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Sound Source Separation and Identification for Aircraft Cockpit Voice Recorder

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Analysis of the background information recorded in aircraft Cockpit Voice Recorders (CVRs) has been proposed as a complement to the analysis of onboard Flight Data Recorders in civil aircraft investigations. This paper explores the feasibility of identifying individual sound sources using an integrated signal processing technique for signal noise cancellation and sound source separation and identification. Experimental results show that at least six different sound sources, simulated as a mixed signal, can be successfully separated and identified, using Adaptive Noise Cancellation (ANC), Blind Signal Separation (BSS) and Back Propagation Neural Network techniques, from the output of a ATR-72 CVR. It is proposed that this concept be applied, not only to aviation investigations and engine monitoring, but also to early identification of abnormal sounds from other aircraft components.

I. Introduction

AS air transportation systems have expanded around the world in recent decades, aviation safety and accident/incident prevention have assumed greater importance to governments and airlines. Even more stringent safety measures have become necessary following the outbreak of world terrorism in the last few years. Aircraft accident investigation has a key role to play when an aircraft has an accident or unexpected incident during flight operations. Traditionally the Flight Data Recorder (FDR) has played the major role in establishing the causes of most accidents or incidents. However, information contained in the Cabin Voice Recorder (CVR) has a useful role to play during such investigations in aiding a better understanding of the true situation.

One reported case provides a good example of the analysis of CVR data playing a key part in an aircraft accident investigation.[1] In 1992, a 19-seater commuter aircraft crashed during an evening training mission. At that time, the US Federal Aviation Agency (FAA) did not require the installation of FDR onboard all small commercial aircraft, and the CVR onboard the crashed small jet was the only flight record available to supply clues to help find the causes of the accident. Fortunately, in this case, the CVR recording included not only the voice communication, but also structural acoustics as well as other sounds and noise sources, and the accident investigation focused on the non-speech sounds taken from the CVR tape. Figure 1 illustrates the acoustic signals taken at the end of the CVR tape of the crashed aircraft.[2] A close inspection of the time series from the CVR track reveals a periodic set of transient components occurring at a frequency of 0.86 Hz. Comparing this frequency with an independent dynamic analysis of the engine mount damage, the 0.86 Hz transient data were demonstrated by independent structural and flutter analyses to be quite close to the frequency experienced from a damaged engine mount. Moreover, there is a sudden loud sound at the end of the tape. This 25 millisecond long event shown in Figure 2 can be seen to be much

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louder than the sound in the cabin. Although the short length of this sound does not provide adequate audio listening time, there is enough signal time and amplitude to perform wavelet and voice recognition analysis. The conclusion drawn after the investigation was that the engine on the starboard wing separated during the flight.[3] Subsequently, the free engine struck the tail of the aircraft, damaging most of the horizontal surfaces. The loss of the engine also led to the separation of the right wing panel outboard of the engine. As a result, the aircraft pitched down, rolled right and crashed. An illustration of the aircraft breakup sequence is at Figure 3.

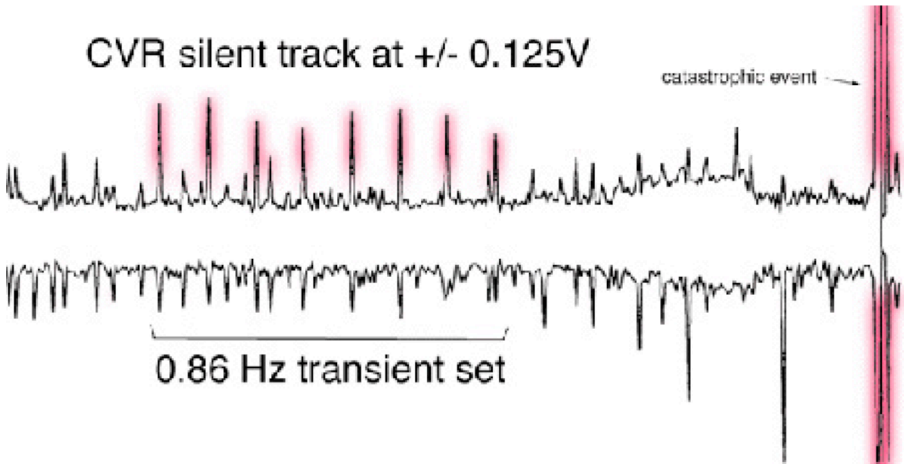

Fig. 1 The acoustic signals at the end of the CVR tape in a crashed aircraft.[2]

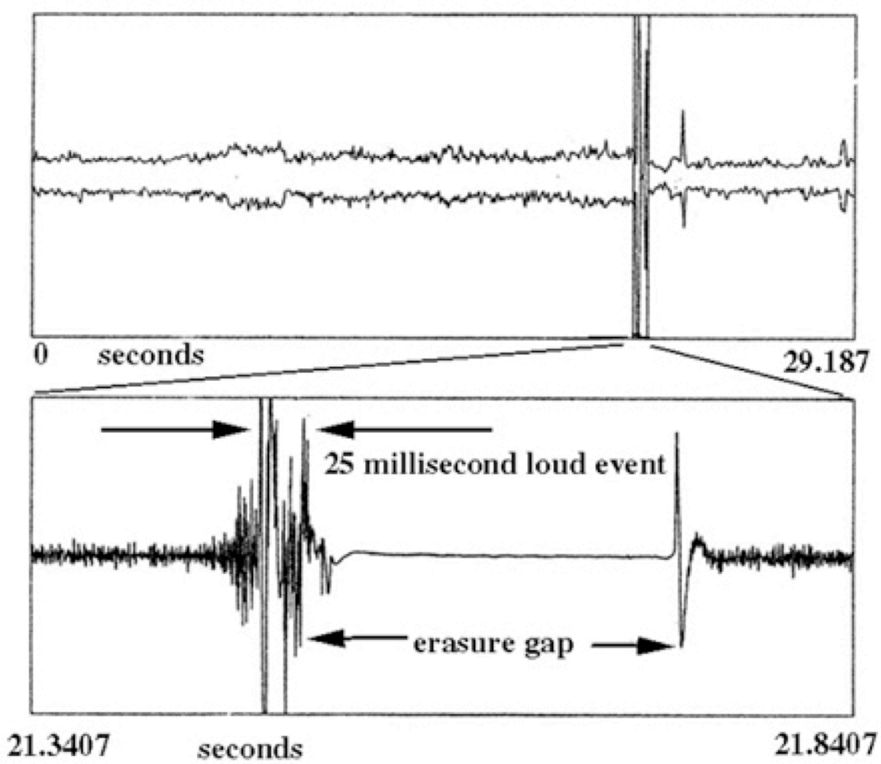

Fig. 2 End-of-tape erasure gap with loud event.[2]

