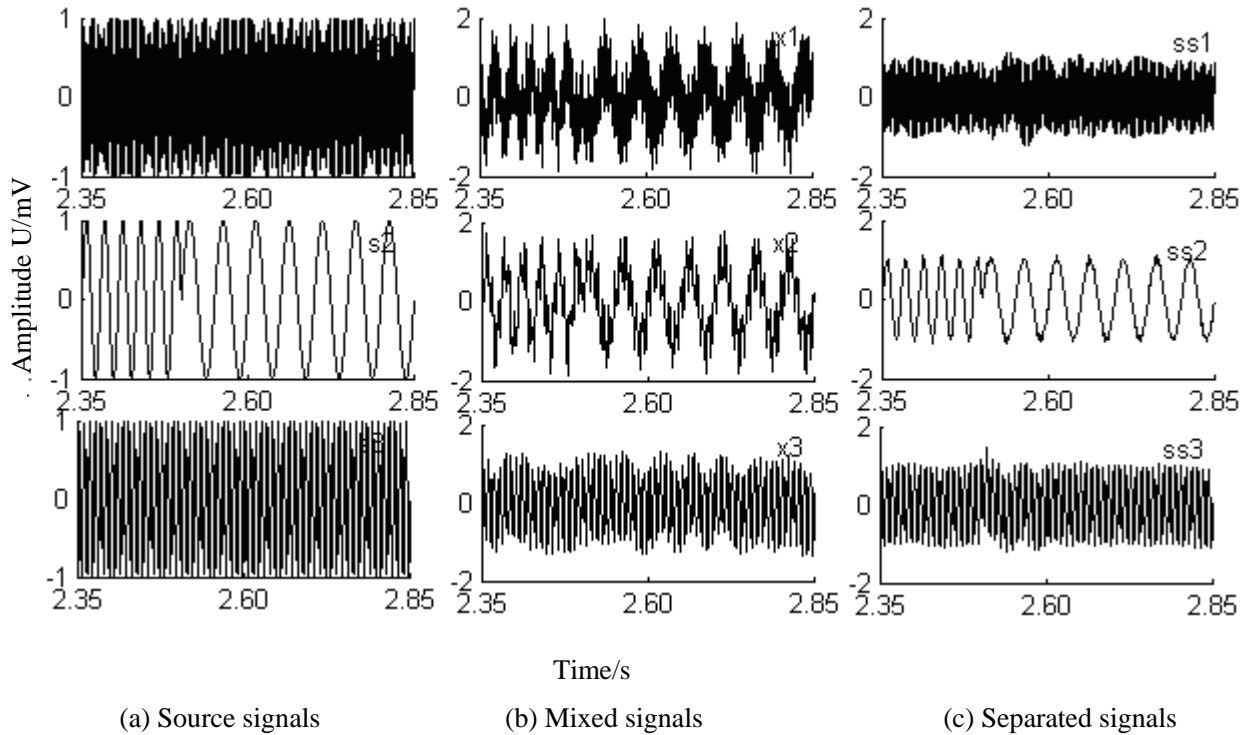(a) Source signals   (b) Mixed signals   (c) Separated signals

Figure 3. Waveforms of simulation signals in time domain

To show the result more obvious, short time fourier transform (STFT) is used to represent the signal frequency characteristics. STFT spectrums of source signals, mixed signals and separated signals are shown in figure 4. It can be seen from figure 4 that early in the separation process, three signals have a strong coupling phenomenon, as time passed, weaker coupling exists in signals, which indicates that the asymptotic convergence of the iterative process. In the vicinity of 2.5 seconds, source 1 and source 3 have been completely separated, but the effect on source 2 from source 1 and source 3 has not completely eliminated. From the waveforms in figure 3 and scale in figure 4, the effect is in fact very small. The impact on source 1 and source 3 is relatively large near the frequency mutations of source 2. After almost 0.2 second iterative process, the effect on source 1 and source 3 from source 2 is completely eliminated, that indicates the source signals are well separated. Simulation results show that the method is effective for non-stationary signals.

