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Stereophonic Acoustic Echo Canceler Based on Two-Filter Scheme**

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SUMMARY This paper presents a novel stereophonic acoustic echo canceling scheme without preprocessing. To accurately estimate echo path keeping the high level of performance in echo erasing, this scheme uses two filters, of which one filter is utilized as *a guideline* which does not erases echo but helps updating of the other filter, which actually erases echo. In addition, we propose a new filter dividing technique to apply to the filter divide scheme, and utilize this as *the guideline*. Numerical examples demonstrate that the proposed scheme improves the convergence behavior compared to conventional methods both in system mismatch (i.e., normalized coefficients error) and Echo Return Loss Enhancement (ERLE).
key words: *stereophonic acoustic echo canceler, adaptive filter, NLMS, non-uniqueness problem*

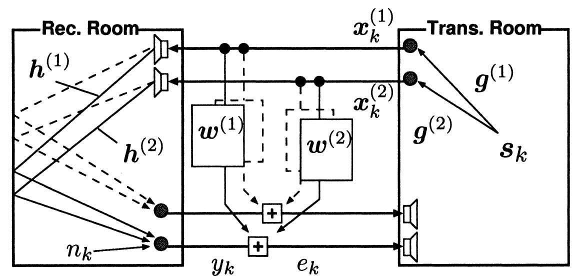

Fig. 1 Stereophonic acoustic echo canceler (SAEC).

1. Introduction

Stereophonic Acoustic Echo Cancelers (SAECs) play a major role in realization of high quality hands-free systems, such as advanced teleconferencing, car-phones, home entertainment, etc. The principal part of SAEC is illustrated in Fig. 1. It is known that SAECs suffer from the so-called *non-uniqueness problem* [1]; i.e., highly cross-correlated input signals prevent filter coefficients from having a unique solution (see Sect. 2.1). For secure echo erasing, however, it is desired for the filter coefficients to well approximate the optimum solution. It is a fundamental difficulty of SAECs problem. SAEC with preprocessing can alleviate this difficulty [1]–[7], whereas the preprocessing causes audible sound distortion. In the viewpoint of realization of high quality communication, this distortion is not a good thing, of course. Meanwhile, some devised schemes for SAECs without preprocessing have also been proposed [8]–[10]. While NLMS aims at the solution set, these devised schemes without preprocessing aim at the point near to the optimum solution, thus, these devised schemes can lead the coefficients closer to the optimum solution than NLMS. However, since NLMS aims straight at the solution set, it is conceivable that these devised schemes inferior to NLMS in terms of the echo erasing performance.

To overcome this problem, we propose a new SAEC algorithm without preprocessing, which uses two filters; one is named a *guideline filter*, and the other is named a *main filter*. The guideline filter is updated by the devised scheme and that filter is utilized only as *a guideline*; does not erase echo but helps updating of the main filter. Thanks to the help of the guideline filter, the main filter can achieve the equivalent echo erasing performance to NLMS and higher level of echo path estimation than the devised scheme (i.e., guideline filter). We introduce a copying process, in which the filter coefficients of the main filter is copied to the guideline filter when the echo path variation is detected. This processing deter the decaying of the estimate performance caused by variation of the echo path.

In this paper, we adopt the filter divide scheme [8] as the guideline. In this scheme, a filter coefficient vector is divided into two sub-filters, and these sub-filters are updated one after another. In [8], the scheme shows a good performance of echo path estimation, but, no details about *how to divide filters* are presented. Thus, introducing more artful divide would improve convergence performance. We propose an efficient filter dividing technique based on the characteristic feature of room impulse responses which can be modeled as exponential decay. This approach is reasonable and can improve the performance of echo path estimation.

Numerical examples demonstrate that the proposed two-filter scheme which utilizes the proposed filter divide scheme as the guideline improves the convergence behavior compared to conventional methods both in system mismatch and ERLE.

2. Formulation of SAEC Problem

Without loss of generality, we concentrate on the one microphone in the Receiving room. Let $M \in \mathbb{N}\backslash\{0\}$ and $L \in \mathbb{N}\backslash\{0\}$ denote the lengths of the impulse responses of Transmitting

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room and of the adaptive filters, respectively. For simplicity, let the length of the echo path be L (analyses for more general cases are presented in [1]). Referring to Fig. 1, the signals are modeled as follows (where $k \in \mathbb{N}$: time index, $i = 1, 2$: stereophonic left-right indexes, superscript T : transposition);

- speech vector : $\boldsymbol{s}_k := [s_k, s_{k-1}, \cdots, s_{k-M+1}]^T$
- i-th impulse response vector of Transmitting room : $\boldsymbol{g}^{(i)} := \left[g_0^{(i)}, g_1^{(i)}, \cdots, g_{M-1}^{(i)}\right]^T$
- i-th input : $x_k^{(i)} := \boldsymbol{s}_k^T \boldsymbol{g}^{(i)}$
- i-th input vector : $\boldsymbol{x}_k^{(i)} := \left[x_k^{(i)}, \cdots, x_{k-L+1}^{(i)}\right]^T$
- input vector : $\boldsymbol{x}_k := \left[\boldsymbol{x}_k^{(1)T}, \boldsymbol{x}_k^{(2)T}\right]^T$
- i-th echo path : $\boldsymbol{h}^{(i)} := \left[h_0^{(i)}, h_1^{(i)}, \cdots, h_{L-1}^{(i)}\right]^T$
- estimundum : $\boldsymbol{h} := \left[\boldsymbol{h}^{(1)T}, \boldsymbol{h}^{(2)T}\right]^T$
- i-th coefficient vector of adaptive filter : $\boldsymbol{w}_k^{(i)} := \left[w_{k,0}^{(i)}, w_{k,1}^{(i)}, \cdots, w_{k,L-1}^{(i)}\right]^T$
- coefficient vector of adaptive filter : $\boldsymbol{w}_k := \left[\boldsymbol{w}_k^{(1)T}, \boldsymbol{w}_k^{(2)T}\right]^T$
- noise : n_k
- echo : $z_k := \boldsymbol{x}_k^T \boldsymbol{h}$
- microphone input : $y_k := z_k + n_k$
- residual echo : $e_k := y_k - \boldsymbol{x}_k^T \boldsymbol{w}$

The goal of SAEC problem is to constantly cancel echo; i.e., $\boldsymbol{x}_k^T \boldsymbol{h} \approx \boldsymbol{x}_k^T \boldsymbol{w}, \forall k \in \mathbb{N}$, only with observable information $(\boldsymbol{x}_k, y_k)_{k \in \mathbb{N}}$.