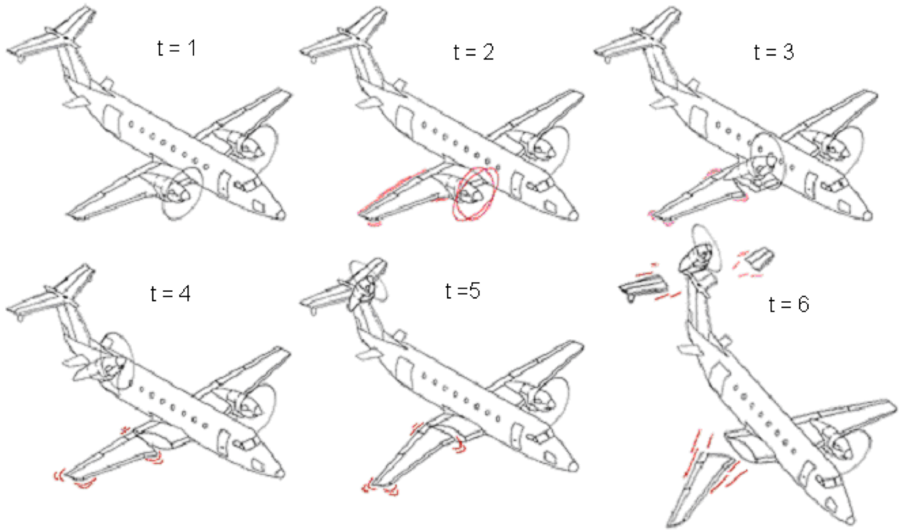

Fig. 3 The aircraft approximation breakup sequence.[3]

The results of the accident investigation described above motivated us to explore the analysis of aircraft CVR sound sources for use in aircraft accident investigation. Associated research to detect damage through structural acoustics and signal processing is also being conducted by the engineering and science communities. The CVR here effectively acts as a latent signal transducer for both the speech and non-speech acoustic information. Some typical techniques, such as voice recognition, sound separation and sound identification, appear to offer significant advantages in the analysis and classification of non-speech CVR signals.

Hence, this paper focuses on the sound analysis of CVR data to provide an integrated technique for sound identification and damage detection in aviation safety investigations. To obtain the individual sound signals from the mixed sounds in the CVR, the first step is to cancel the background noise in the recorded sound, to reduce the complexity of the analysis, by using Adaptive Noise Cancellation (ANC). The second step is to separate the pre-cleaned sound sources into individual sound sources by Blind Signal Separation (BSS). There are two different sources of the mixed sound has been separated successfully in this paper. Another contribution of this paper is to identify the specific sound from the Back Propagation Neural Network (BPNN), which has been trained by the sound samples first. The entire process of sound separation and identification will be justified by employing a real set of sound source data taken from the sound tracks of an ATR-72's CVR.

II. Adaptive Noise Cancellation Algorithm

The Adaptive Noise Cancellation (ANC) algorithm is used to reduce the background noise level from the useful sound sources.[4] The only assumption made here is that the background noise is uncorrelated with the other sounds in the analysis. The noise source signal is processed by an adaptive filter to generate the replica of the background noise in the cabin. Considering the input signal $x(n)$, the noise source signal $N_1(n)$ is compared with a desired signal $d(n)$, which consists of a signal $s(n)$ corrupted by another noise signal $N_0(n)$, as shown in Figure 4. It is intended to find the adaptive filter coefficients $w(n)$ adapted to allow the error signal $e(n)$ to be a noiseless version of the signal $s(n)$.

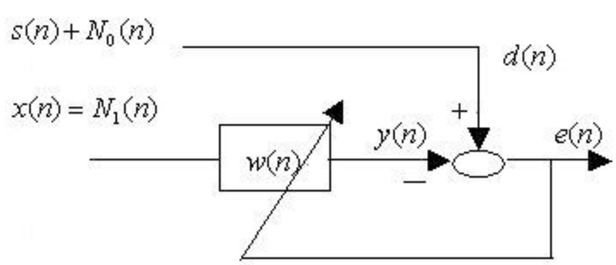

Fig. 4 The structure of the adaptive noise cancellation.

Considering the input *x(n)*, an impulse response *w(n)* and the output *y(n)* are assumed to have the relationship as follows:

$$y(n) = w^T(n)x(n) \tag{1}$$

where , $x(n) = \left[x(n), x(n-1), \cdots, x(n-(N-1))\right]$, $w^T(n) = \left[w_0(n), w_1(n), \cdots, w_{N-1}(n)\right]$

Use the cost function to estimate the impulse response *w(n)*:

$$w(n+1) = w(n) - \mu e(n)x(n) \tag{2}$$

where $e(n) = d(n) - y(n)$, $y(n) = x^T(n)w(n)$, μ = scaling factor.

The procedure of calculation iteration will repeat over and over again until the derivative of the mean square error *e(n)* approaches zero.

In the application of the Adaptive Noise Cancellation (ANC) algorithm to the real CVR sound source information, the concept of the ANC analysis is represented in Figure 5. The sound source information in the simulation is directly obtained from the ATR-72's CVR, which includes the panel switch sound as the main sound source and the engine noise as the background noise intended for cancellation or filtering. By using the ANC algorithm, the engine noise can be cancelled or filtered to some extent from the combined sound. The spectral diagrams of the simulation results depicted in Figure 6 respectively illustrate the unfiltered sound, the top line of the figure, represented as the switch sound combined with the engine noise heard in the aircraft cabin, the filtered sound, the middle line of the figure, represented the switch sound after ANC processing, and the noise as the engine sound, the bottom line of the figure heard in the cabin. From Figure 7, showing the mean square error of *e(n)* after the ANC processing, it is clear that the amplitude of the unfiltered sound has been filtered out of the engine noise part to become the filtered one. From this stage, the complexity of the mixed sound is reduced as the noise has been filtered out. In other words, if there are more different and independent sounds mixed together, then the background noise, when it exists, can be filtered out using the current algorithm in the beginning stage of the sound source processing. Using these cleaner sound signals, then the next step is to proceed with the signal separation and identification of their individual physical sound sources for the real applications.

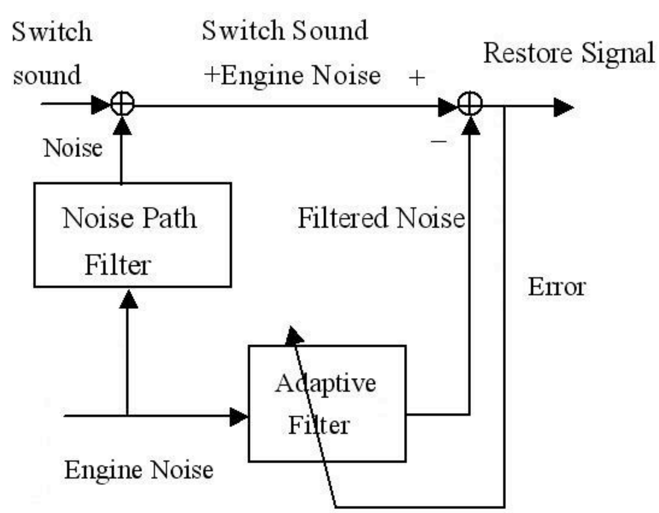

Fig. 5 Adaptive noise cancellation in the Cockpit Voice Recorder analysis.

