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ADAPTIVE NOISE CANCELING USING CONVOLVED REFERENCE NOISE BASED ON INDEPENDENT COMPONENT ANALYSIS

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ABSTRACT

This paper presents adaptive noise canceling(ANC) using convolved reference noise. In many practical ANC applications, the reference noise has channel distortion, which may degrade its performance. If the distortion includes nonminimum-phase parts, the inverse cannot be implemented as a causal filter. Therefore, the conventional ANC system may not provide a satisfactory performance. In this paper, we propose the delayed ANC system to deal with the problem, and derive learning rules for the adaptive FIR and IIR filter coefficients based on independent component analysis(ICA). Simulation results show that the proposed algorithms are adequate for the considered situations.

1. INTRODUCTION

Among many fields of signal processing, noise reduction has been considered as interesting area for many applications since it is one of the most essential fields in many applications such as communication, speech enhancement, image processing, medical signal processing, and so on. In the case that we can acquire reference noise, we can use adaptive noise canceling(ANC) as an efficient method for noise reduction. ANC is an approach to reduce noise in a corrupted signal based on the reference noise. The most popular training method for ANC is the least-mean-squares(LMS) algorithm, which minimizes second-order correlation between the corrupted signal and the reference noise [1][2]. However, ANC based on independent component analysis(ICA) was recently developed, which shows better performance than the conventional LMS algorithm [3]. In order to reduce noise, this method utilizes ICA which finds independent signals from given mixed signals by considering higher-order statistics [4][5][6]. Consequently, in contrast to the LMS algorithm, ANC based on ICA removes not only second-order correlation but also higher-order dependency between the corrupted signal and the reference noise.

So far, we have often assumed that we acquire the reference noise and the primary input, in which the desired signal is corrupted by a convolved version of the reference noise. However, in many real-world applications, the reference noise is another convolved noise from an unknown noise source, that is, the reference noise experiences a channel distortion. Thus we should consider the channel distortion of the reference noise. When the distortion is nonminimum-phase, the problem gets worse. In this case, the adaptive filter should be a noncausal filter, which cannot be a noncausal filter in the conventional ANC system. Therefore, the performance of the conventional ANC system may be degraded. In order to deal with the problem, we propose a delayed ANC, and derive learning rules for the adaptive FIR and IIR filter coefficients based on ICA.

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2. ANC BASED ON ICA

An ANC system is shown in Fig. 1, where a signal $s(t)$ is transmitted to a sensor, and a noise $n_0(t)$ is added from noise source $n(t)$ through a convolutive channel h. Another sensor only receives a noise signal to form the reference input signal $r(t)$. To get an output $u(t)$ as the best estimate of the signal $s(t)$, the learning rule based on LMS of adaptive

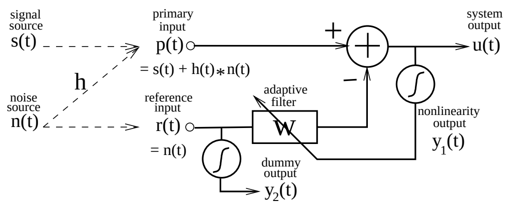


Fig. 1. The structure of ANC system based on ICA

filter coefficients are

$$\Delta w(k) \propto u(t)r(t-k), \quad 0 \le k \le L-1, \tag{1}$$

where the output of the system $u(t)$ is

$$u(t) = p(t) - \sum_{k=0}^{L-1} w(k)r(t-k). \tag{2}$$

This method reduces the noise components of the primary input from the reference input based on second-order statistics only. In general, non-Gaussian signals may depend upon higher-order statistics. Thus, for a better performance, we need to consider higher-order statistics, for which ICA can be utilized.