2.1 Non-uniqueness Problem

For simplicity, in this section, we review the problem only in noise free situations; i.e., $n_k = 0, \forall k \in \mathbb{N}$. In this case, because we can only observe $\left(x_k^{(i)}\right)_{k \in \mathbb{N}}$ and $(y_k)_{k \in \mathbb{N}}$, all what we can do is to find a point in

$$\mathcal{V} := \{\boldsymbol{w} : \ e_k(\boldsymbol{w}) = 0, \ \forall k \in \mathbb{N}\}. \tag{1}$$

Because of high correlation between two input signals $\left(\boldsymbol{x}_k^{(1)}, \boldsymbol{x}_k^{(2)}\right)$, unfortunately, solution set $\mathcal{V}$ has infinitely many components. Thus we cannot get a unique solution. This is the so-called *non-uniqueness problem*.

If $\boldsymbol{w}_k$ is in $\mathcal{V}$, echo is canceled, but, since solution set $\mathcal{V}$ depends on $\boldsymbol{g}^{(1)}, \boldsymbol{g}^{(2)}$ (impulse responses of Transmitting room), without well-approximating $\boldsymbol{h}$, echo reappears by change of $\boldsymbol{g}^{(1)}$ or $\boldsymbol{g}^{(2)}$. Thus, it is strongly desired to keep $\boldsymbol{w}_k$ close to $\boldsymbol{h}$.

3. Two-Filter Scheme

3.1 Algorithm

To overcome the non-uniqueness problem, many devised schemes which aim at the point near to the optimum solution are proposed [8]–[10]. These schemes can lead filter coefficients closer to the optimum solution, but, since NLMS aims straight at the solution set, NLMS can approach to the solution set faster than the devised schemes. It is thus conceivable that the devised schemes inferior to NLMS in echo erasing performance (Fig. 2). This degradation is inherent.

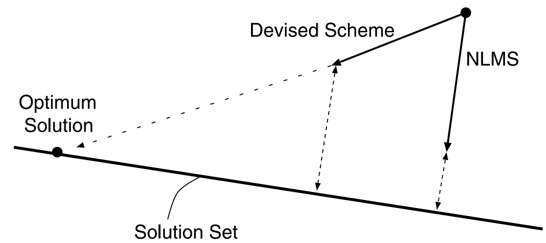

Fig. 2 While NLMS aims straight at the solution set, the ideal devised scheme aim at the optimum solution, in other words, since NLMS is optimal scheme in the viewpoint of echo erasing performance, the device to aim at the optimum solution deteriorate echo erasing performance.

From another point of view, NLMS is updated only in perpendicular direction to the solution set, i.e., when we think about parallel direction to the solution set, NLMS cannot approach to the optimum solution. Thus, the accurate echo path estimate which is achieved by the conventional devised schemes arises from updating in the parallel direction to the solution set.

Since NLMS updates the filter coefficients toward the solution set perpendicularly, the improved updating components of the devised scheme (i.e., the parallel components of update vector to the solution set, represented as $\Delta \boldsymbol{w}_k^{(p)}$) is calculated as

$$\Delta \boldsymbol{w}_k^{(p)} = \Delta \boldsymbol{w}_k^{(g)} - \lambda_k \Delta \boldsymbol{w}_k^{(N)}, \ \lambda_k := \frac{\Delta \boldsymbol{w}_k^{(g)T} \Delta \boldsymbol{w}_k^{(N)}}{\|\Delta \boldsymbol{w}_k^{(N)}\|^2}, \tag{2}$$

where $\Delta \boldsymbol{w}_k^{(g)}$ and $\Delta \boldsymbol{w}_k^{(N)}$ represent the update vector of the devised scheme and of NLMS, respectively (Note that $\Delta \boldsymbol{w}_k^{(p)}$ is the orthographic projection of $\Delta \boldsymbol{w}_k^{(g)}$ onto the hyperplane whose normal vector is $\Delta \boldsymbol{w}_k^{(N)}$). Thanks to this component, the devised scheme can lead coefficients closer to the optimum solution. Since this component is perpendicular to the updating direction of NLMS, adding this component to the update vector of NLMS does not effect the updating behavior of NLMS.