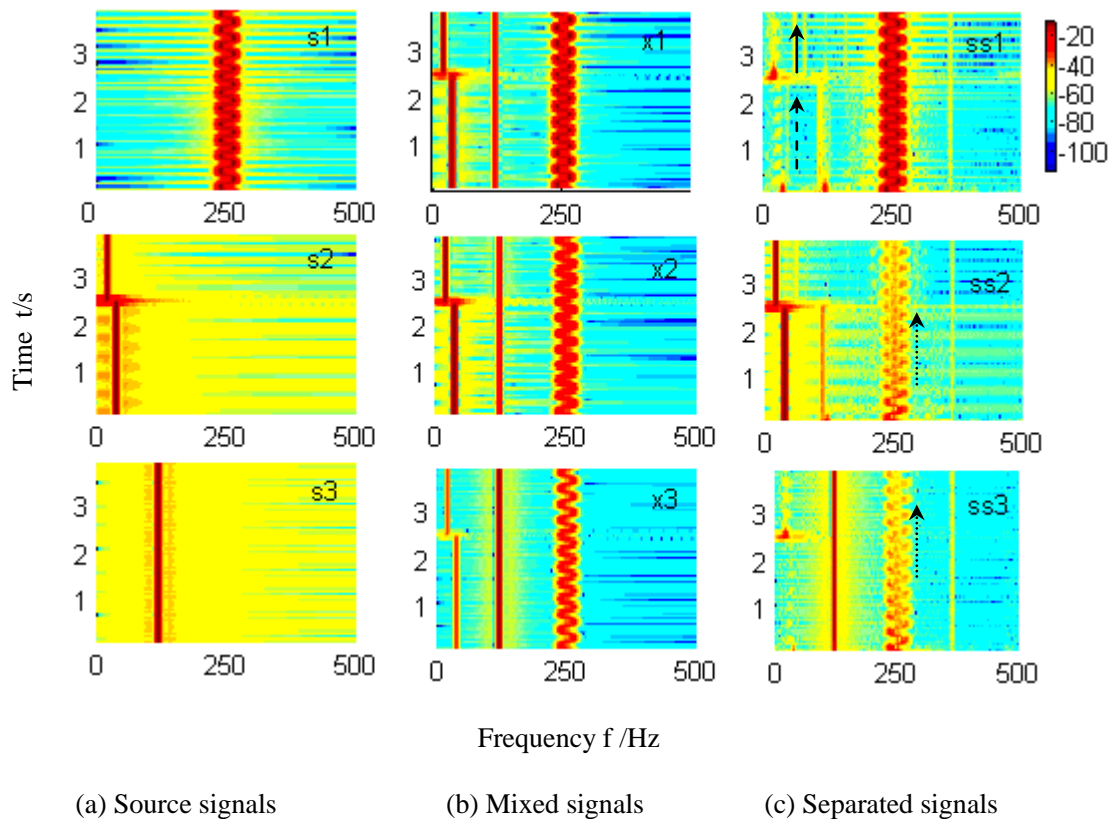(a) Source signals   (b) Mixed signals   (c) Separated signals

Figure 4. STFT spectrum of simulation signals

The iterative process of the filter coefficients is shown in figure 5. The filter coefficients fluctuate when the frequency mutate. The filter coefficients are gradually convergence in the iteration without frequency mutation.
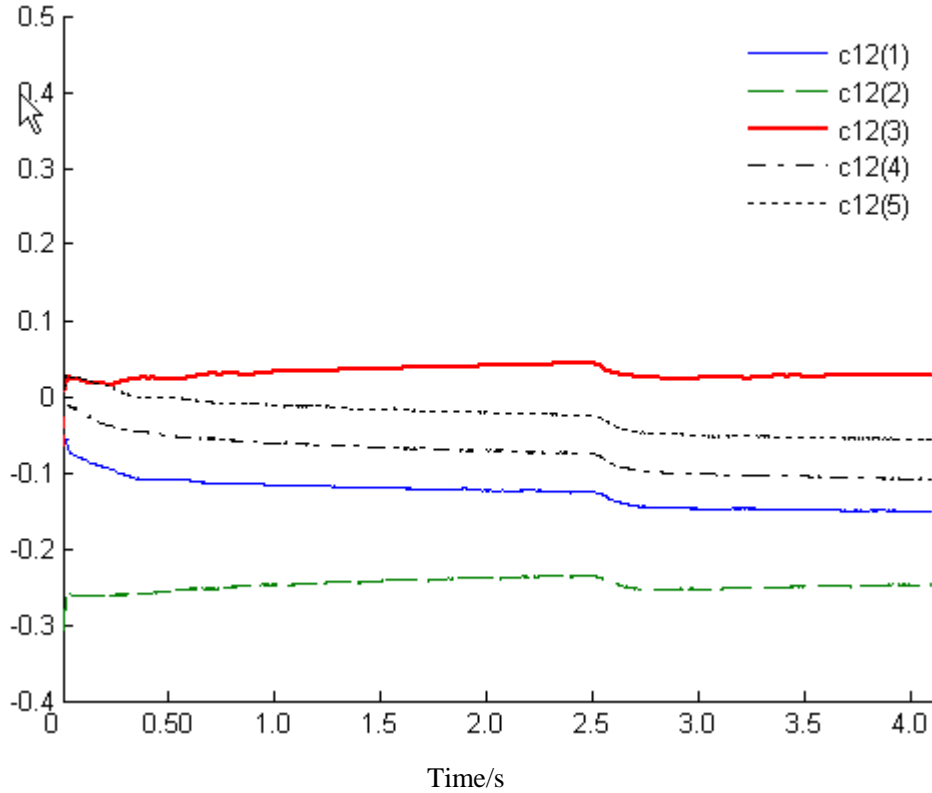