When the signal $\mathbf{x}$ is a linear summation of independent signal $\mathbf{s}$,

$$\mathbf{x} = \mathbf{A}\mathbf{s}. \tag{3}$$

ICA algorithms provide the independent signal $\mathbf{u}$ by estimating an unmixing matrix $\mathbf{W}$, which gives

$$\mathbf{u} = \mathbf{W}\mathbf{x}. \tag{4}$$

Bell and Sejnowski proposed to learn the unmixing matrix $\mathbf{W}$ by minimizing the mutual information among components of $\mathbf{y} = \mathbf{g}(\mathbf{u})$, where $\mathbf{g}$ denotes a function approximating the cumulative density function(cdf) of the sources, and $\mathbf{u}$ denotes the recovered sources [5]. They also showed that the mutual information among components of $\mathbf{y}$ is minimized by maximizing entropy of $\mathbf{y}$ for positively kurtotic signals. Since the entropy of $\mathbf{y}$ is expressed in terms of the Jacobian J, maximizing the entropy of $\mathbf{y}$ is equal to maximizing the absolute value of the Jacobian J.

$$\begin{aligned} H(\mathbf{y}) &= -E\{\log(f_y(\mathbf{y}))\} \\ &= -E\{\log(f_x(\mathbf{x}))\} + E\{\log|J|\}, \end{aligned} \tag{5}$$

where $f_x(\mathbf{x})$ and $f_y(\mathbf{y})$ are the probability density functions(pdf) of $\mathbf{x}$ and $\mathbf{y}$, respectively. Based on the entropy maximization, Torkkola and Lee *et al.* have proposed an algorithm to deal with convolved mixtures [7][8].

By setting the reference input $r(t)$ to a dummy output, the entropy maximazation algorithm is easily applied to ANC. In this case, the Jacobian of the system is

$$J = \frac{\partial y_1}{\partial p}\frac{\partial y_2}{\partial r} - \frac{\partial y_1}{\partial r}\frac{\partial y_2}{\partial p} = \frac{\partial y_1}{\partial u}\frac{\partial y_2}{\partial r}, \tag{6}$$

where $p = s + n_0$; y_1 and y_2 are outputs of the nonlinearities $\mathbf{g}$. By maximizing $\log|J|$, the learning rule of adaptive filter coefficients is obtained as follows:

$$\begin{aligned} \Delta w(k) &\propto \frac{\partial}{\partial w(k)} \log|J| = \frac{\partial \log|J|}{\partial u}\frac{\partial u}{\partial w(k)} && (7) \\ &= \varphi(u(t))r(t-k), \quad 0 \le k \le L-1, && (8) \end{aligned}$$

where the output of the system is the same as that of conventional ANC system based on LMS, which is Eq. 2, and the score function $\varphi(u)$ is

$$\varphi(u) = -\frac{\partial \log(f_u(u))}{\partial u}. \tag{9}$$

3. PROBLEM FORMULATION

In the previous section, we assumed that the reference input $r(t)$ was simply the noise source $n(t)$, and the noise component added to the primary input is set to a convolved version of the noise source. However, it is impossible to get the noise source $n(t)$ without any channel distortion for the reference input. In many practical applications, such as ANC on audio signals recorded by microphones in acoustic environments, the assumption of the reference input does not hold any more. The acoustic environments impose different impulse responses from the noise source to the microphone. Moreover, different microphones have different characteristics, and even the same microphone may have different characteristics according to directions from sources. In this case, the primary input and the reference input are as follows:

$$\begin{aligned} P(z) &= S(z) + H_1(z)N(z) && (10) \\ R(z) &= H_2(z)N(z), && (11) \end{aligned}$$

where $H_1(z)$ and $H_2(z)$ denote arbitrary channels in z-transform domain. In this case, the noise source is transmitted not only to the primary input but also to the reference input through channel $H_1(z)$ and $H_2(z)$, respectively. In order for the output of the system $U(z)$ to be the best estimate of the signal $S(z)$, the adaptive filter $W(z)$ should be

$$W(z) = H_1(z)H_2^{-1}(z), \tag{12}$$

since

$$\begin{aligned} U(z) &= P(z) - W(z)R(z) \\ &= S(z) + H_1(z)N(z) - W(z)H_2(z)N(z) \\ &\simeq S(z). \end{aligned} \tag{13}$$