Based on the above idea, we propose an efficient echo canceling scheme using two filters. One filter is named a *guideline filter*; which is updated by the conventional devised scheme and utilized only as the guideline (this filter is not directly utilized as echo canceler, i.e., output of this filter does not come back to the Transmitting room). The other filter, which is named a *main filter*, is updated by addition of the update vector of NLMS and the component of the guideline filter's update vector which is perpendicular to the update vector of NLMS, and calculated by (2). This filter actually performs as the echo canceler, i.e., output of this filter is the residual echo, which comes back to the Transmitting room. In sum, the filter coefficient vectors of the main and the guideline filter are updated as

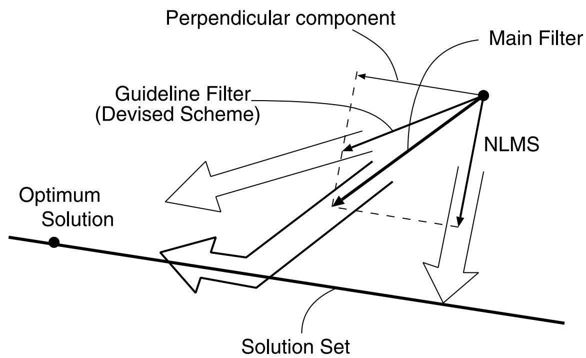

Fig. 3 Updating direction of the proposed scheme. In parallel direction to the solution set, the main filter is updated by the devised scheme (i.e., the guideline filter), and in perpendicular direction, updated by NLMS.

$$\boldsymbol{w}_{k+1}^{(g)} = \boldsymbol{w}_k^{(g)} + \mu^{(g)} \Delta \boldsymbol{w}_k^{(g)}, \tag{3}$$

$$\boldsymbol{w}_{k+1}^{(m)} = \boldsymbol{w}_k^{(m)} + \mu^{(m)} \Delta \boldsymbol{w}_k^{(N)} + \mu^{(g)} \Delta \boldsymbol{w}_k^{(p)}, \tag{4}$$

where $\boldsymbol{w}_k^{(g)}$ $\left(\boldsymbol{w}_k^{(m)}\right)$ and $\mu^{(g)}$ $\left(\mu^{(m)}\right)$ represent the coefficient vector of the guideline filter (of the main filter) and the step size of the guideline filter (of the main filter), respectively. Specific formula of $\Delta \boldsymbol{w}_k^{(g)}$ depends on the scheme which is adopted for the guideline, and $\Delta \boldsymbol{w}_k^{(p)}$ is calculated by (2).

In this scheme, the main filter is updated by NLMS in perpendicular direction to the solution set, and updated by the devised scheme (i.e. the guideline filter) in parallel direction to the solution set, respectively (see Fig. 3). Thus, this algorithm has the equivalent echo erasing performance to NLMS, and can improve the echo path estimate performance of the devised scheme.

3.2 For Variation of Impulse Responses

In the above section, change of the impulse responses to be estimated (*estimundam*) has not been considered. Although the two-filter scheme can achieve good estimate for estimundam without variation, because of the feature that two filters are utilized in the scheme, the case where the estimate performance can be degraded is conceivable. For example, in Fig. 4, the estimundam changes to the point *between* the main filter and the guideline filter, so that, the help of the guideline degrade the estimate performance of the main filter, i.e., of the two-filter scheme.

To solve this problem, we introduce a copying process; when the impulse responses are varied, the coefficients of the main filter are copied to the guideline filter, i.e., guideline filter is moved to the point of the main filter (see Fig. 5). The objective of this processing is to make the update vectors of the main and the guideline filters calculated from the same coefficient vector whenever any kinds of echo path variation occurs. This processing deter the two-filter scheme from decaying of the estimate performance caused by variation of the impulse responses. However, when the guideline filter is in the solution set, its convergence stops, since $e_k = 0$. Thus, when the main filter is in the solution set, the copying surceases the convergence of the guideline filter.

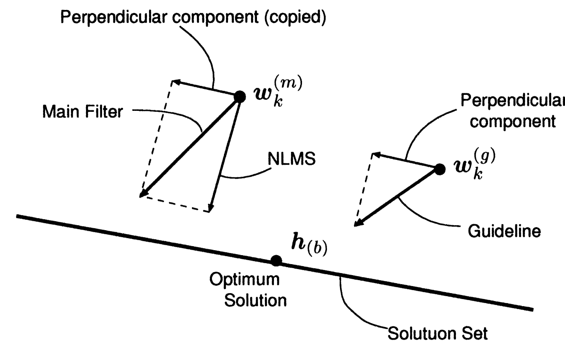

Fig. 4 When the echo paths change to the point *between* the main filter ($\boldsymbol{w}_k^{(m)}$) and the guideline filter ($\boldsymbol{w}_k^{(g)}$), the help of the guideline (i.e., the copied perpendicular component) decay the echo path estimate performance of the main filter.

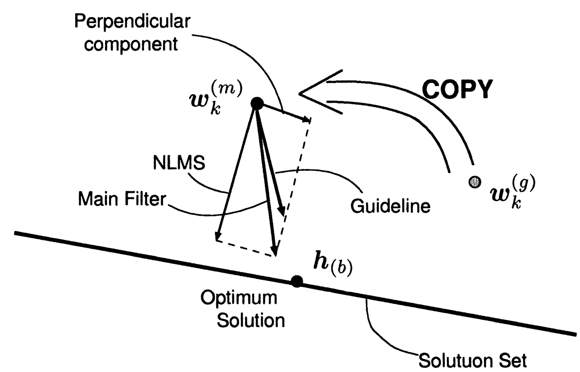

Fig. 5 When the change of impulse responses is detected, the filter coefficients of the main filter is copied to the guideline filter, i.e., the guideline filter is transferred to the point of the main filter. Thanks to this processing, the estimate performance of the main filter is not degraded.

After NLMS converges in the solution set, the main filter is updated only by the help of the guideline (see Fig. 3), thus, the copying when the impulse responses do not change degrades the estimate performance of the main filter. For this reason, periodic copying may degrade the estimate performance, thus, the copying process is executed only when the impulse responses change. Here is another problem, i.e., *how to know the change of the impulse responses*.

To detect the change of impulse responses, we focus attention on the residual echo e_k. When the impulse responses are varied, e_k get large. Thus, when e_k get large, it is conceivable that impulse responses may change. However, even without change of impulse responses, sometimes residual echo get large; for example, emergent large noise makes the residual echo large. To distinguish between such *accidental* large residual echo and the large residual echo caused by variation of the impulse responses, we utilize the difference of time length needed to erase the large residual echo; while *accidental* large residual echo is erased in a moment, it needs some length of time to erase the large residual echo caused by change of the impulse responses.

