

Applying the remote microphone method in the filtered error least mean squares algorithm

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Abstract

An active noise control (ANC) system generates an anti-noise wave to reduce the noise level at a control point, where the error microphone is conventionally placed. Virtual sensing techniques are developed for situations when the error microphone cannot be permanently placed at the control point. The remote microphone (RM) method is one of the most straightforward virtual sensing methods. Previous studies have demonstrated that the performance of the RM method is influenced by the causality between the monitoring and virtual error microphones, which can be resolved by introducing a delayed version of the virtual error signal. So far, the RM method has mainly been examined with the filtered reference least mean squares (FeLMS) algorithm. This paper applies the RM method in the filtered error least mean squares (FeLMS) algorithm, which can reduce the computational complexity of the ANC system and achieve better noise reduction performance.

1. INTRODUCTION

The ANC provides an alternative noise control measure for the passive noise control [1-3]. The ANC system utilizes electro-acoustic devices to transmit an anti-noise wave that has the same amplitude and opposite phase as the unwanted noise wave. The anti-noise wave interferes with the noise wave, resulting in a reduced sound pressure level based on the principle of acoustic wave superposition.

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ANC systems can be categorized by their control structures into the feedforward and feedback ANC systems [4–6]. The feedforward ANC system includes reference microphones to provide the reference signal as the input of the control filter, while the feedback ANC system estimates the reference signal based on the error signal, which is the output of the error microphone. Since the reference microphone can be placed to enhance the coherence between the reference signal and the error signal, the feedforward ANC system is likely to have better noise reduction performance especially when the noise frequency occupies a broad band.

The FxLMS algorithm is the most widely used adaptive algorithm in ANC systems. The goal of the FxLMS algorithm is to minimize the power of the error signal. The control point of the ANC system is therefore achieved at the location of the error microphone. However, in several circumstances, it is not allowed to place the error microphone permanently at a target control point. To resolve this difficulty, virtual sensing methods have been proposed [7–11]. Among them, the RM method adopts a monitoring microphone placed at a reachable location to provide the error signal and estimates the virtual error signal, which is the output of the virtual error microphone that can only be temporarily placed at the target control point [12, 13]. There is a causality constraint for the RM method, *i.e.* the error signal should be time-advanced as compared to the virtual error signal. When the causality constraint is not satisfied, only a delayed virtual error signal can be estimated in a feedforward way. As this delay will also appear in the virtual secondary path, it may slow down the convergence and should be kept to a minimum in practical applications [12].

ANC systems are also categorized into the single-channel and multi-channel systems. The singlechannel ANC system consists of one secondary loudspeaker, one error microphone and at most one reference microphone, while the multi-channel ANC system consists of multiple loudspeakers and microphones. The multiple error LMS algorithm is the multi-channel generalization of the FxLMS algorithm, where the filtered reference signals are calculated between all the reference signals and secondary path models. This results in a very high computational load on the processor when the multi-channel FxLMS algorithm is implemented.

In contrast, there is also the FeLMS algorithm, which significantly reduces the computational complexity in the multi-channel ANC system [14, 15]. In the FeLMS algorithm, the error signal is filtered by an inverse model of the secondary path. Since the secondary path includes an acoustical delay from the secondary loudspeaker to the error microphone, the inverse of the secondary path is non-causal in theory. The inverse model of the secondary path has to introduce a delay to make itself causal. Therefore, this paper studies the case of applying the RM method in the FeLMS algorithm, in order for virtual sensing in the multi-channel ANC system to be implemented with reduced complexity.

2. THEORY AND METHODS

2.1. RM Method

Figure 1 shows the block diagram of the RM method in a single-channel feedforward ANC system, where the FxLMS algorithm is adopted.

The control signal is generated as

$$y(n) = \boldsymbol{w}(n) * \boldsymbol{x}(n) = \boldsymbol{w}^{T}(n)\boldsymbol{x}(n),$$
(1)

where *n* is the discrete time; * denotes the convolution operation; $\boldsymbol{x}(n) = [x(n), x(n-1), \dots, x(n-L)]^T$ is the reference signal vector; $\boldsymbol{w}(n) = [w(n), w(n-1), \dots, w(n-L)]^T$ is the control filter; *L* denotes the length of a vector; and the superscript *T* denotes the transpose of a vector.