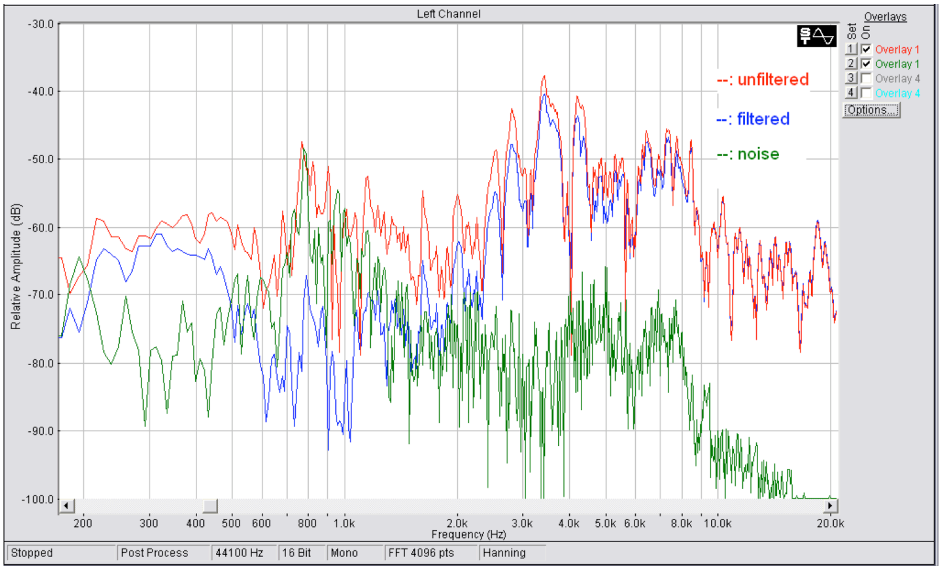

Fig. 6 The spectral diagram of the ANC simulation results.

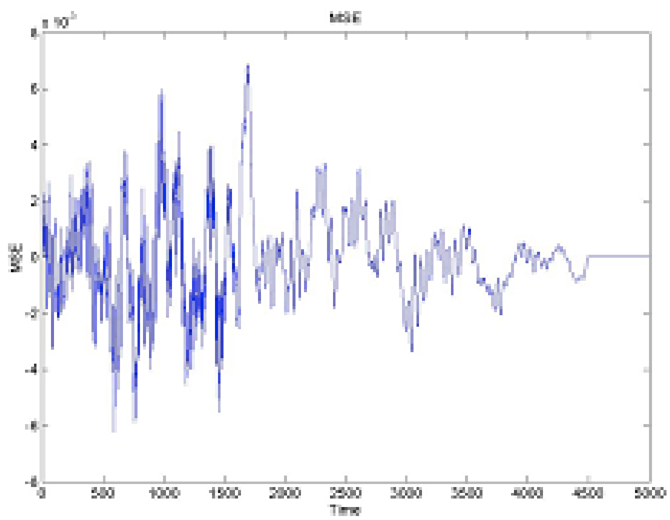

Fig. 7 Mean squared error of the ANC simulation.

III. Blind Signal Separation Algorithm

The problem of Blind Signal Separation (BSS) is fundamental and challenging, and it has received a great deal of attention in recent years. It is a technique that recovers the independent source signals from the observed ones. Consider a situation where there are a number of signals emitted by some sources and there are several sensors in the different positions to receive the source signals, as shown in Figure 8. Note that these sensors are located in different positions and each of them records a mixture of the source signals with slightly different weightings. This kind of problem is usually referred to as the cocktail party problem, and has been widely investigated as an audio signal separation problem in the past few years.[5] In the aviation situation, there are four microphones set up in the different position of the cabin so that there only exists four sound channels of CRV. The cocktail party problem can be discussed here.

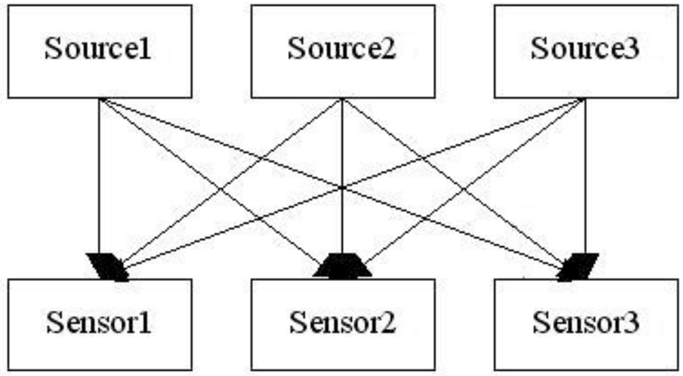

Fig. 8 The typical multisources and multisensors situation.

The BSS problem can be treated to find a linear representation in which the components are statistically independent, as in Independent Component Analysis (ICA), which was first introduced by Comon.[6] Herault and Jutten[7] however introduced a different approach for solving the BSS problem using a "Neuromimetic" architecture approach. In their study, the assumption of statistical independence for the output signals is used as the signal separation criterion when using the separation method. To de-correlate the output signals at different time lags is sufficient, provided that the normalized autocorrelation functions of the source signals are sufficiently distinct.

A. Problem Statement and Mathematical Description

Blind Signal Separation (BSS) deals with the problem of recovering the independent source signals from the observed ones. The mathematical system considered in the present study is formulated in this section. As mentioned previously, output signal independence is the criterion of this separation method. That is, the source signals are assumed to have zero mean and to be statistically independent.[8] For the realistic situation in nature, the sounds are delayed before they reach the sensors. In addition, they are convolved with room responses; hence the convolutive system shown in Figure 9 is used in this study.

Consider there are n independent source signals, $s_1(k)$, $s_2(k)$, …, $s_n(k)$, which are mixed by n sensors to generate n mixing signals, $x_1(k)$, $x_2(k)$,…, $x_n(k)$. N output signals $y_1(k)$, $y_2(k)$,…, $y_n(k)$ are generated only from the observed signals by using the signal separation method. The framework of this problem is displayed in Figure 10, from which the BSS problem can be described by the following equation:

$$\tilde{X} = \tilde{H}\tilde{S} \tag{3}$$

where $\tilde{S}$ is the source signal vector, $\tilde{X}$ the mixing signal vector, and $\tilde{H} \in R^{n\times n}$ the mixing matrix. When the inverse matrix $\tilde{H}^{-1}$ exists, then Eq. (4) can be obtained as follows:

$$\tilde{S} = \tilde{H}^{-1}\tilde{X} \tag{4}$$

Since the mixing matrix is unknown, it is preferable to estimate the separation matrix by finding the relationship such that:

$$\tilde{W} = \tilde{P}\tilde{H}^{-1} \tag{5}$$

where $\tilde{P} \in R^{n\times n}$ is the scaling and permutation matrix with only one non-zero element in each row and column. In addition, the separated signal vector of the output $\tilde{Y}$ has the relationship as follows:

$$\tilde{Y} = \tilde{W}\tilde{X} \tag{6}$$

Combining Eq. (3) with Eq. (6) gives

$$\tilde{Y} = \tilde{W}\tilde{X} = \tilde{W}\tilde{H}\tilde{S} \tag{7}$$

However, when the following condition is satisfied

$$\tilde{W} = \tilde{H}^{-1} \tag{8}$$

then $\tilde{Y} = \tilde{S}$ will be obtained.

Through this method, the separation matrix $\tilde{W}$ can be calculated and the input source signal matrix $\tilde{S}$ can be recovered simply from the mixed sound signals.