Based on the above idea, we introduce the following two quantities,

$$\xi_{k+1} = \alpha\xi_k + (1-\alpha)\, e_k^{(m)^2}, \tag{5}$$

$$\psi_{k+1} = \beta\psi_k + (1-\beta)\, e_k^{(m)^2}, \tag{6}$$

where $e_k^{(m)}$ represents residual echo of the main filter, α and β are forgetting factors, which are set as $\alpha > \beta$. Both ξ_k and ψ_k are smoothed square of residual echo, whose initial values are set to zero. During the filter coefficient vector converges, $e_k^{(m)}$ gradually gets smaller, so that, $\xi_k > \psi_k$ (because of $\alpha > \beta$). However, if variation of the impulse responses occur, $e_k^{(m)}$ gets bigger, i.e., ξ_k and ψ_k get bigger. Since $\alpha > \beta$, ψ_k grow large more rapidly than ξ_k, thus, if large $e_k^{(m)}$ is prolonged in some length of time, ψ_k can get bigger than ξ_k. We consider this as an indication of the impulse response variation. In sum, at the point where the relation between ξ_k and ψ_k switches from $\xi_k - \psi_k > \eta$ to $\xi_k - \psi_k \leq \eta$ (η is a threshold), the coefficients of the main filter are copied to the guideline filter.

The detail of the entire algorithm of the two-filter scheme with the copying process is shown below.

algorithm 1 : Two-filter scheme

1. $\xi_k = 0, \psi_k = 0$, and $\boldsymbol{w}_k^{(m)}, \boldsymbol{w}_k^{(g)}$ are zero vectors.
2. Update $\boldsymbol{w}_k^{(g)}$ and $\boldsymbol{w}_k^{(m)}$.
3. Update ξ_k and ψ_k.
4. If $\xi_k - \psi_k \leq \eta$, go to 6.
5. Go to 2.
6. The filter coefficients of main filter is copied to guideline filter.
7. Update $\boldsymbol{w}_k^{(g)}$ and $\boldsymbol{w}_k^{(m)}$.
8. Update ξ_k and ψ_k.
9. If $\xi_k - \psi_k > \eta$, go to 2.
10. Go to 7.

The above is the proposed two-filter scheme. By definition, in this scheme, the performance of the guideline has great importance. In this paper, we adopt the filter divide scheme [8] as the guideline. In the following section, the detail of the filter divide scheme is shown, and, to improve the estimate performance, an efficient filter dividing technique which utilizes the characteristic feature of room impulse responses is proposed.

4. Filter Divide Scheme as the Guideline

4.1 Filter Divide Scheme

In an ideal case, input signals are linearly dependent, so that the unique solution of SAEC is not obtainable. But, in real cases, since the filter lengths (L) is shorter than the lengths of Transmitting room impulse responses (M), input signals are not strictly linearly dependent. This relation of input signals can be expressed as

$$\boldsymbol{g}_L^{(2)^T}\boldsymbol{x}_k^{(1)} + \sigma_k^{(1)} = \boldsymbol{g}_L^{(1)^T}\boldsymbol{x}_k^{(2)} + \sigma_k^{(2)}, \tag{7}$$

where

$$\boldsymbol{g}^{(i)} = \left[\boldsymbol{g}_L^{(i)^T}, \boldsymbol{g}_{tail}^{(i)\ T}\right]^T, \tag{8}$$

$$\boldsymbol{g}_L^{(i)} = \left[g_0^{(i)}, g_1^{(i)}, \cdots, g_{L-1}^{(i)}\right]^T, \tag{9}$$

$$\boldsymbol{g}_{tail}^{(i)} = \left[g_L^{(i)}, g_{L+1}^{(i)}, \cdots, g_{M-1}^{(i)}\right]^T, \tag{10}$$

$$\sigma_k^{(1)} := \sum_{i=L}^{M-1} x_{k-i}^{(1)} g_i^{(2)}, \quad \sigma_k^{(2)} := \sum_{i=L}^{M-1} x_{k-i}^{(2)} g_i^{(1)}. \tag{11}$$

When L is much shorter than M (i.e., $\sigma_k^{(i)}$ are large), non-uniqueness of solution is alleviated, but, echo canceling performance is poor when L is much shorter than the lengths of Receiving room impulse responses. In most practical situations, while L is enough large to achieve good echo canceling performance, $\sigma_k^{(i)}$ are small, thus, non-uniqueness is serious. To overcome this problem, the filter divide scheme was proposed [8]. In that scheme, a filter coefficient vector is divided into two sub-filters, and two sub-filters are updated one after another, i.e., when currently updated sub-filter converges, switch to the other sub-filter. In each iteration, since only one sub-filter is updated, $\sigma_k^{(i)}$ becomes large, thus, this scheme can achieve good estimation.

4.2 Even-Energy Filter Dividing Technique

4.2.1 Algorithm

Although, in [8], a filter coefficient vector is simply divided to make lengths of two sub-filters equal, more artful divide could improve the convergence performance. In this section, we propose an efficient filter dividing technique in consideration of a characteristic feature of room impulse response.

Under diffusing sound field assumption, it can be shown that the ensemble average of the squared room impulse response is modeled as decaying exponential [11]:

$$\epsilon_n := E\left({g_n}^2\right) = \epsilon_0 \exp\left(-\delta n\right), \tag{12}$$

where $E\{\cdot\}$ denotes expectation, $\{g_n\}_{n=0}^{M-1}$ is a causal room impulse response, and the damping constant δ is defined as

$$\delta := \frac{\log 10^6}{T_{60} Fs}, \tag{13}$$

with Fs: the sampling frequency and T_{60}: the time interval in which the reverberant sound energy drops down by 60 dB.