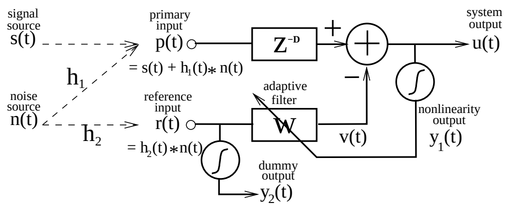


Fig. 2. The structure of delayed ANC system based on ICA

As shown in Eq. 12, the adaptive filter $W(z)$ includes $H_2^{-1}(z)$. Whether stable causal $H_2^{-1}(z)$ exists or not depends on the position of zeros of $H_2(z)$ since zeros of $H_2(z)$ is the poles of $H_2^{-1}(z)$. If a zero of $H_2(z)$ exists outside the unit circle, that is, if $H_2(z)$ is nonminimum-phase filter, no stable causal inverse exists. However, the filter can have a stable noncausal inverse. A nonminimum-phase filter can be decomposed into minimum-phase filter and all-pass filter, that is, $H(z) = H_m(z)H_a(z)$, which is so called all-pass decomposition. Thus, its inverse $H_m^{-1}(z)H_a^{-1}(z)$ is a product of the inverse of a minimum-phase filter, which is a stable causal filter, with the inverse of an all-pass filter representing time lag, which is time advance. The overall inverse is a noncausal filter. For details, see [9][10].

Unless the channel from the noise source to the reference input is nonminimum-phase, the conventional ANC with enough number of adaptive filter coefficients works very well. Unfortunately, it is not guaranteed that the channel is always minimum-phase. In many practical applications, such as ANC with room acoustics, we often have to deal with nonminimum-phase channels whose inverse is noncausal and very complicated [11][10][12]. Consequently, adaptive filter $W(z)$ should be a noncausal filter.

4. DELAYED ANC

As discussed in previous section, in the case that $H_2(z)$ is nonminimum-phase, to remove noise successfully, the adaptive filter $W(z)$ should be a noncausal filter. While the present output of a causal filter depends on the present and the past input, that of a noncasal filter depends on not only those but also the future input. However, note that ANC systems remove noise by subtracting a corresponding output of the adaptive filter from the primary input To bypass the problem that the future input is required to get the corresponding output, we propose to delay the primary input. In this case, we can obtain the corresponding output without the future input.

4.1. Learning rule for adaptive FIR filter

As shown in Fig. 2, to construct the delayed ANC system, we put the delay term in the primary input of the conventional ANC system. Thus, the output of this system $u(t)$ is re-defined as

$$u(t) = p(t-D) - \sum_{k=0}^{L-1} w(k)r(t-k). \tag{14}$$

Because putting the delay term does not introduce any other parameters, Jacobian of the system is exactly the same as Eq. 6. By minimizing $\log|J|$, the learning rule of adaptive filter coefficients can be derived, and they provide the same forms in Eq. 8

4.2. Learning rule for adaptive IIR filter

Since the adaptive filter includes the $H_2^{-1}(z)$ component as shown in Eq. 12, the adaptive filter should have both of zeros and poles in general, that is, it can be modelled by IIR filter. The number of filter taps is too large to implement $H_2^{-1}(z)$ by using FIR filter. Using IIR filter as the adaptive filter reduces the number of filter coefficients to be learned.

In the case of IIR adaptive filter, Jacobian is also the same one for the adaptive FIR filter. The outputs of the IIR adaptive filter and the system are changed to

$$\begin{aligned} v(t) &= \sum_{k=0}^{L_1-1} w_n(k)r(t-k) \\ &\qquad - \sum_{k=1}^{L_2-1} w_d(k)v(t-k) \end{aligned} \tag{15}$$

$$\begin{aligned} u(t) &= p(t-D) - v(t) \\ &= p(t-D) - \sum_{k=0}^{L_1-1} w_n(k)r(t-k) \\ &\qquad + \sum_{k=1}^{L_2-1} w_d(k)v(t-k). \end{aligned} \tag{16}$$

In order to maximize $\log|J|$, differenciating it with respect to $w_n(k)$ and $w_d(k)$ provides the learning rule of adaptive filter coefficients as follows:

$$\begin{aligned} \Delta w_n(k) &\propto \varphi(u(t))r(t-k), \quad 0 \le k \le L_1-1, \\ \Delta w_d(k) &\propto -\varphi(u(t))v(t-k), \quad 1 \le k \le L_2-1, \end{aligned} \tag{17}$$

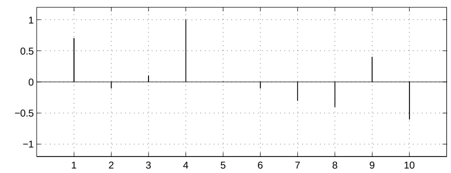
where the score function $\varphi(u)$ is the same as Eq. 9.