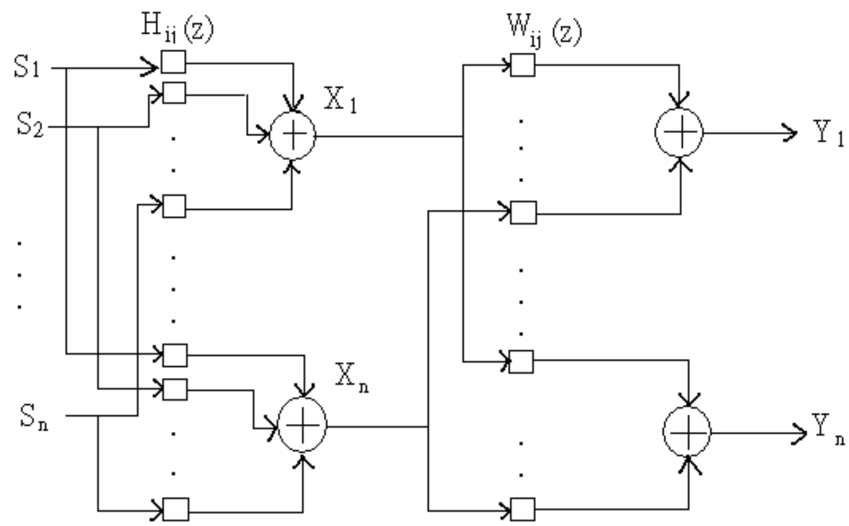

Fig. 9 The convolutive model of the blind source separation problem.

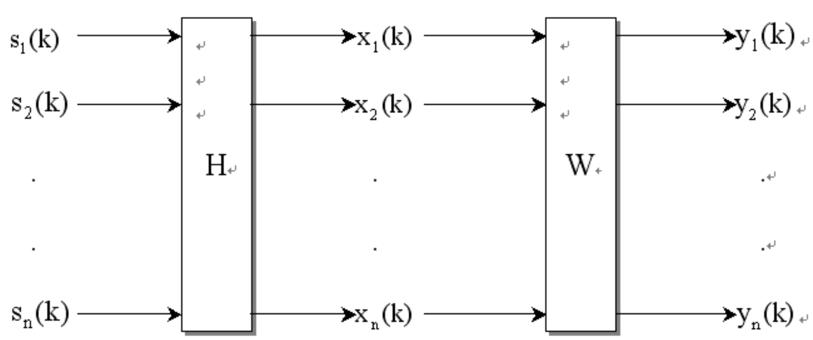

Fig. 10 The working frame of the blind source separation problem.

B. Separation Algorithm

The Constant Diagonal Algorithm (CDA) is used as the separation method in the study.[9] For simplicity, the separation matrix $\tilde{W}$ is assumed to have the constraint as following:

$$W_{ii}(z) = 1, \qquad i = 1, \cdots, n \tag{9}$$

From the assumptions of zero mean and statistical independence, the cross-correlation of the input signals $\tilde{S}$ should be zero as given in Eq. (10) below:

$$r_{y_i y_j}(\tau) = E[y_i(k) y_j(k+\tau)] = 0 \ \forall \tau, \forall \ i \neq j \tag{10}$$

Meanwhile, the cross-correlation of the output signals $\tilde{Y}$ is:

$$r_{y_i y_j}(\tau) = E[y_i(k) y_j(k+\tau)] = 0 \ \forall \tau, \forall \ i \neq j \tag{11}$$

The sum of the square of the cross-correlation between each different pair of outputs $y_i(k)$ and $y_j(k)$ is the cost function C in Eq. (12) as follows:

$$C = \sum_{i \neq j} \tilde{r}_{y_i y_j}{}^T \tilde{r}_{y_i y_j} \tag{12}$$

If all the output signals are statistically independent, then the sum of the square of cross-correlation C is equal to zero. In practice, the separation matrix $\tilde{W}$ can be estimated by minimizing the cost function C. Therefore, the source signals $\tilde{S}$ can be recovered through the calculation of the separation matrix without difficulty.

C. Simulation Results

There are two cases of simulation that are performed for sound separation in this study. The first case uses the mobile phone ring as the sound source and the second case uses the real master caution sound of the cockpit in a real aircraft as the sound source. The first case simulation is regarded as an artificially mixed signal separation, where two different mobile phones were used to generate two different ring sounds while keeping the independence of the source sound signals. Each one of those two ring sounds, named as s_1 and s_2, were recorded by the same microphone individually at 48,000 Hz sampling under the same surrounding conditions. The second case simulation is for a real mixed signal separation. The simulation here presents a two-source and two-sensor problem with the experimental data directly recorded in the cabin of a turbo-prop airliner ATR-72 of TransAsia Airways. The sound sources in the cabin consist of the caution alert x_1 and background noise x_2, which were recorded simultaneously and separately by two tape recorders located in two different positions. The sound sources were digitally sampled at 44,100 Hz with the data points of 44,051, which were acquired by the microphones of the recorder sets. However, both cases respectively apply the technique of CDA to conduct the sound separation as described previously.

1. Artificially mixed signals

In this case of simulation, two different mobile phones are used to generate two different ring sounds while keeping the independence of the source sound signals. Figure 11 shows the calculation of Eq. (10) for the cross-correlation between the two source signals to provide the evidence of the assumption of statistical independence for the source sound signals. Here, each one of those two ring sounds, named as s_1 and s_2, were recorded by the same microphone individually at 48000 Hz sampling under the same surrounding conditions. Figure 12 presents these two sound sources in time traces. These two sound source signals were then mixed artificially to generate two mixing sound signals x_1 and x_2 by setting the mixing matrix H_1 and H_2, where the order of the mixing matrix p is set to 2, as Table 1 presents. Figure 13 shows these two time traces of the mixing sound signals.

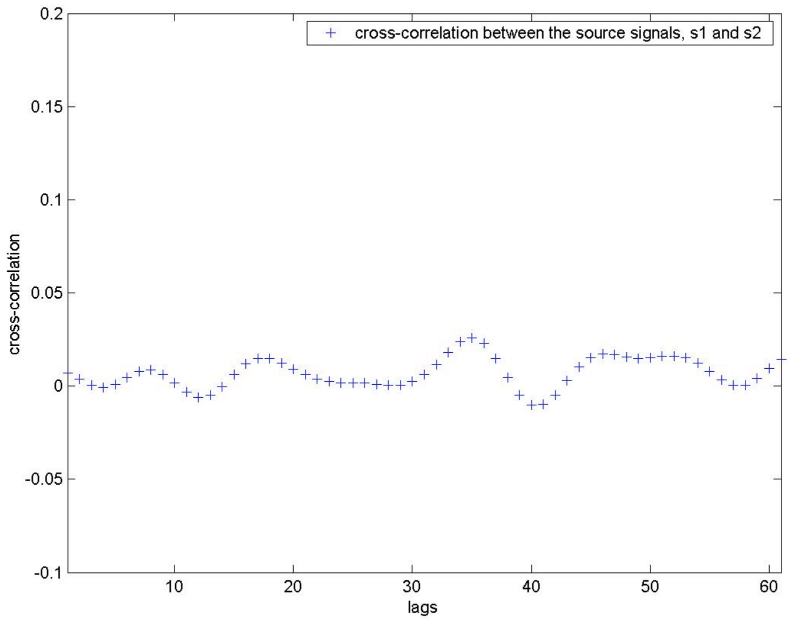

Fig. 11 The cross-correlation of the source signals s_1 and s_2.