Consequently, if a filter coefficient vector is divided to make lengths equal, the energy of Transmitting room impulse responses are much larger in front part than in back part, so that, when the front sub-filter is updated, $\sigma_k^{(i)}$ are still small (cf. (7), (11)), i.e., non-uniqueness is hardly alleviated.

To overcome the above problem, we propose a dividing technique to balance the impulse response energy in each divided part, i.e., divide the impulse energy equally (even-energy dividing). When one filter is divided into K sub-filters, such $K-1$ dividing points (I_i, $i = 1, 2, \cdots, K-1$) are expressed as

$$\sum_{i=0}^{I_1-1}\epsilon_i = \sum_{i=I_1}^{I_2-1}\epsilon_i = \cdots = \sum_{i=I_{K-1}}^{M-1}\epsilon_i. \tag{14}$$

By the substitution of (12) into (14), required dividing points are obtained as

$$I_i = -\frac{1}{\delta}\log\left(1 - \frac{i\,(1-\exp(-\delta L))}{K}\right). \tag{15}$$

Since T_{60} depends on the room environment, δ is an unknown value. To estimate accurate T_{60}, an efficient technique is proposed in [11], but, considering computational complexity, we propose an algorithm which can be executed without estimating T_{60}.

Typical values of T_{60} is from about 300 ms (e.g. living rooms) up to 10000 ms (e.g. large churches, reverberation chambers), and most large rooms (e.g. conference rooms) have T_{60} between 700 ms and 2000 ms [12]. Thus, for our purpose, we set a pertinent assumption that T_{60} lies between 300 ms and 2000 ms. Based on this assumption, we define two dividing point sets, $\boldsymbol{I}^{(1)} := \left[I_1^{(1)},\cdots,I_{K-1}^{(1)}\right], \boldsymbol{I}^{(2)} := \left[I_1^{(2)},\cdots,I_{K-1}^{(2)}\right]$, where $I_i^{(1)}$ is on presupposing $T_{60} = 300$ ms and $I_i^{(2)}$ is on presupposing $T_{60} = 2000$ ms. The details of $I_i^{(1)}$ and $I_i^{(2)}$ are as follows.

$$I_i^{(1)} = -\frac{0.3Fs}{6\log 10}\log\left(1 - \frac{i\left(1-10^{-6L/(0.3Fs)}\right)}{K}\right), \tag{16}$$

$$I_i^{(2)} = -\frac{2.0Fs}{6\log 10}\log\left(1 - \frac{i\left(1-10^{-6L/(2.0Fs)}\right)}{K}\right), \tag{17}$$

$$\text{where} \quad i = 1,2,\cdots,K-1. \tag{18}$$

The optimal dividing point (depending on unknown actual T_{60}) is to be found between $I_i^{(1)}$ and $I_i^{(2)}$. Thus, in our algorithm, a filter coefficient vector is divided in two ways, i.e., with $\boldsymbol{I}^{(1)}$ or $\boldsymbol{I}^{(2)}$. If all sub-filters which are divided with one dividing point set are through in the same manner as conventional filter divide scheme, switch to the other dividing point set, and update these sub-filters by rotation. Repeating these stages, the adaptive filters are believed to achieve good estimation as divided at the optimal dividing point set. The detail of the algorithm in the case of $K = 3$ is shown below.

algorithm 2 : Even-energy filter divide scheme

1. update the sub-filter *anterior to* $I_1^{(1)}$
2. update the sub-filter *between* $I_1^{(1)}$ *and* $I_2^{(1)}$
3. update the sub-filter *posterior to* $I_2^{(1)}$
4. update the sub-filter *anterior to* $I_1^{(2)}$
5. update the sub-filter *between* $I_1^{(2)}$ *and* $I_2^{(2)}$
6. update the sub-filter *posterior to* $I_2^{(2)}$
7. go to 1

4.2.2 Convergence Analysis

This section presents an analysis for convergence of filter coefficients. For simplicity, in this section, we consider only in noise free situation and the case where filter coefficient vector is divided into two sub-filters (i.e., $K = 2$). First, to consider the sub-filters divided with $\boldsymbol{I}^{(1)}$, we define the following notations;

$$\boldsymbol{x}_{k,i}^{(f1)} := \left[x_k^{(i)}, x_{k-1}^{(i)},\cdots,x_{k-I_1+1}^{(i)}\right]^T \in \mathbb{R}^{I_1}, \tag{19}$$

$$\boldsymbol{x}_{k,i}^{(b1)} := \left[x_{k-I_1}^{(i)}, x_{k-I_1-1}^{(i)},\cdots,x_{k-L+1}^{(i)}\right]^T \in \mathbb{R}^{L-I_1}, \tag{20}$$

$$\boldsymbol{w}_{k,i}^{(f1)} := \left[w_0^{(i)}, w_1^{(i)},\cdots,w_{I_1-1}^{(i)}\right]^T \in \mathbb{R}^{I_1}, \tag{21}$$

$$\boldsymbol{w}_{k,i}^{(b1)} := \left[w_{I_1}^{(i)}, w_{I_1+1}^{(i)},\cdots,w_{L-1}^{(i)}\right]^T \in \mathbb{R}^{L-I_1}, \tag{22}$$

$$\boldsymbol{h}_{(i)}^{(f1)} := \left[h_0^{(i)}, h_1^{(i)},\cdots,h_{I_1-1}^{(i)}\right]^T \in \mathbb{R}^{I_1}, \tag{23}$$

$$\boldsymbol{h}_{(i)}^{(b1)} := \left[h_{I_1}^{(i)}, h_{I_1+1}^{(i)},\cdots,h_{L-1}^{(i)}\right]^T \in \mathbb{R}^{L-I_1}, \tag{24}$$

