

Active Noise Cancellation using a Teacher Forced BSS Learning Algorithm

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Abstract

In this paper, we propose a new Active Noise Control (ANC) system using a teacher forced Blind Source Separation (BSS) algorithm. The Blind Source Separation based on the Independent Component Analysis (ICA) separates the desired sound signal from the unwanted noise signal. In the proposed system, the BSS algorithm is used as a preprocessor of ANC system. Also, we develop a teacher forced BSS learning algorithm to enhance the performance of BSS. The teacher signal is obtained from the output signal of the ANC system. Computer experimental results show that the proposed ANC system in conjunction with the BSS algorithm effectively cancels only the ship engine noise signal from the linear and convolved mixtures with human voice.

Key Words : active noise control, blind source separation, selective attention system

1. Introduction

An Active Noise Control (ANC) system removes a noise signal by generating an anti-noise signal of equal magnitude and opposite phase^[1-3]. ANC system using feedforward algorithm needs an input signal which is obtained from the noise source. When we can not obtain the noise source, feedback algorithm can be applied. But it is known that the performance of feedback ANC is low in comparison with feedforward ANC.

When we can not obtain noise source, in order to cancel only the noise signal, the Blind Source Separation (BSS) algorithm can be incorporated into the feedforward ANC system as a preprocessor to discriminate between the noise signal and the desired sound signal. A BSS algorithm can separate the independent source signals from the mixture without any prior information except a number of independent sources^[4-6]. Selective attention system is achieved by removing only the noise signal from the mixture at a local area using ANC and BSS^[7].

In this paper, we propose a new active noise control system that employs BSS algorithm as preprocessor to separate original signal from mixture. The coefficients

of ANC are updated to reduce the difference between the separated target signal and received signal at the specific microphone that is located at the place to be silent. In order to enhance the separation performance of the BSS and whole selective attention system, we use an additional microphone to consider the loudspeaker in the ANC system as an additional independent source. Also, we use a priori knowledge of the output of the ANC system in constructing the BSS algorithm. The loudspeaker signal output of the ANC system, that is a priori information, is used for finding the coefficients of demixing matrix. This creates a new learning algorithm for the separation of the mixtures, or so called "teacher forced BSS learning algorithm.

Computer experimental results show that speech signals successfully remain around a microphone by selectively reducing a ship engine noise. The proposed ANC system with an additional microphone and the teacher forced BSS learning algorithm is more effective to cancel only the noise signal than that combined with BSS algorithm without an additional microphone and the teacher forced BSS learning algorithm.

2. Selective Noise Control System Using Active Noise Control and Blind Source Separation

Fig. 1 shows the proposed ANC system with two microphones using a blind source separation^[8]. Our aim

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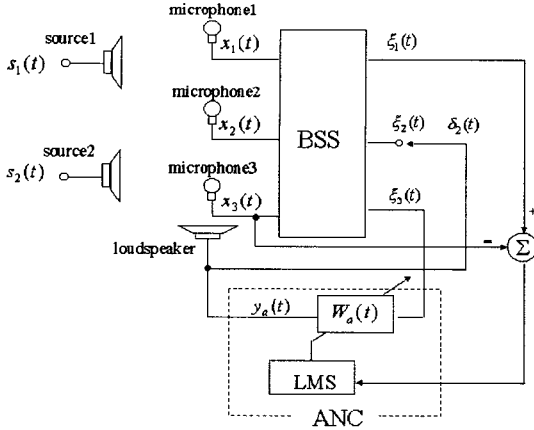


Fig. 2. The selective noise control system with teacher forced BSS learning algorithm.