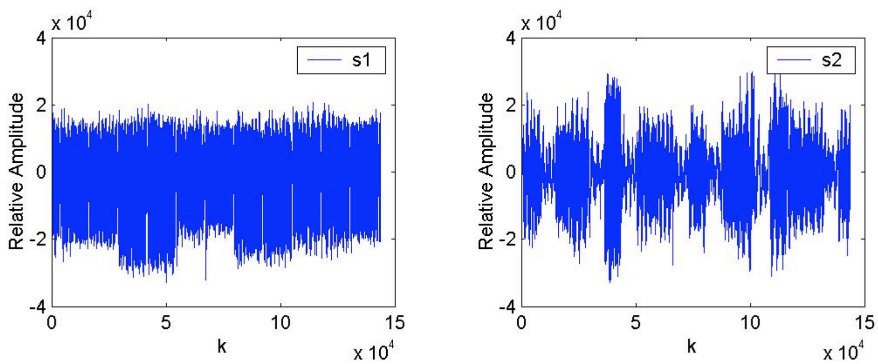

Fig. 12 The time and relative amplitude diagram of source signals s_1 and s_2.

Table 1 The elements of the mixing matrix $\tilde{H}$

p	h_{11}	h_{21}	p	h_{12}	h_{22}
0	1	0.1	0	0.2	1
1	0	-0.3	1	-0.1	0
2	0	0.2	2	0.1	0

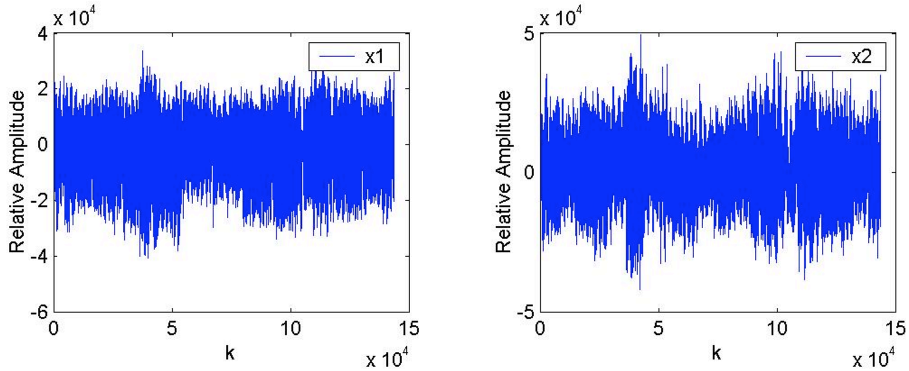

Fig. 13 The time and relative diagram of mixing signals s_1 and s_2.

The aim now is to separate the mixed signals, in other words, it is expected that the original sounds can be recovered from the mixed sounds using the algorithm discussed above. That is, it is done by estimating the separation matrix W using the BSS with the CDA method. By setting the order of the separation matrix W to q = 2, the result of the separation matrix is illustrated in Table 2.

Table 2 The elements of the separation matrix $\tilde{W}$

q	w_{11}	w_{21}	q	w_{12}	w_{22}
0	1	-0.16669	0	-0.2244	1
1	0	0.35041	1	0.12831	0
2	0	-0.20316	2	-0.10985	0

In comparison of Tables 1 and Table 2, it is clear that Eq. (8) is a satisfactory assumption, which means that these mixed sounds can be successfully separated by the separation matrix. Figure 14 shows the time traces of the separated sound signals y_1 and y_2 after separation. In comparison between Figures 12 and 14, it is clearly found that the highly similarity is obtained between them in the shape of the amplitude but a little increase in the intensity of the amplitude. It is further confirmed by calculating the cross-correlation of the separated sound signals shown in Figure 15, indicating that these two separated sound signals are almost uncorrelated after the sound separation processing. Another evidence is to calculate the regression function between the original sound source signals and the separated sound signals (recovered sound signals), which is illustrated in Figure 16, which clearly indicates that a highly correlated relationship is obtained between the original sound signals and the separated sound signals. This comparison demonstrates that the recovered sound is very similar to the original source sound. The result in the simulation here gives authenticity to the sound separation with Blind Signal Separation in this study.

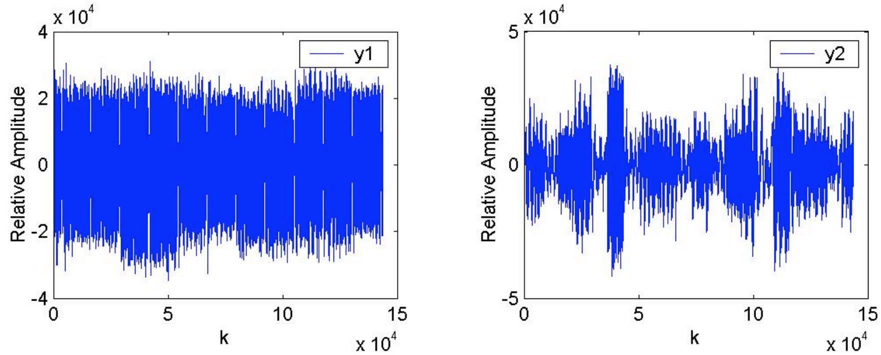

Fig. 14 The time and relative diagram of separated signals y_1 and y_2.

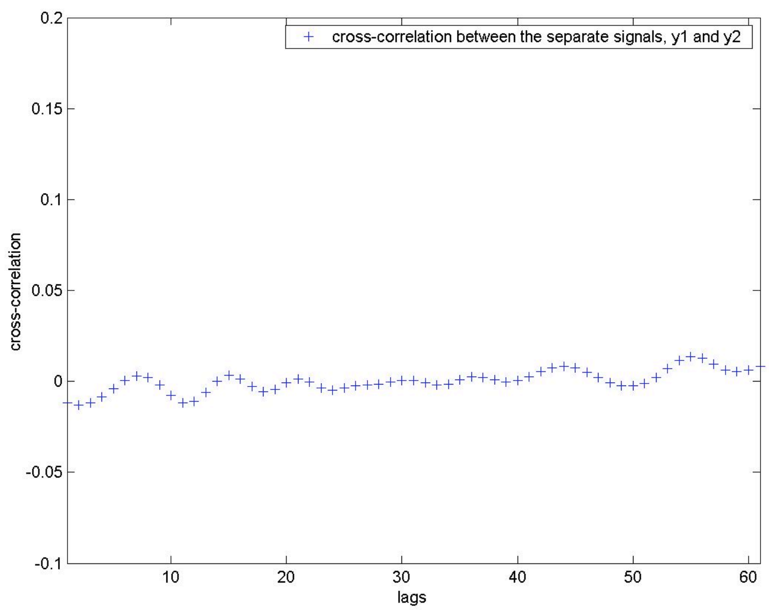

Fig. 15 The cross-correlation of the separated sound signals y_1 and y_2.