$$i = 1,2, \tag{25}$$

$$\boldsymbol{x}_k^{(p)} := \left[\boldsymbol{x}_{k,1}^{(p)T}\,\boldsymbol{x}_{k,2}^{(p)T}\right]^T, \tag{26}$$

$$\boldsymbol{w}_k^{(p)} := \left[\boldsymbol{w}_{k,1}^{(p)T}\,\boldsymbol{w}_{k,2}^{(p)T}\right]^T, \tag{27}$$

$$\boldsymbol{h}^{(p)} := \left[\boldsymbol{h}_{(1)}^{(p)T}\,\boldsymbol{h}_{(2)}^{(p)T}\right]^T, \tag{28}$$

$$p = f1, b1, \tag{29}$$

$$\boldsymbol{d}_k^{(f1)} := \boldsymbol{h}^{(f1)} - \boldsymbol{w}_k^{(f1)} \in \mathbb{R}^{2I_1}, \tag{30}$$

$$\boldsymbol{d}_k^{(b1)} := \boldsymbol{h}^{(b1)} - \boldsymbol{w}_k^{(b1)} \in \mathbb{R}^{2(L-I_1)}. \tag{31}$$

If $\boldsymbol{w}_k^{(f1)}$ is currently updated, with these notations, the residual echo (e_k) is represented as

$$e_k = \boldsymbol{d}_k^{(f1)^T}\boldsymbol{x}_k^{(f1)} + \boldsymbol{d}_{(m)}^{(b1)^T}\boldsymbol{x}_k^{(b1)}, \tag{32}$$

where $\boldsymbol{d}_{(m)}^{(b1)}$ represents the misalignment of the currently fixed sub-filter, which is converged in the last (m-th) stage. Taking an ensemble average of e_k^2 leads to

$$\begin{aligned} E(e_k^2) &= \overline{\boldsymbol{d}}_k^{(f1)^T}\boldsymbol{X}_{ff,1}\overline{\boldsymbol{d}}_k^{(f1)} \\ &\quad + 2\overline{\boldsymbol{d}}_k^{(f1)^T}\boldsymbol{X}_{fb,1}\boldsymbol{d}_{(m)}^{(b1)} + \boldsymbol{d}_{(m)}^{(b1)^T}\boldsymbol{X}_{bb,1}\boldsymbol{d}_{(m)}^{(b1)}, \end{aligned} \tag{33}$$

where

$$\boldsymbol{X}_{ff,1} := \overline{\boldsymbol{x}_k^{(f1)}\boldsymbol{x}_k^{(f1)^T}} \in \mathbb{R}^{2I_1\times 2I_1}, \tag{34}$$

$$\boldsymbol{X}_{fb,1} := \overline{\boldsymbol{x}_k^{(f1)}\boldsymbol{x}_k^{(b1)^T}} \in \mathbb{R}^{2I_1\times 2(L-I_1)}, \tag{35}$$

$$\boldsymbol{X}_{bb,1} := \overline{\boldsymbol{x}_k^{(b1)}\boldsymbol{x}_k^{(b1)^T}} \in \mathbb{R}^{2(L-I_1)\times 2(L-I_1)}, \tag{36}$$

and, $\overline{\boldsymbol{d}}_k^{(f1)}$ denotes an average of $\boldsymbol{d}_k^{(f1)}$. $\overline{\boldsymbol{x}}_k^{(f1)}$ and $\overline{\boldsymbol{x}}_k^{(b1)}$ denote averages of $\boldsymbol{x}_k^{(f1)}$ and $\boldsymbol{x}_k^{(b1)}$, respectively.

From

$$\frac{\partial E(e_k^2)}{\partial \overline{\boldsymbol{d}}_k^{(f1)}} = 2\boldsymbol{X}_{ff,1}\overline{\boldsymbol{d}}_k^{(f1)} + 2\boldsymbol{X}_{fb,1}\boldsymbol{d}_{(m)}^{(b1)} = 0, \tag{37}$$

the filter coefficient error which minimizes $E(e_k^2)$ is determined as

$$\boldsymbol{d}_{(m+1)}^{(f1)} = \boldsymbol{Q}_{f1}\boldsymbol{d}_{(m)}^{(b1)}, \tag{38}$$

$$\text{where } \boldsymbol{Q}_{f1} := -\boldsymbol{X}_{ff,1}^{-1}\boldsymbol{X}_{fb,1}. \tag{39}$$

By similar procedure, the misalignment of each subfilter converges as

$$\boldsymbol{d}_{(4m+2)}^{(b1)} = \boldsymbol{Q}_{b1}\boldsymbol{d}_{(4m+1)}^{(f1)} \tag{40}$$

$$\boldsymbol{d}_{(4m+3)}^{(f2)} = \boldsymbol{Q}_{f2}\boldsymbol{d}_{(4m+2)}^{(b2)} \tag{41}$$

$$\boldsymbol{d}_{(4m+4)}^{(b2)} = \boldsymbol{Q}_{b2}\boldsymbol{d}_{(4m+3)}^{(f2)} \tag{42}$$

where

$$\boldsymbol{x}_{k,i}^{(f2)} := \left[x_k^{(i)}, x_{k-1}^{(i)}, \cdots, x_{k-I_1+1}^{(i)}\right]^T \in \mathbb{R}^{I_2}, \tag{43}$$

$$\boldsymbol{x}_{k,i}^{(b2)} := \left[x_{k-I_1}^{(i)}, x_{k-I_2-1}^{(i)}, \cdots, x_{k-L+1}^{(i)}\right]^T \in \mathbb{R}^{L-I_2}, \tag{44}$$