The virtual error signal can be written as

$$e_{v}(n) = d_{v}(n) + s_{v}^{T}(n)\boldsymbol{y}(n), \qquad (2)$$



Figure 1: Block diagram of the RM method in a single-channel feedforward ANC system adopting the FxLMS algorithm.

where $s_v(n) = [s_v(n), s_v(n-1), \dots, s_v(n-L)]^T$ is the virtual secondary path; $y(n) = [y(n), y(n-1), \dots, y(n-L)]^T$ is the control signal vector; and the disturbance signal $d_v(n)$ at the virtual error microphone can be considered as

$$d_{\nu}(n) = \boldsymbol{p}_{\nu}^{T}(n)\boldsymbol{x}(n), \qquad (3)$$

where $p_v(n) = [p_v(n), p_v(n-1), \dots, p_v(n-L)]^T$ is the so-called virtual primary path that is always unknown to the ANC system.

A model of the virtual secondary path is required for the FxLMS algorithm, which is written as $\hat{s}_{\nu}(n) = [\hat{s}_{\nu}(n), \hat{s}_{\nu}(n-1), \dots, \hat{s}_{\nu}(n-L)]^{T}$. Afterwards, the update equation of the control filter is written as

$$w(n+1) = w(n) - \mu e_{\nu}(n)\hat{x}_{\nu}(n), \tag{4}$$

where μ is step size; $\hat{x}_{\nu}(n) = [\hat{x}_{\nu}(n), \hat{x}_{\nu}(n-1), \cdots, \hat{x}_{\nu}(n-L)]^T$ and

$$\hat{x}_{\nu}(n) = \hat{\boldsymbol{s}}_{\nu}^{T}(n)\boldsymbol{x}(n).$$
(5)

In the situation when the virtual error microphone cannot be permanently placed at the target control point, the RM method estimates $d_v(n)$ based on the estimate of $d_m(n)$. The latter is the disturbance signal at the monitoring microphone. Hence, the estimate of the virtual error signal can also be obtained, which is written as

$$\hat{e}_{v}(n-\Delta) = \boldsymbol{c}^{T}(n)\hat{\boldsymbol{d}}_{m}(n) + \hat{\boldsymbol{s}}_{v}^{T}(n)\boldsymbol{y}(n-\Delta)$$
(6)

where $\hat{d}_m(n) = [\hat{d}_m(n), \hat{d}_m(n-1), \dots, \hat{d}_m(n-L)]^T$; the estimate of $d_m(n)$ is given by $\hat{d}_m(n) = e_m(n) - \hat{s}_m^T(n)y(n)$; $e_m(n)$ is the monitoring error signal; $\hat{s}_m(n)$ is the model of the monitoring secondary path;



Figure 2: Block diagram of the FeLMS algorithm

c(n) is a pre-trained filter, also known as the relative primary path, that takes $d_m(n)$ as the input and $d_v(n - \Delta)$ as the output; and Δ is a delay amount, in order for c(n) to be causal.

2.2. FeLMS Algorithm

Figure 2 shows the block diagram of the FeLMS algorithm in a single-channel feedforward ANC system.

The update equation of the control filter is written as

$$w(n+1) = w(n) - \mu e'(n)x(n-\Delta), \tag{7}$$

where the filtered error signal is calculated by

$$e'(n) = s_{\dagger}^{T}(n)e(n); \tag{8}$$

and $e(n) = [e(n), e(n-1), \dots, e(n-L)]^T$ is the error signal vector; $s_{\dagger}(n)$ is a pre-trained causal filter, satisfying

$$s_{\dagger}^{T}(n)s(n) \approx s^{-1}(n-\Delta) * s(n) = \delta(n-\Delta).$$
⁽⁹⁾

2.3. Applying the RM method in the FeLMS algorithm

Figure 3 shows the block diagram of the RM method in a single-channel feedforward ANC system, where the FeLMS algorithm is adopted.

The update equation of the control filter is written as

$$w(n+1) = w(n) - \mu \tilde{e}_{\nu}(n-\Delta)x(n-\Delta), \tag{10}$$

where the filtered virtual error signal $\tilde{e}_{\nu}(n - \Delta)$ is calculated by

$$\tilde{e}_{v}(n-\Delta) = \tilde{c}^{T}(n)\hat{d}_{m}(n) + y(n-\Delta);$$
(11)

and $\tilde{c}(n)$ functions as a combined filter of c(n) and $s_{\dagger}(n)$. $\tilde{c}(n)$ is called the combined relative primary path.

The training process of the combined relative primary path is shown in Figure 4, which is very similar to the FxLMS algorithm. In the multi-channel ANC system, although the FeLMS algorithm reduces the computational complexity of updating the control filters, the computational complexity of training the combined relative primary path is significantly increased. In other words, the real-time on-line processing load is shifted to the non real-time off-line processing load.