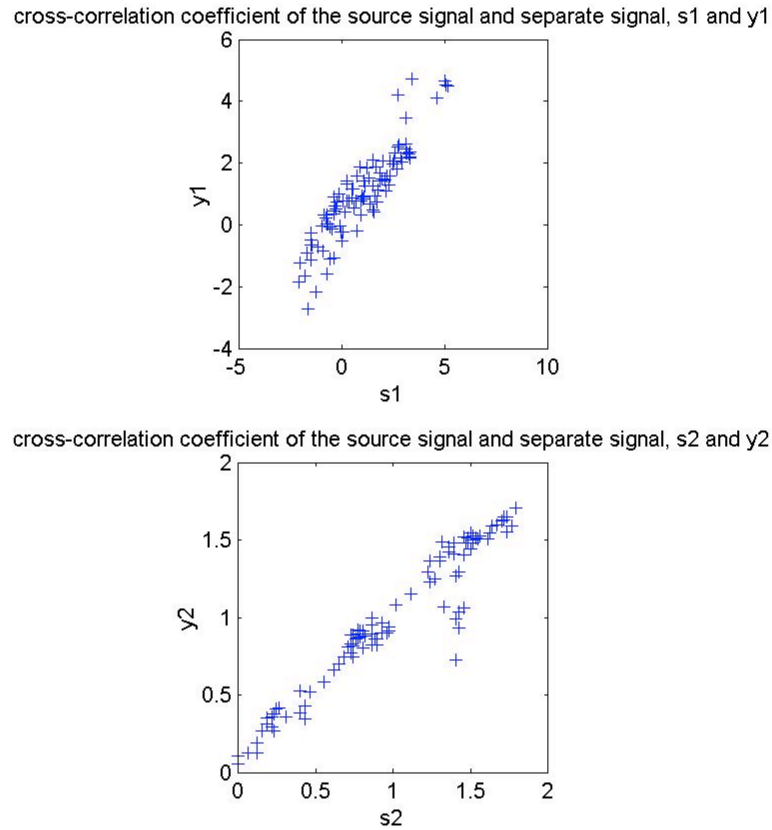

Fig. 16 The cross-correlation between the source signals and the separated signals.

2. Real Mixed Signals

The simulation here presents a two-source and two-sensor problem with the experimental data are obtained in the cabin of a turbo-prop airliner ATR-72 of TransAsia Airways. The sound sources in the cabin consist of the caution alert x_1 and background noise x_2, which were recorded simultaneously and separately by two tape recorders located in two different positions. The sounds were digitally sampled at 44100 Hz with the data length of 44051, which were acquired by the microphones of the recorder sets. Their mixing matrixes, represented as H_1 and H_2, are both unknown. Figure 17 illustrates the time traces of these two mixing signals.

Use the Fast Fourier Transform (FFT) technique to generate the three-dimensional spectral analysis diagram, which contains three factors such as time, frequency and relative amplitude, as shown in Figure 18 for x_1 and Figure 19 for x_2. By using the BSS method to obtain the separation signals y_1 and y_2, the time traces generated by the sound separating calculation are presented in Figure 20.

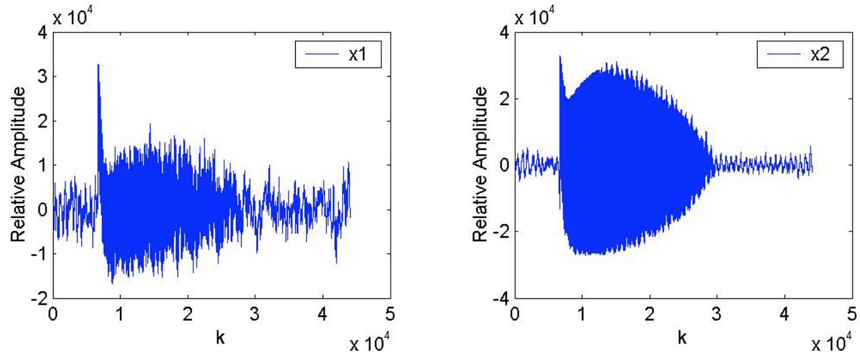

Fig. 17 The time and relative amplitude diagram of mixing signals x_1 and x_2.

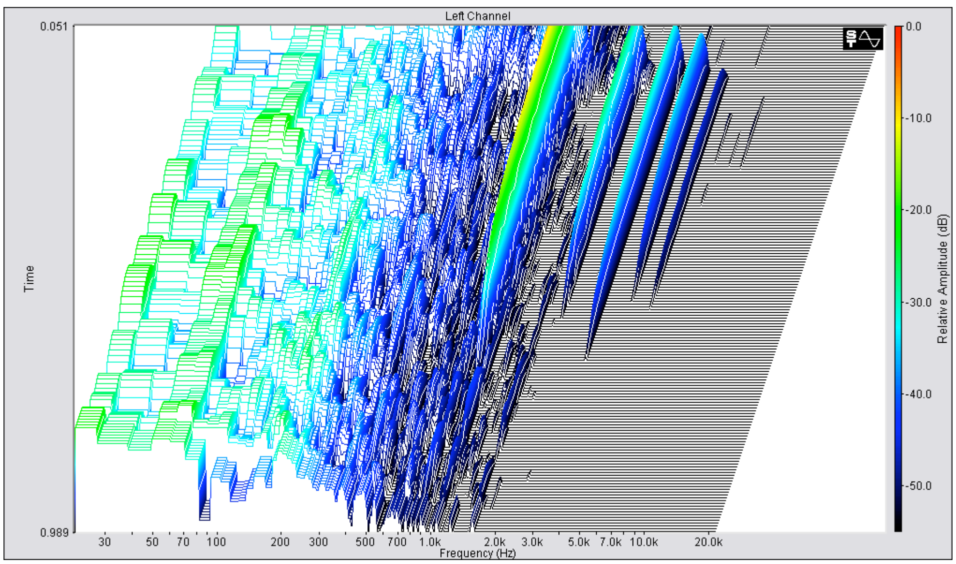

Fig. 18 Three-dimensional spectral analysis diagram of mixed signal x_1.

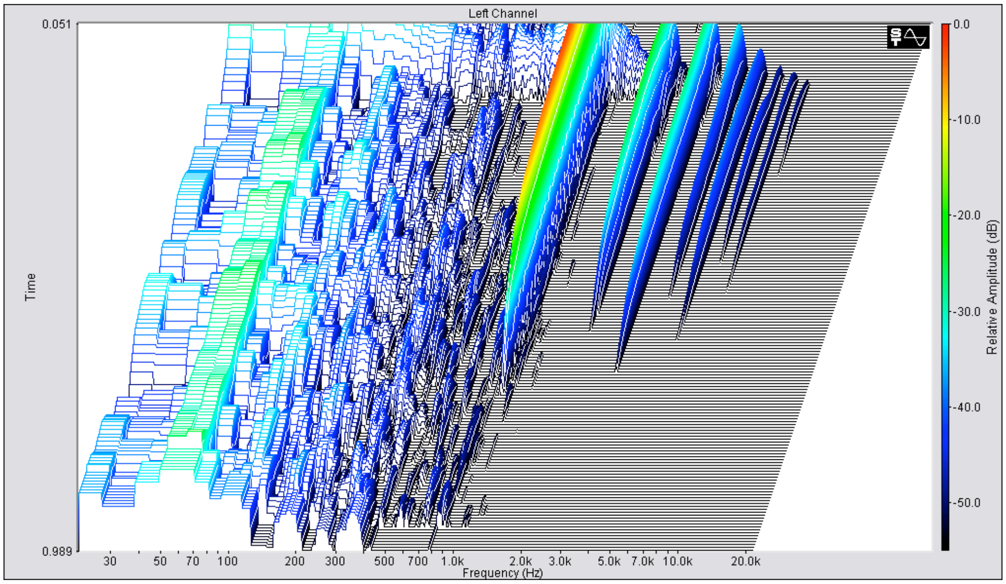

Fig. 19 Three-dimensional spectral analysis diagram of mixed signal x_2.