known loudspeaker signal as target to enhance the separation performance of the BSS that is implemented by dynamic recurrent neural network. This gives us the chance to apply teacher forced learning algorithm into our selective noise control system. Fig. 2 shows the proposed selective noise control system with teacher forced learning algorithm. In this figure, the line between microphone3 and third output node of BSS allocates ANC output value to BSS output directly. The i -th output signal, $\xi_i(t)$, of a dynamic recurrent neural network can be represented as

$$\xi_i(t) = f(x_i(t), \xi_j(t), \xi_j(t-k), W) \quad (5)$$

where the delay parameter $k = 1, 2, \dots, L$ and $j \neq i$, and $x_i(t)$ is an external input signal for the i -th output node. $\xi_j(t)$ and $\xi_j(t-k)$ are the signals of i -th output node and its delayed values, respectively. W represents the weight vector. if we know the delayed value of a target signal for j -th output node, the Eq. (5) can be replaced by Eq. (6).

$$\xi_i(t) = f(x_i(t), \xi_j(t), \delta_j(t-k), W) \quad (6)$$

where $\delta_j(t-k)$ represents the delayed value of target signal for j -th output node. Using the exact delay signals of known output as shown in Eq. (6) enhances the separation performance of the BSS algorithm through avoiding the adverse effect of the dynamic recurrent neural network's inexact output signal during training phase^[11,12]. The accurate delayed value of the recurrent neural network helps learning process by reducing the training time and increasing the accuracy, and thus, we

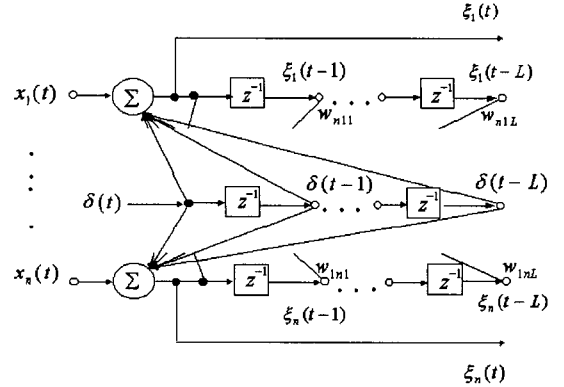


Fig. 3. The dynamic recurrent neural network model with teacher forced BSS learning algorithm.

can obtain more accurate training result^[12,13]. Two further nodes, of which the values were obtained through an unsupervised learning process to minimize the mutual information, are still unknown. One of these two outputs is a desired source signal, which is used to make the error function in Eq. (2) for the adaptation of the filter coefficient with the ANC system. The other is the separated noise signal, which is used as the input of the ANC system.

Fig. 3 shows the dynamic recurrent neural network with a teacher forced BSS learning algorithm for realizing the BSS algorithm. Where, $\delta_i(t)$ is the target value of i -th output node, which is given by $y_a(t)$, and $\delta_i(t-k)$ is its delayed value. The delayed value of $\xi_i(t)$ is presented by $\xi_i(t-k)$. Since the output of the ANC system's loudspeaker can be used, the delayed values of known signal are used as a teacher signal for the delayed neurons of the recurrent neural network. Thus, two kinds of outputs are considered. One is the independent source signals that are separated by BSS algorithm and the other is the loudspeaker signal that is known without learning. In the latter case, the teacher forced learning algorithm can be applied with a structure possibly similar to the nonlinear filter built on a static neural network^[13]. The output of this neural network is given as the following equation:

$$\xi_i(t) = x_i(t) + \sum_{k=0}^L \sum_{j \neq i, j \in T \cup Y} w_{ijk}(t) \xi_j(t-k) \quad (7)$$

where

$$\xi_j(t-k) = \begin{cases} \delta_j(t-k) & j \in T \\ y_j(t-j) & j \in Y \end{cases}$$

in which $\delta_j(t-k)$ and $y_j(t-k)$ represent the delayed target value obtained from the loudspeaker output and the delayed output of the network obtained through unsupervised learning, respectively. The T and Y denote the teacher domain and output domain, respectively. $w_{ijk}(t)$ is the synaptic weight between $x_i(t)$ and $x_j(t-k)$, and $x_i(t)$ is the input signal of the neural network for i -th output node of the recurrent neural network. In the proposed scheme, the weights connected to the teacher node are not necessary, as the target value for the teacher node by the loudspeaker output can be directly used. The delayed term of the teacher node is also known and used for learning and separating the unknown independent sources. The delayed values in teacher node are the weighted sum that determines the values of another output nodes.