$$\boldsymbol{w}_{k,i}^{(f2)} := \left[w_0^{(i)}, w_1^{(i)}, \cdots, w_{I_1-1}^{(i)}\right]^T \in \mathbb{R}^{I_2}, \tag{45}$$

$$\boldsymbol{w}_{k,i}^{(b2)} := \left[w_{I_2}^{(i)}, w_{I_2+1}^{(i)}, \cdots, w_{L-1}^{(i)}\right]^T \in \mathbb{R}^{L-I_2}, \tag{46}$$

$$\boldsymbol{h}_{(i)}^{(f2)} := \left[h_0^{(i)}, h_1^{(i)}, \cdots, h_{I_2-1}^{(i)}\right]^T \in \mathbb{R}^{I_2}, \tag{47}$$

$$\boldsymbol{h}_{(i)}^{(b2)} := \left[h_{I_2}^{(i)}, h_{I_2+1}^{(i)}, \cdots, h_{L-1}^{(i)}\right]^T \in \mathbb{R}^{L-I_2}, \tag{48}$$

$$i = 1, 2, \tag{49}$$

$$\boldsymbol{x}_k^{(p)} := \left[\boldsymbol{x}_{k,1}^{(p)T} \boldsymbol{x}_{k,2}^{(p)T}\right]^T, \tag{50}$$

$$\boldsymbol{w}_k^{(p)} := \left[\boldsymbol{w}_{k,1}^{(p)T} \boldsymbol{w}_{k,2}^{(p)T}\right]^T, \tag{51}$$

$$\boldsymbol{h}^{(p)} := \left[\boldsymbol{h}_{(1)}^{(p)T} \boldsymbol{h}_{(2)}^{(p)T}\right]^T, \tag{52}$$

$$p = f2, b2, \tag{53}$$

$$\boldsymbol{d}_k^{(f2)} := \boldsymbol{h}^{(f2)} - \boldsymbol{w}_k^{(f2)} \in \mathbb{R}^{2I_2}, \tag{54}$$

$$\boldsymbol{d}_k^{(b2)} := \boldsymbol{h}^{(b2)} - \boldsymbol{w}_k^{(b2)} \in \mathbb{R}^{2(L-I_2)}, \tag{55}$$

$$\boldsymbol{X}_{ff,2} := \overline{\boldsymbol{x}_k^{(f2)}\boldsymbol{x}_k^{(f2)T}} \in \mathbb{R}^{2I_2\times 2I_2}, \tag{56}$$

$$\boldsymbol{X}_{fb,2} := \overline{\boldsymbol{x}_k^{(f2)}\boldsymbol{x}_k^{(b2)T}} \in \mathbb{R}^{2I_2\times 2(L-I_2)}, \tag{57}$$

$$\boldsymbol{X}_{bb,2} := \overline{\boldsymbol{x}_k^{(b2)}\boldsymbol{x}_k^{(b2)T}} \in \mathbb{R}^{2(L-I_2)\times 2(L-I_2)}, \tag{58}$$

$$\boldsymbol{Q}_{b1} := -\boldsymbol{X}_{bb,1}^{-1}\boldsymbol{X}_{fb,1}^T, \tag{59}$$

$$\boldsymbol{Q}_{f2} := -\boldsymbol{X}_{ff,2}^{-1}\boldsymbol{X}_{fb,2}, \tag{60}$$

$$\boldsymbol{Q}_{b2} := -\boldsymbol{X}_{bb,2}^{-1}\boldsymbol{X}_{fb,2}^T. \tag{61}$$

From (38), (40), (41), (42), with

$$\boldsymbol{P}_{f1} := \begin{bmatrix} \boldsymbol{E}_{I_1\times I_1} & \boldsymbol{O}_{I_1\times L-I_1} & \boldsymbol{O}_{I_1\times I_1} & \boldsymbol{O}_{I_1\times L-I_1} \\ \boldsymbol{O}_{I_1\times I_1} & \boldsymbol{O}_{I_1\times L-I_1} & \boldsymbol{E}_{I_1\times I_1} & \boldsymbol{O}_{I_1\times L-I_1} \end{bmatrix}, \tag{62}$$

$$\boldsymbol{P}_{b1} := \begin{bmatrix} \boldsymbol{O}_{L-I_1\times I_1} & \boldsymbol{E}_{L-I_1\times L-I_1} & \boldsymbol{O}_{L-I_1\times I_1} & \boldsymbol{O}_{L-I_1\times L-I_1} \\ \boldsymbol{O}_{L-I_1\times I_1} & \boldsymbol{O}_{L-I_1\times L-I_1} & \boldsymbol{O}_{L-I_1\times I_1} & \boldsymbol{E}_{L-I_1\times L-I_1} \end{bmatrix}, \tag{63}$$

$$\boldsymbol{P}_{f2} := \begin{bmatrix} \boldsymbol{E}_{I_2\times I_2} & \boldsymbol{O}_{I_2\times L-I_2} & \boldsymbol{O}_{I_2\times I_2} & \boldsymbol{O}_{I_2\times L-I_2} \\ \boldsymbol{O}_{I_2\times I_2} & \boldsymbol{O}_{I_2\times L-I_2} & \boldsymbol{E}_{I_2\times I_2} & \boldsymbol{O}_{I_2\times L-I_2} \end{bmatrix}, \tag{64}$$

$$\boldsymbol{P}_{b2} := \begin{bmatrix} \boldsymbol{O}_{L-I_2\times I_2} & \boldsymbol{E}_{L-I_2\times L-I_2} & \boldsymbol{O}_{L-I_2\times I_2} & \boldsymbol{O}_{L-I_2\times L-I_2} \\ \boldsymbol{O}_{L-I_2\times I_2} & \boldsymbol{O}_{L-I_2\times L-I_2} & \boldsymbol{O}_{L-I_2\times I_2} & \boldsymbol{E}_{L-I_2\times L-I_2} \end{bmatrix}, \tag{65}$$