Figure 5. The iterative process of the filter coefficients in simulation

VI.   EXPERIMENTS

Simulation results show that the algorithm is valid for non-stationary signals. In this section, the research is carried out to test the algorithm with non-stationary mechanical vibration. The mechanical vibration signals are obtained from the test-bed on the body of two electromotor. The test system is shown in figure 6. Piezoelectric sensors are installed on the chassis to collect mechanical vibration signals. One of the electromotor is 750W (electromotor 1), and another one is 2.2kW (electromotor 2). Two sensors are set on the top of electromotor 1 (sensor 1) and electromotor 2 (sensor 2), and one on the board (sensor 3). The rotating speed of the electromotor 2 is controlled by the inverter frequency control to obtain non-stationary vibration signals. The

rotating speed of the electromotor 1 is uniform. The test-bed is used to simulate such situations in the factory: multi rotating machineries are operating at the same time; the vibration signals from each machine are mixed with the vibration signals from other machines, even with the noise.

Figure 6. Test system

PCL-1800 data acquisition card is used to data acquisition. Structural principle of the test system is shown in figure 7.

The rotation frequency of the electromotor in the test system is 25Hz. PCL-1800 is a high-speed communication card which is compatible with ISA bus. A 12 bit A/D chip with high performance, wide dynamic range, excellent resistance to noise and low power consumption is used to complete A/D conversion. The card also come with high-performance with 1K byte FIFO to reduce CPU load, with 16 single-ended or 8 differential analog inputs, 2-port 12 bits D/A output, 16-port digital inputs, 16-port digital outputs and a 16-port counter channel. The PCL-1800 has four kinds of data communication ways. The performances of each kind of communication ways
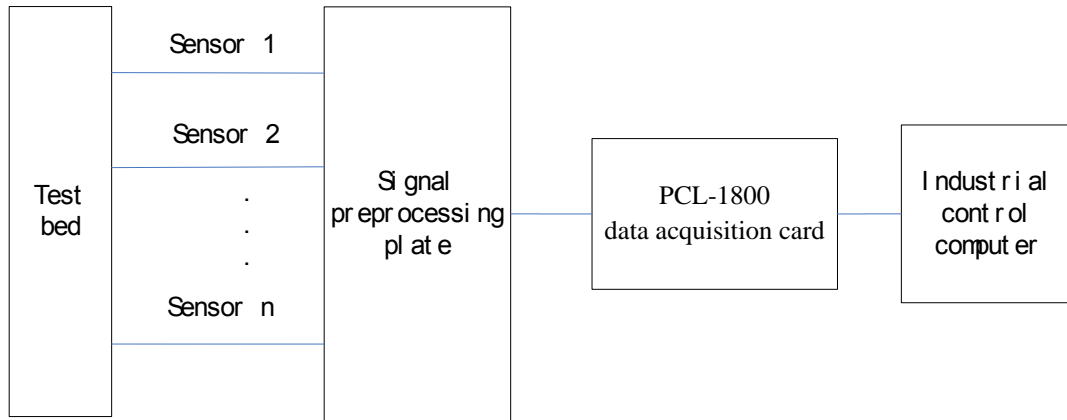
are shown in table 1.

Figure 7. Structural principle of the test system

Table 1: The performance data communication ways of PCL-1800[23]

Data communication ways	A/D speed
Software query	10~20KHz
Interrupt	10~30KHz
DMA	200KHz
FIFO	330KHz

In the program of multi-port data acquisition, the interrupt data communication way is used to data acquisition. The sampling data are read by means of FIFO. The flow of data acquisition is shown in figure 8.