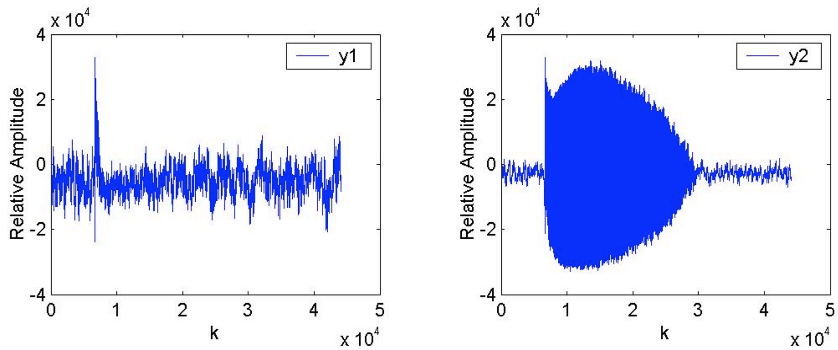

Fig. 20 The relative amplitude diagram of the separated signals, y_1 and y_2.

In comparing Figure 17 with Figure 20, it is found that the feature of the amplitude has some changes and can be divided into two different sound signals. It is clear to check the three-dimensional spectral analysis diagram of these two separation signals, as plotted in Figures 21 and 22. These two diagrams indicate that the sounds in the present case can be separated into two sounds; one corresponds to the background noise in the cabin as y_1 and the other the sound of caution alert as y_2. Comparing Figure 21 with Figure 18, it is found that the amplitude of the frequencies higher than 1000 Hz are mostly close to zero after the employment of the sound separation technique. Similarly, the amplitude of the noise nearby the frequency 1000 Hz is mostly removed in comparison between Figures 19 and 22. In addition, Figure 23 displays the calculation of the cross-correlation function between the two mixing sound signals to verify the less uncorrelated relationship. Therefore, it is approved that the originally mixed sounds are successfully separated to two well-uncorrelated sounds by using the BSS method in the present study that deals with the problem of recovering the independent source signals from the observed ones.

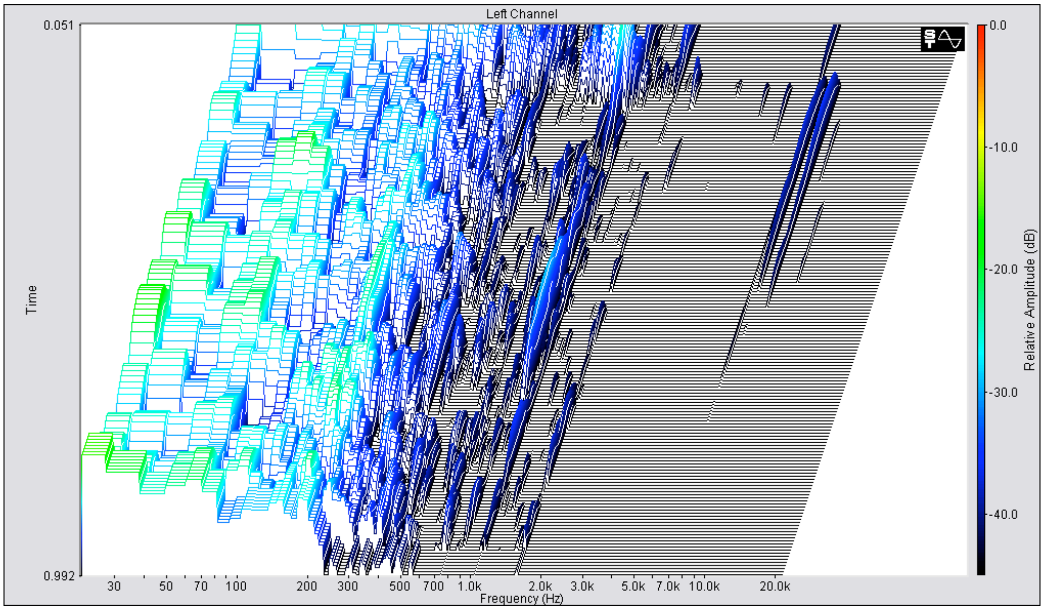

Fig. 21 Three-dimensional spectral analysis diagram of the separated signal y_1.

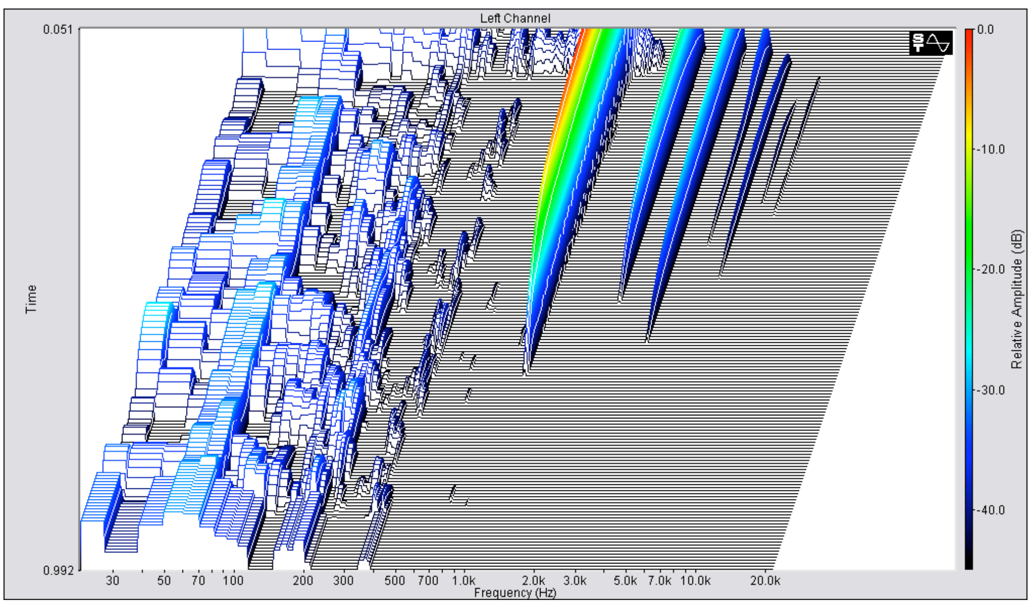

Fig. 22 Three-dimensional spectral analysis diagram of the separated signal y_2.