4. Computer Experimental Results

The speech signal and the sound noise signal induced by a ship engine were used as the two original independent source signals. Fig. 4(a) and (b) show the two independent source signals, that is, the speech signal and an engine noise signal in a ship, respectively. The received signals $x_i(t)$ in the linear mixtures were generated using the linear mixing matrix which has random elements in $[-1, 1]$ and the received signals in the convolved mixtures were generated by $H(z)$ that has 100th order delay terms and random values in $[-1, 1]$.

It is assumed that the desired source signal is the speech signal and thus, the goal is to cancel the effect

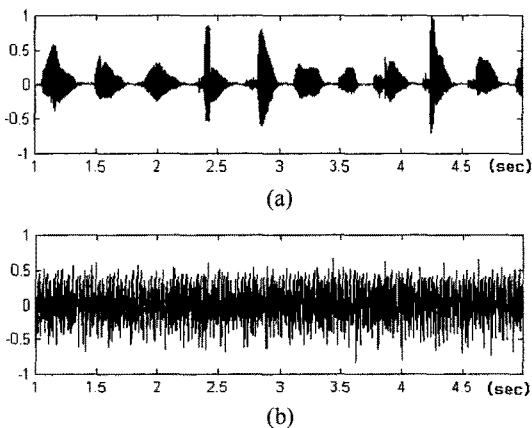


Fig. 4. Two independent source signals; (a) the speech signal and (b) the engine noise in a ship.

of noise signal by a ship engine around a specific microphone. The nonlinear functions for the outputs in the dynamic recurrent neural network are obtained from the relationship between the kurtosis and Gaussian exponent. We set the Gaussian exponents for the voice and noise and anti-noise signal at 0.5519 and 2.022, respectively.

Fig. 5 shows the received signal by convolved mixing matrix at same microphone without our proposed noise cancellation system. Fig. 6 shows the result of canceling the noise signal from convolved mixtures by the system in Fig. 1. As shown in Fig. 6, the proposed system more or less removes only the noise signal, but the perform-

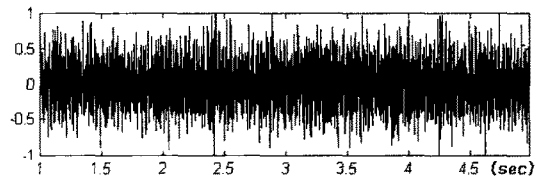


Fig. 5. The received convolved mixture signal at the microphone2 when the proposed system does not operating.

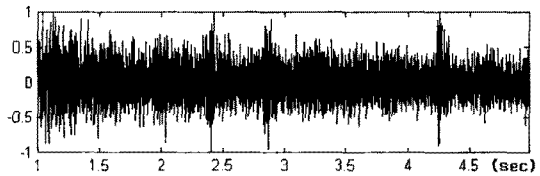


Fig. 6. The received signal at specific microphone when the proposed system with two microphones operates.

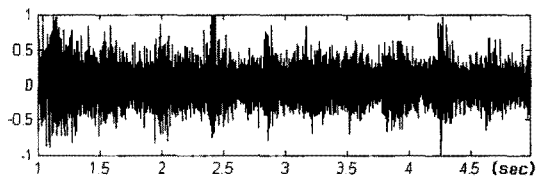


Fig. 7. The received signal at specific microphone when the proposed system with three microphones operates.

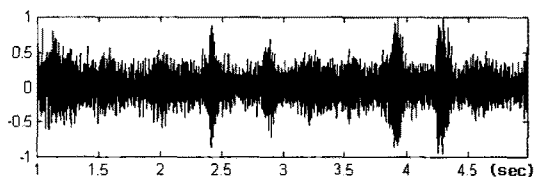


Fig. 8. The received signal at specific microphone when the proposed system with teacher forced learning algorithm operates.