The measurements of electromotor vibration are used as vibration source signal when they run individually, which are shown in figure 9. The vibration signal measured from sensor 1 when only electromotor 1 run is denoted as source signal s1. The vibration signal measured from sensor 2 when only electromotor 2 run is denoted as source signal s2. The STFT spectrums of source signals are shown in figure10. The arrow point in figure 10 shows the change point of the rotating frequency of electromotor 2.

```
            ┌─────────────┐
            │    Begin    │
            └──────┬──────┘
                   ▼
            ┌─────────────┐
            │Turn on the data│
            │  equipment  │
            └──────┬──────┘
                   ▼
            ┌─────────────┐
            │Configuration│
            └──────┬──────┘
         ┌─────────┴─────────┐
         ▼                   ▼
  ┌─────────────┐    ┌─────────────┐
  │  Configure  │    │Configure Sampling│
  │ Interupt way│    │  information │
  └──────┬──────┘    └──────┬──────┘
         └─────────┬─────────┘
                   ▼
            ┌─────────────┐
            │  Scan port  │
            └──────┬──────┘
                   ▼
            ┌─────────────┐
            │Read data with FIFO│
            └──────┬──────┘
                   ▼
            ┌─────────────┐
            │Combine and save data│
            └──────┬──────┘
                   ▼
            ┌─────────────┐
            │Release memory│
            └──────┬──────┘
                   ▼
            ┌─────────────┐
            │     end     │
            └─────────────┘
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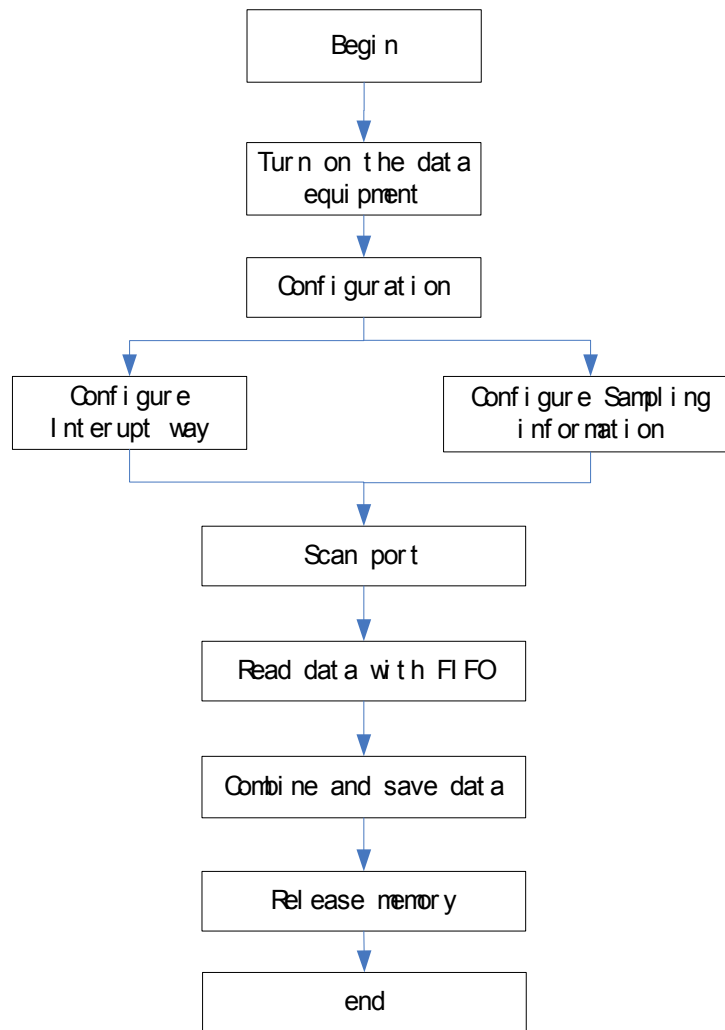
Figure 8. The flow of data acquisition

The measurements are used as mixtures as two electromotor run together, which are shown in figure 11. The vibration signal measured from sensor 1 when two electromotor run together is denoted as mixture signal x1. The vibration signal measured from sensor 2 is denoted as mixture signal x2. The