5. EXPERIMENTAL RESULTS

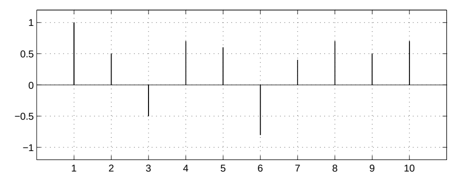
The delayed ANC algorithm was applied to speech enhancement. The channel from the signal source to the primary input is assumed as a linear scale α. On the other hand, FIR filter h_1 and h_2 were used for modelling channels from the

SNR[dB]		Gaussian	Laplacian	Babble	Music
Input		-3.11	-3.08	-3.04	-3.07
Output	(1)	1.67	1.54	4.47	1.42
	(2)	29.51	28.91	24.16	28.23
	(3)	29.78	30.40	24.41	29.90

Table 1. The results for simple convolutive channels



(a) Impulse respone h_1



(b) Impulse response h_2

Fig. 3. Simple convolutive channels

noise source to the primary input and the reference input, respectively. Thus, the primary input and the reference input were as follows:

$$p(t) = \alpha s(t) + \sum_{k=0}^{N-1} h_1(k)n(t-k) \qquad (18)$$

$$r(t) = \sum_{k=0}^{N-1} h_2(k)n(t-k) \qquad (19)$$

We used a clean speech from TIMIT DB for the signal source $s(t)$, and artificially generated i.i.d. Gaussian or Laplacian signal, recored babble noise, or music for the noise source $n(t)$, respectively. The sampling rate of each signal is 16kHz, and the length of each signal is 60000 samples. $sign(\cdot)$ was used as the score function because desired output signal is speech, which approximately follows Laplacian distribution. The performance of the system was compared in terms of signal-to-noise ratio(SNR). Because the primary input is delayed, in the delayed ANC system, the expected output $u(t)$ is not $s(t)$ but $s(t-D)$. Therefore, SNR is expressed as

$$SNR = 10 \log \frac{\sum(\alpha s(t-D))^2}{\sum(u(t) - \alpha s(t-D))^2}, \qquad (20)$$

where D is the delay of the primary input.

5.1. Simple convolutive channels

First, we used 2 simple filters for convolutive channel h_1 and h_2, which are shown in Fig. 3. As shown in Fig. 4, some zeros of h_2 exist outside the unit circle, that is, h_2 is nonminimum-phase. We compared the performance of each of the 3 different ANC systems to another. In Table 1, (1) denotes the conventional ANC system which has 300 tap adaptive FIR filter, (2) denotes the delayed ANC system which has 300 tap adaptive FIR filter with 150 tap delay, and (3) denotes the delayed ANC system which has 160 taps for $w_n(k)$ and 10 taps for $w_d(k)$ in the adaptive IIR filter with 150 tap delay. In this experiment, most of zeros of h_2 are outside the unit circle. Hence, without delay of the primary input, the corrupting noise in primary input could not be removed successfully. The results show that the performance of the delayed ANC system is much better than that of the conventional ANC system, and the adaptive IIR

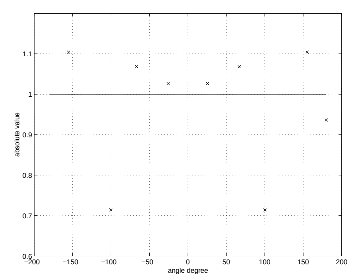


Fig. 4. Zeros of impulse response h_2

filter reduces the number of filter coefficients to be learned without performance degradation.