Figure 3: Block diagram of the RM method in a single-channel feedforward ANC system adopting the FeLMS algorithm.



Figure 4: Block diagram of the training process of $\tilde{c}(n)$.

3. SIMULATION RESULTS

Firstly, the single-channel virtual sensing simulation is carried out on the configuration of a case (1,1,2) ANC system. There are 2 primary paths and 2 secondary paths [16]. One error microphone is assigned as the monitoring microphone and the other error microphone is assigned as the virtual error microphone. The sampling rate is set to 16000 Hz. The length of the control filter is set to 400 taps. Both the relative primary path and the combined relative primary path are pre-trained with the length of 2000 taps. The primary noise is a band-limited white noise, of which the frequency ranges from 400 to 800 Hz. The noise reduction curves are shown in Figure 5.



Figure 5: Noise reduction curves of the single-channel virtual sensing simulation: (a) when the monitoring microphone is closer to the secondary loudspeaker; (b) when the virtual error microphone is closer to the secondary loudspeaker.

Secondly, the multi-channel virtual sensing simulation is carried out on the configuration of a case (2,2,4) ANC system. There are 4 primary paths and 8 secondary paths [16]. Two error microphones are assigned as the monitoring microphones and the other two error microphones are assigned as the virtual error microphones. The lengths of the control filters are all set to 400 taps. Both the relative primary paths and the combined relative primary paths are pre-trained with the length of 600 taps. The primary noises are two band-limited white noises, of which the frequencies range from 400 to 800 Hz. The noise reduction curves are shown in Figure 6.

In both the single-channel and multi-channel simulations, the FeLMS algorithm outperforms the FxLMS algorithm when the RM method is applied and an appropriate delay amount is set. This is likely due to the observation that the combined relative primary path is easier to converge as compared to the relative primary path in the training process. When the monitoring microphones are closer to the secondary loudspeakers than the virtual error microphones, only the FxLMS algorithm can incorporate with the RM method for $\Delta = 0$. However, the steady-state noise reduction performance can be improved in this case by setting Δ to a non-zero amount. Once there is a non-zero delay amount, the FeLMS algorithm can incorporate with the RM method again.

Furthermore, Table 1 presents the number of multiplications consumed in the FxLMS and FeLMS algorithms incorporated with the RM method, where J, K, M and N denote the numbers of reference microphones, secondary loudspeakers, monitoring microphones and virtual error microphones, respectively. The lengths of the control filters are denoted by L, while the lengths of the relative primary paths and the combined relative primary paths are counted as kL. The computational complexity incurred in the training process is not considered in Table 1. Taking the multi-channel simulation as an example, J = K = M = N = 2, L = 400 and k = 1.5. Therefore, the numbers of multiplications consumed in the FxLMS and FeLMS algorithms are 15200 and 8800, respectively. The FeLMS algorithm reduces the computational complexity by about 42%.



Figure 6: Noise reduction curves of the multi-channel virtual sensing simulation: (a) when the monitoring microphones are closer to the secondary loudspeakers; (b) when the virtual error microphones are closer to the secondary loudspeakers.

Table 1: Number of multiplications consumed in the FxLMS and FeLMS algorithms incorporated with the RM method.

Multiplications	RM with FxLMS	RM with FeLMS
Calculating the control signals	$J \times K \times L = 1600$	$J \times K \times L = 1600$
Remote microphone method	$K \times M \times L + M \times N \times kL + K \times N \times L = 5600$	$K \times M \times L + M \times N \times kL = 4000$
Calculating the filtered reference signals	$J \times K \times N \times L = 3200$	0
Updating the control filters	$J \times K \times (N+1) \times L = 4800$	$J \times K \times 2 \times L = 3200$
total	15200	8800

4. CONCLUSIONS

In this paper, the RM method is incorporated with the FeLMS algorithm to reduce the computational complexity of the multi-channel virtual sensing method. In both the single-channel and multi-channel simulations, the FeLMS algorithm outperforms the FxLMS algorithm when the RM method is applied with an appropriate delay amount. Adding in a delay amount in the RM method also results in better noise reduction performance of the FxLMS algorithm. The theoretical reason for these observations lies in the training process. It is noted that the combined relative primary path is easier to converge than the relative primary path, and an appropriate delay amount can improve the training accuracy of both paths. Last but not least, although the FeLMS algorithm reduces the computational complexity of updating the control filters, the computational complexity of training the combined relative primary path is significantly increased. The training process can be carried out in an off-line manner, which does not increase the difficulty of real-time implementation

of the ANC system.

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