vibration signal measured from sensor 3 is denoted as mixture signal x3. The STFT spectrums of mixture signals are shown in figure12. It can be seen from figure 12, the electromotor 2 has greater effect on the mixture signal x1 and x3, and the effect of electromotor 1 on the mixture signal x2 is weak.
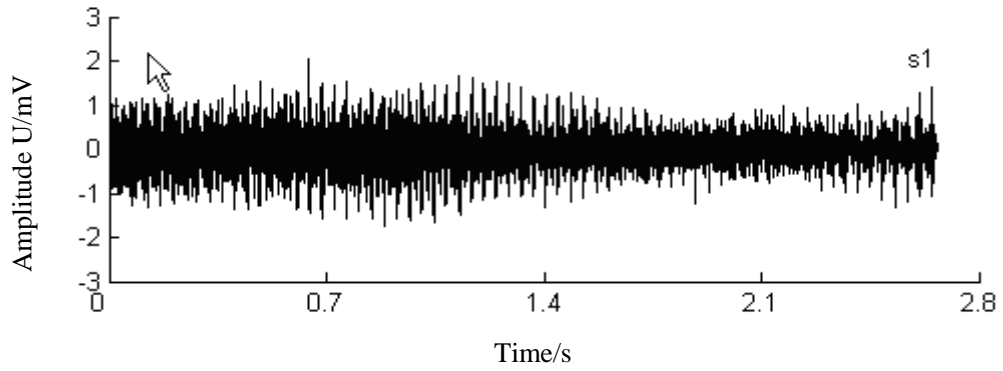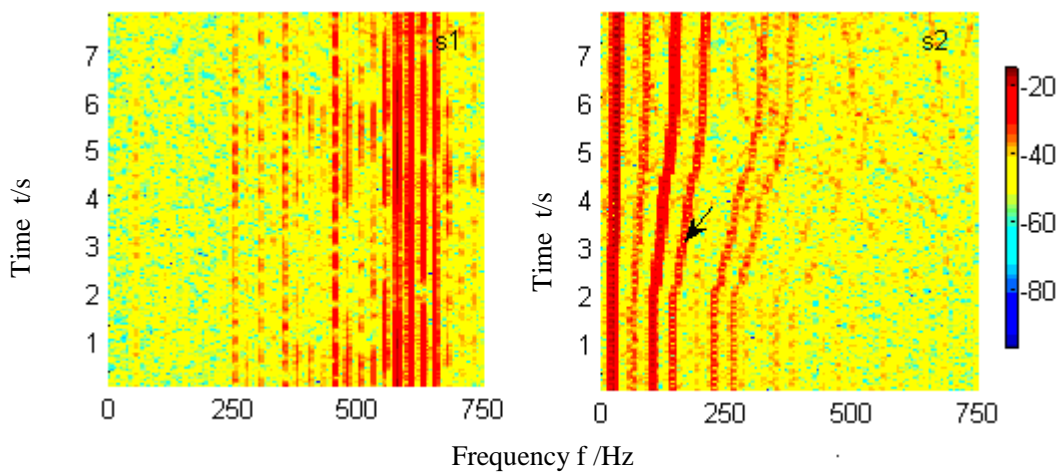
(a) Electromotor 1
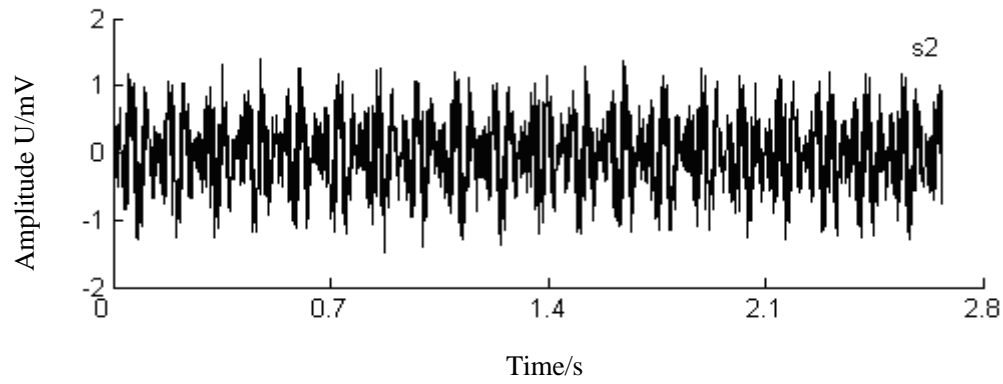
(b) Electromotor 2

Figure 9. Waveforms of source signals in time domain

(a) Electromotor 1   (b) Electromotor 2

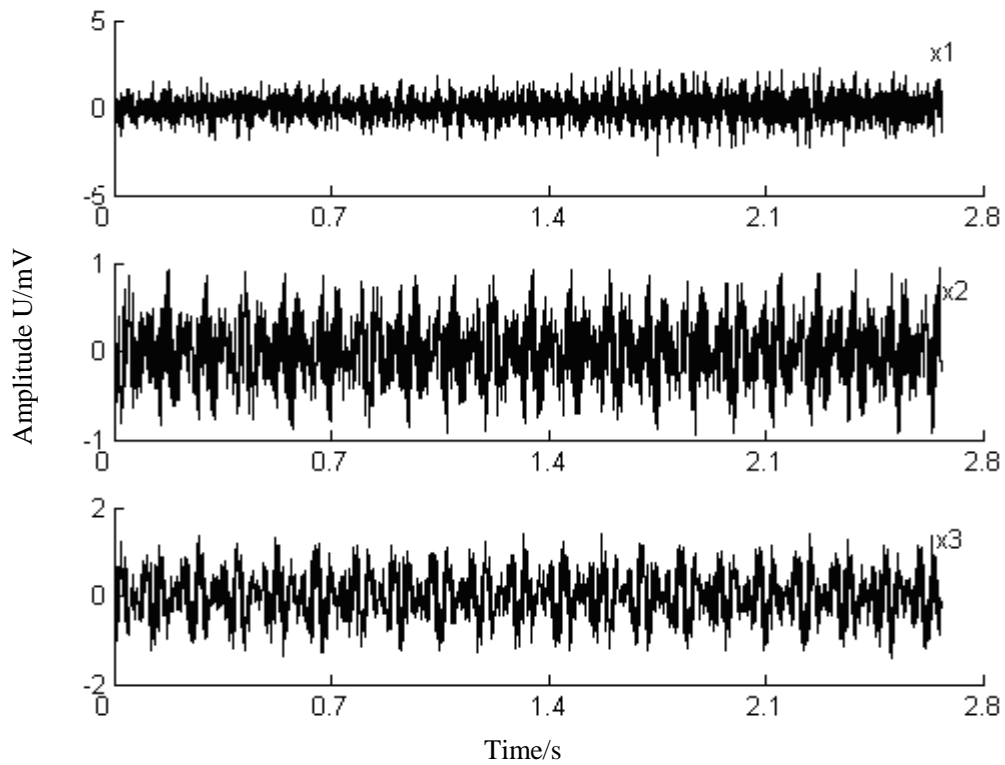Figure 10. STFT spectrum of source signals

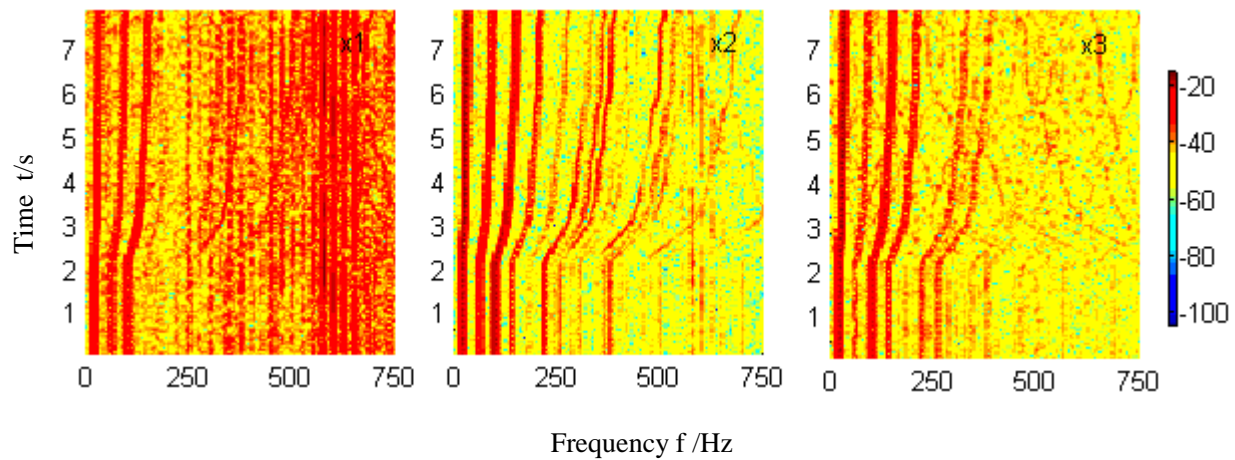Figure 11. Waveforms of mixed signals in time domain

Figure 12. STFT spectrum of mixed signals

In this test, what we concerned is the separation performance, so the physics meaning of the value of the spectrum is not specified. The algorithm is used to separate the measurements to get the estimation source signals, which are denoted as ss1, ss2 and ss3. The waveforms of separated