Table 1. The comparison of the degree of residual noise

	Before the proposed system operates	In case of using two mic.	In case of using three mic.	In case of using three mic. and teacher forced learning
Degree of residual noise	-27.1705 dB	-31.8571 dB	-32.708 dB	-35.0269 dB

ance of noise cancellation is not satisfied in case of convolved mixture especially. Thus, we modified the proposed system shown in Fig. 1 by the system with three microphones shown in Fig. 2. Fig. 7 shows the results of canceling noise at the same microphone in cases of using convolved mixture. Comparing the performances of the system in Fig. 2 with that of the system in Fig. 1, the additive microphone helps to enhance the performance of the proposed system by avoiding the overcomplete situation. Fig. 8 shows the result of canceling noise from convolved mixture by the system with teacher forced BSS learning algorithm. From these results, we can know that the proposed system with teacher forced learning algorithm considerably improves the performance of canceling only the noise signal, selectively. We compare the performance of the proposed systems by the degree of residual noise in the Table 1. As shown in this table and figures, our proposed systems are effective to remove only the noise signal, and additive microphone and employment of teacher forced BSS learning algorithm remarkably improve the selective cancellation performance of noise signal only.

5. Conclusions

We proposed a new selective noise control system using blind source separation algorithm and showed the efficiency of the proposed system for convolved mixtures. In order to enhance performance of the proposed system, we used another microphone for the output of ANC and developed teacher forced BSS learning algorithm. Through the computer experimental results in linear mixtures and convolved mixtures, our proposed scheme considerably improves efficiency of the system. As a future work, more efficient BSS algorithm for convolved mixture should be developed, and the experiment using DSP board is under investigation.

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References

- [1] S. M. Kuo and D. R. Morgan, "Active noise control systems; Algorithm and DSP Implementations", John Wiley & Sons, pp. 1-51, 1996.
- [2] S. J. Elliott, I. M. Stothers, and P. A. Nelson, "A multiple error LMS algorithm and its application to the active control of sound and vibration", *IEEE Trans. Acoust., Speech & Signal Processing*, vol. ASSP-35, no. 10, pp. 1423-1434, 1987.
- [3] S. J. Elliott, C. C. Boucher, and P. A. Nelson, "The behavior of a multiple channel active control system," *IEEE Trans. Signal Processing*, vol. 40, no. 5, pp. 1041-1052, 1992.
- [4] H. H. Yang and S. I. Amari, "Adaptive on-line learning algorithms for blind separation: Maximum entropy and minimum mutual information", *Neural Computation*, vol. 9, pp. 1457-1482, 1997.
- [5] K. Torkkola, "Blind separation of delayed sources based on information maximization", *The IEEE Inter. Conf. on Acoustics, Speech & Signal Processing*, pp. 7-10, 1996.
- [6] T. W. Lee, A. Bell, and R. Orglmeister, "Blind source separation of real world signals", *International Conference on Neural Network*, vol. 4, pp. 2129-2134, 1997.
- [7] J. I. Sohn and M. Lee, "Active noise control for selective attention using blind source separation", *International Conference on Neural Information Processing*, pp. 198-203, 1999.
- [8] J. I. Sohn and M. Lee, "Selective attention system using active noise controller", *Neurocomputing*, vol. 31, pp. 197-204, 2000.
- [9] T. W. Lee, "Independent component analysis, theory and applications", *Kluwer Academic Publishers*, Boston, pp. 27-66, 1998.
- [10] T. W. Lee, M. S. Lewicki, M. Girolami, and T. J. Sejnowski, "Blind source separation of more sources than mixtures using overcomplete representations", *IEEE Signal Processing Letters*, vol. 4, no. 4, April 1999.
- [11] U. M. Bae and S. Y. Lee, "Combining ICA and top-down attention for robust speech recognition", *Neural Information Processing Systems*, vol. 13, 2000.
- [12] M. Lee, S. Y. Lee, and C. H. Park, "Neural control-

ler of nonlinear dynamic systems using higher order neural networks”, *Electronics Letters*, vol. 28, no. 3, pp. 276-277, 1992.

[13] R. J. Williams and D. A. Zipsper, “Learning algo-

rithm for continually running fully recurrent neural network”, *Neural Computation*, vol. 1, pp. 270-280, 1989.



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