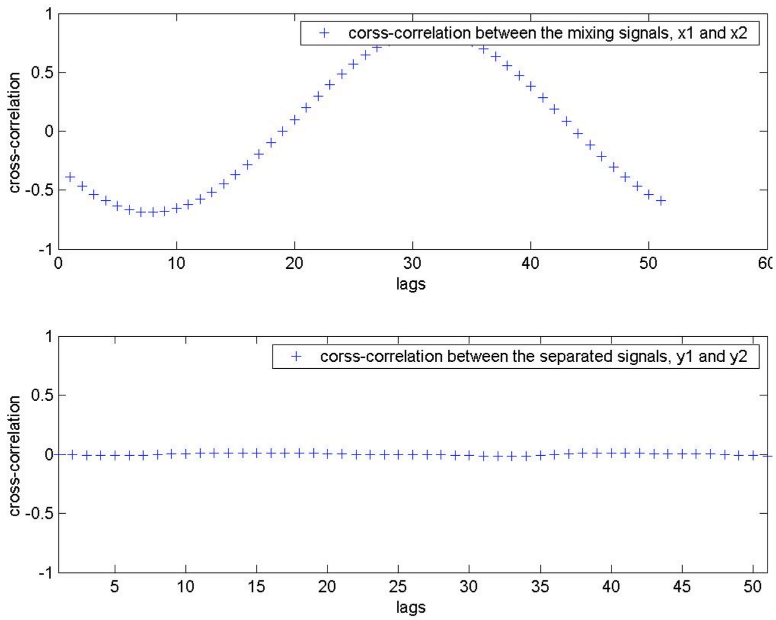

Fig. 23 The cross-correlation of the mixed and separated signals.

IV. Sound Identification

A. Back Propagation Neural Network

In this study, the Back Propagation Neural Network (BPNN) is used as the tool for the identification of the sound sources.[10] This is a method of supervised learning for multi-layer nets, which uses the error-correction learning rule as the algorithm. In the BPNN model, two layers are chosen including the input layer and output layer, which are represented by neurons. The structure of the network setup by the MATLAB® program is shown in Figure 24. The parameters used in the network are illustrated in Table 3.

Table 3 The parameters in the Back Propagation Neural Network

Items	Parameters
Neuron number of input layer	30
Neuron number of output layer	1
Learning rate	0.01
Error tolerance	1E-07
Learning epoch	2000

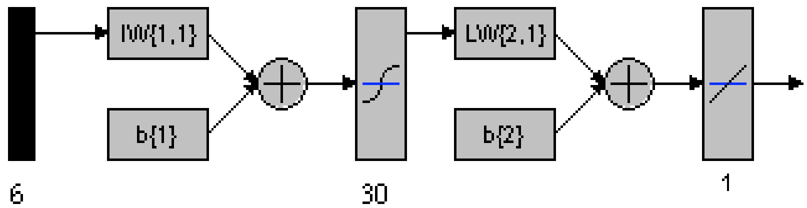

Fig. 24 The network structure in the MATLAB® program.

B. Training Process

In the training process, the training samples are composed of the spectrum data of the sounds, in which the sounds are recorded in the cabin of the ATR-72 and have been separated from the background noise by using the ANC method. The sound sources taken from the cabin include six elements in the identification study: Attendant Call, Autopilot Disengage, VMO, Master Caution, Master Warning and Shaker. The data of the training sample are produced from the spectrum data by setting the target output of the network, T = [123456], to represent six types of the sound sources: 1) Attendant call, 2) Autopilot Disengage, 3) VOM, 4) Master Caution, 5) Master Warning, and 6) Shaker. Figure 25 and Table 5 respectively display the training results.

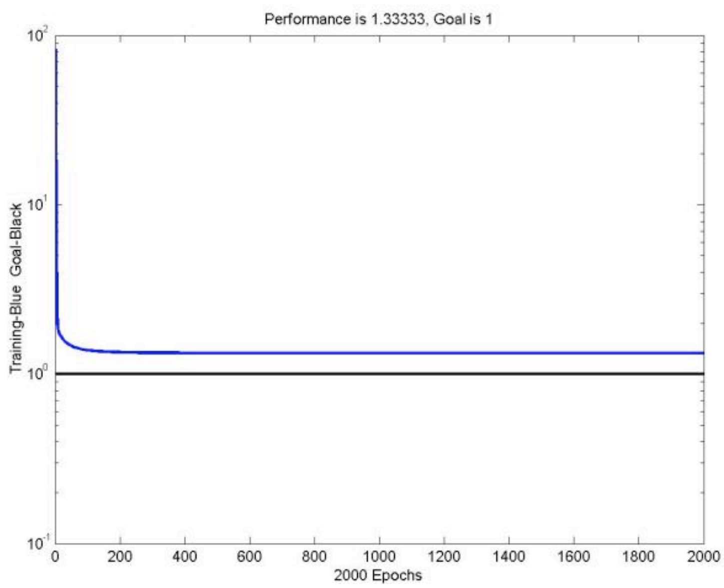

Fig. 25 Training result of the neural network.

Table 5 Training result of the back propagation neural network

Sound source	1	2	3	4	5	6
Result	1.0007	2.0062	2.9981	3.998	5.0000	5.9980

C. Testing Process

From the results shown in Table 5, one can easily realize that the six types of sounds have already been learned by the network and been recognized by the six numbers as the name tags. The mean square error of the training process is less than 8.44374×10^{-6}, which is in the tolerance range of calculation. At this stage, it can be claimed that the training process is successfully completed.

In the testing process, the testing sample is composed of the spectrum data of the sounds, which is the sound of Master Caution and recorded in the cabin of ATR-72. After the identification process by the network, it comes to the result of 3.9794, which clearly corresponds to the training sample of the sound 4, that is, the Master Caution. This demonstrates the unknown sound can be successfully identified with the Back Propagation Neural Network in the present study as long as the database of the sound in the cabin can be set up completely.

Another testing sample is the mixed sound without performing the preceding sound separation, which contains two different sounds but mixed intentionally, the Master Caution and the VMO. After 200,000 iterations of calculation, it however still cannot reach the result as expected in sound identification process. This indicates that the BP neural network technique cannot effectively identify the mixed sounds without pre-sound separation. This shows that the sound separation technique is necessary for improving the sound identification effectively.

V. Concluding Remarks

This paper studies the data processing techniques of sound separation and sound identification using Blind Signal Separation and a Back-Propagation Neural Network. The simulated signals of sound sources for separation and identification are directly recorded from the cabin of an ATR-72 civil jet transport. From the simulation results, it is clearly to see that the mixed sound signals can be successfully separated by the Blind Signal Separation method. The sound separation will enhance the accuracy in an accident or incident investigation by recognizing the sounds in the CVR. It is worth noting that there is only one channel of the CVR (there is only one microphone in the cabin) being used. As far as we know, the number of the sensors should be equal or more than the number of the sound sources in the BSS problem. It means that the more sensor we have, the more possibility we can separate the source of the sound.

After the sound sources are separated by the BSS technique in the present study, the critical sound then can be effectively identified and classified by means of the Back-Propagation Neural Network. Hence, the outcome after the sound separation and identification may provide some evidence of the causing factor for accident investigations. The sound recorded in the CVR can be separated and identified automatically in the future by setting up the program following the sequence in this study to reduce the erroneous judgment probability by aviation investigator. The technique developed here, in monitoring sounds of specific frequency, could also contribute to effective aircraft maintenance, in helping to detect damage or fatigue in elements of the aircraft before disaster occurs.

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