signals in time domain are shown in figure 13. The STFT spectrums of source signals, mixture signals and separated signals are shown in figure14.
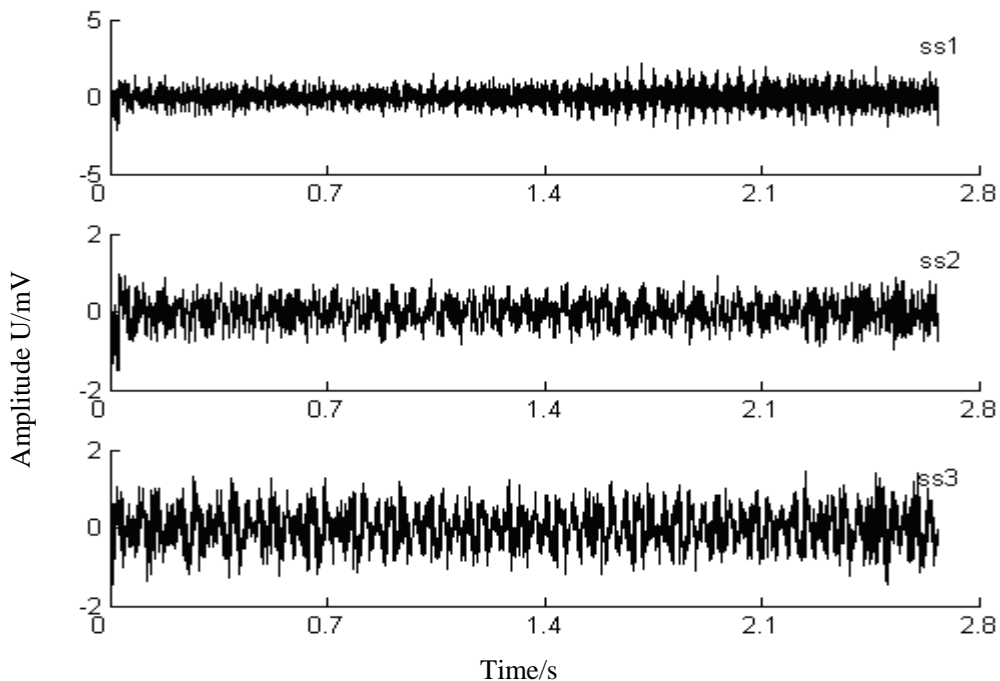

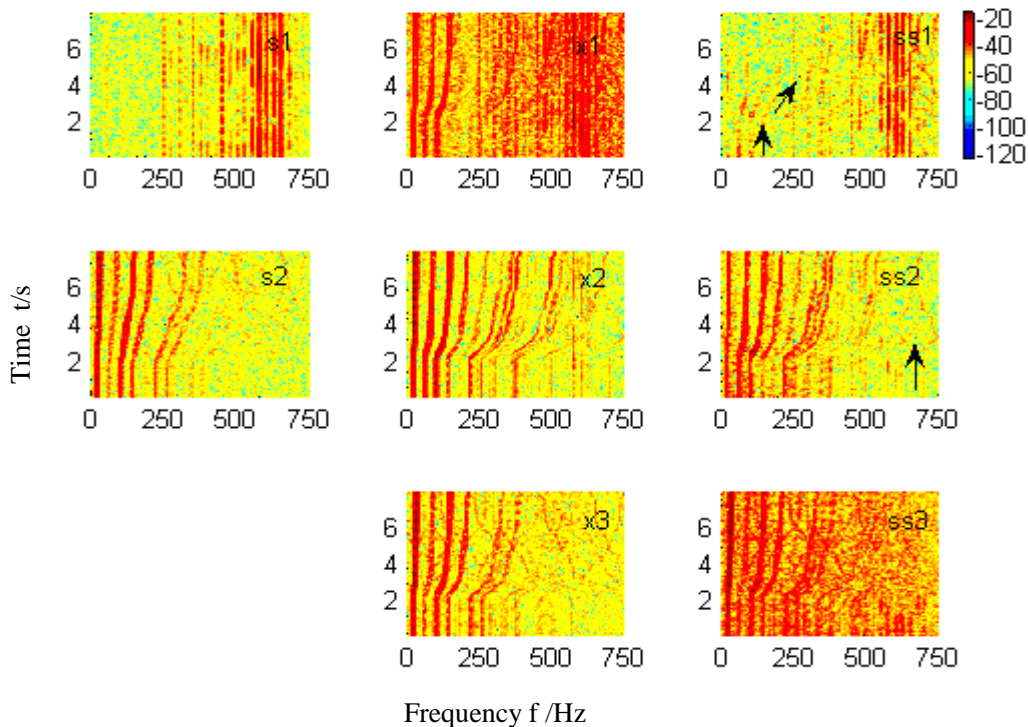Figure 13. Waveforms of separated signals in time domain

Figure 14. STFT spectrum of the signals

Compared figure 9 with figure 13, it can be seen that ss1 is similar to s1, and ss2 is similar to s2 in time domain. Which illustrate that ss1 is corresponding to the vibration signal of electromotor 1, and ss2 is corresponding to the vibration signal of electromotor 2. The arrow points on the spectrum of separated signal ss1 show the gradual separation process of the non-stationary signals. Although some lines do not get completely separate, the interaction is weak between signals by comparing source signals with mixture signals and separated signals. The two source signals are well separated.