5.2. Simulated room acoustic channel

For a more practical experiment, simulated room impulse responses were used for convolutive channels which were obtained by the method in [13][14]. It was assumed that the condition of the room and the location of the sources and the sensors were the same as Fig. 5. Reverberation time was 62.5ms, which corresponded to 1000 taps, and the velocity of sound is 340m/s. The heights of sensors were 50cm, whereas those of the sources were 30cm. Fig. 6 shows the obtained room impulse response h_1 and h_2, which were 1000 tap FIR filters. Zeros of h_1 and h_2 are plotted in Fig. 7. There are also lots of zeros outside the unit circle. In the same manner as the previous experiment, the performance of each of the 3 different ANC systems was compared to another. The results are shown in Table 2, where (1) denotes

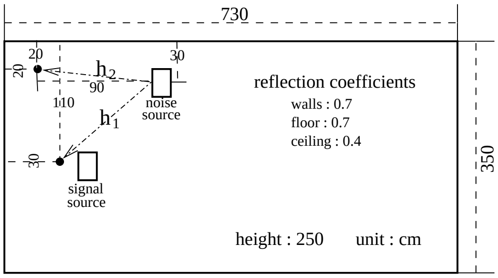
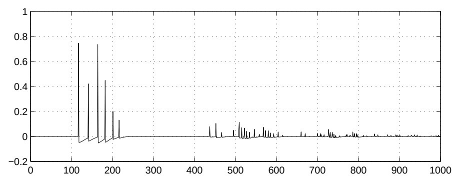
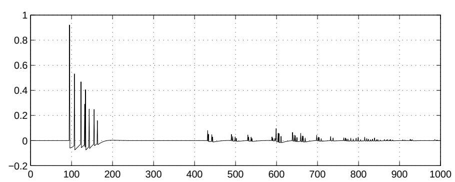


Fig. 5. The environment of simulated room



(a) Impulse response h_1



(b) Impulse response h_2

Fig. 6. Simulated room acoustic channels

the conventional ANC system which has 4000 tap adaptive FIR filter, (2) denotes the delayed ANC system which has 4000 tap adaptive FIR filter with 2000 tap delay, and (3) denotes the delayed ANC system which has 3000 taps for $w_n(k)$ and 1000 taps for $w_d(k)$ in the adaptive IIR filter with 2000 tap delay. These results also show that the performance of the delayed ANC systems is better than that of the conventional ANC system, and the performance of the delayed ANC system was improved by using the adaptive IIR filter with the same number of coefficients.

5.3. Real room recording

Finally, we applied the proposed ANC algorithms to signals recorded in a real office room. The condition of the room, and the location of the sources and the sensors are similar to those of the previous experiment which is shown in Fig. 5 We used 4000 tap adaptive FIR filter with no delay and 2000 tap delay. In this experiment, it is impossible to calculate

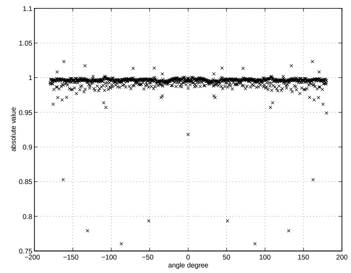


Fig. 7. Zeros of impulse response h_2

SNR[dB]		Gaussian	Laplacian	Babble	Music
Input		-3.03	-3.16	-3.07	-2.98
Output	(1)	5.0	4.92	7.8	7.8
	(2)	14.37	14.33	12.6	12.97
	(3)	16.99	17.04	13.22	15.02

Table 2. The results for simulated room acoustic channels

exact SNRs given by Eq. 20 because we do not know the signal source. Therefore, we just presented the waveforms of the input and the output signals. Fig. 8 displays the real-recorded input signals whereas Fig. 9 displays the output signals of the ANC systems. In Fig. 9, it is not difficult to know that the performance of the delayed ANC is much better than that of the conventional ANC system.

6. CONCLUSION

In this paper, we considered ANC problems which have a nonminimum-phase filter for the channel from the noise source to the reference input. In this case, the adaptive filter should be a very long and noncausal filter. To learn the adaptive filter as a noncausal filter, we have proposed the delayed ANC which has a delay in the primary input. In addition, we have derived the learning rule for the adaptive IIR filter to reduce the number of the adaptive filter coefficients. The simulation results show that the proposed methods provide a much better performance than the conventional method.

7. REFERENCES

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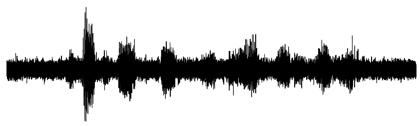

(a) Primary input

(b) Reference input

Fig. 8. Recorded input signals

(a) conventional ANC

(b) delayed ANC

Fig. 9. Output signals

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