The iterative process of the filter coefficients is shown in Figure 15. The filter coefficients fluctuate slightly with the signal frequency and gradually tend to be stable as the iterative process proceeding.
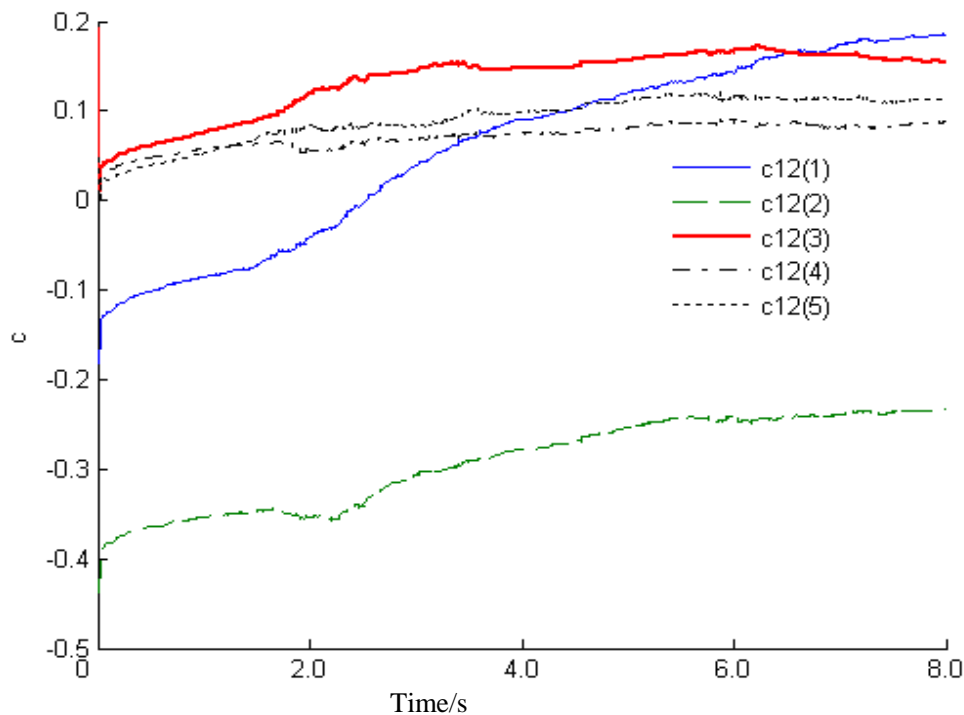

Figure 15. The iterative process of the filter coefficients in experiment

VII. CONCOLUTIONS

From the simulation experiment, the non-stationary convolutive mixed signal separation algorithm has good separation performance. The experiments on non-stationary mechanical vibration signal show that the algorithm can well separate different mechanical vibration signals.

Therefore, further study of the algorithm in gearbox fault diagnosis is worthy to carry out to eliminate non-stationary signals from another machine on the mechanical vibration of the gearbox, and to improve the accuracy of diagnostic methods. At the same time, the algorithm can also be extended to non-stationary internal gearbox vibration signal separation, provide a basis for precise fault position.

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