where $\boldsymbol{E}_{x\times x}$ represents $x \times x$ identity matrix and $\boldsymbol{O}_{x\times y}$ represents $x \times y$ zero matrix, we can rewrite the misalignment of adaptive filter $\boldsymbol{d}_k := \boldsymbol{h} - \boldsymbol{w}_k \in \mathbb{R}^{2L}$ as

$$\boldsymbol{d}_{(4m+1)} = \left(\boldsymbol{P}_{f1}^T\boldsymbol{Q}_{f1}\boldsymbol{P}_{b1} + \boldsymbol{P}_{b1}^T\boldsymbol{P}_{b1}\right)\boldsymbol{d}_{(4m)}, \tag{66}$$

$$\boldsymbol{d}_{(4m+2)} = \left(\boldsymbol{P}_{f1}^T\boldsymbol{P}_{f1} + \boldsymbol{P}_{b1}^T\boldsymbol{Q}_{b1}\boldsymbol{P}_{f1}\right)\boldsymbol{d}_{(4m+1)}, \tag{67}$$

$$\boldsymbol{d}_{(4m+3)} = \left(\boldsymbol{P}_{f2}^T\boldsymbol{Q}_{f2}\boldsymbol{P}_{b2} + \boldsymbol{P}_{b2}^T\boldsymbol{P}_{b2}\right)\boldsymbol{d}_{(4m+2)}, \tag{68}$$

$$\boldsymbol{d}_{(4m+4)} = \left(\boldsymbol{P}_{f2}^T\boldsymbol{P}_{f2} + \boldsymbol{P}_{b2}^T\boldsymbol{Q}_{b2}\boldsymbol{P}_{f2}\right)\boldsymbol{d}_{(4m+3)}. \tag{69}$$

Thus, $\boldsymbol{d}_k$ converges as

$$\boldsymbol{d}_{(4m+1)} = \boldsymbol{S}_{f1}\boldsymbol{C}^m\boldsymbol{d}_{(0)}, \tag{70}$$

$$\boldsymbol{d}_{(4m+2)} = \boldsymbol{S}_{b1}\boldsymbol{S}_{f1}\boldsymbol{C}^m\boldsymbol{d}_{(0)}, \tag{71}$$

$$\boldsymbol{d}_{(4m+3)} = \boldsymbol{S}_{f2}\boldsymbol{S}_{b1}\boldsymbol{S}_{f1}\boldsymbol{C}^m\boldsymbol{d}_{(0)}, \tag{72}$$

$$\boldsymbol{d}_{(4m+4)} = \boldsymbol{C}^{m+1}\boldsymbol{d}_{(0)}, \tag{73}$$

where,

$$\boldsymbol{S}_{f1} := \left(\boldsymbol{P}_{f1}^T\boldsymbol{Q}_{f1}\boldsymbol{P}_{b1} + \boldsymbol{P}_{b1}^T\boldsymbol{P}_{b1}\right), \tag{74}$$

$$\boldsymbol{S}_{b1} := \left(\boldsymbol{P}_{f1}^T\boldsymbol{P}_{f1} + \boldsymbol{P}_{b1}^T\boldsymbol{Q}_{b1}\boldsymbol{P}_{f1}\right), \tag{75}$$

$$\boldsymbol{S}_{f2} := \left(\boldsymbol{P}_{f2}^T\boldsymbol{Q}_{f2}\boldsymbol{P}_{b2} + \boldsymbol{P}_{b2}^T\boldsymbol{P}_{b2}\right), \tag{76}$$

$$\boldsymbol{S}_{b2} := \left(\boldsymbol{P}_{f2}^T\boldsymbol{P}_{f2} + \boldsymbol{P}_{b2}^T\boldsymbol{Q}_{b2}\boldsymbol{P}_{f2}\right), \tag{77}$$

$$\boldsymbol{C} := \boldsymbol{S}_{b2}\boldsymbol{S}_{f2}\boldsymbol{S}_{b1}\boldsymbol{S}_{f1}. \tag{78}$$

If the maximum absolute eigenvalue of $\boldsymbol{C}$ is less than 1, the misalignment of filter converges at zero, thus, the filter coefficients converge at the optimum value.

5. Numerical Examples

This section presents numerical comparisons among the proposed two-filter scheme which utilizes the proposed filter divide scheme as the guideline and the conventional schemes.

The tests were performed, for estimating $\boldsymbol{h} \in \mathbb{R}^{4096}, (M = L = 2048)$, under the noise situation of SNR $:= 10\log_{10}\left(E\{z_k^2\}/E\{n_k^2\}\right) = 30\,\text{dB}$, where $z_k := \boldsymbol{x}_k^T\boldsymbol{h}$. We utilize a female's speech signal, for $(s_k)_{k\in\mathbb{N}}$, which was sampled at 11.025 kHz.

To measure the achievement level for echo path identification as well as that of echo cancellation, we evaluated the following quantities:

$$\text{System Mismatch}(k) := 10\log_{10}\frac{\|\boldsymbol{h}-\boldsymbol{w}_k\|^2}{\|\boldsymbol{h}\|}, \tag{79}$$

$$\text{ERLE}(k) := 10\log_{10}\frac{\sum_{i=1}^{k}(z_i)^2}{\sum_{i=1}^{k}(z_i-\boldsymbol{x}_i^T\boldsymbol{w}_i)^2}, \tag{80}$$

In all schemes, NLMS is utilized as the adaptation algorithm. For NLMS and the main filter of the proposed two-filter scheme, the step size is set to $\mu_k = 0.2$, $\forall k \in \mathbb{N}$. For the conventional and the proposed filter divide schemes, the maximum step size is set to $\mu_{max} = 0.06$; these schemes utilize adaptive step sizes (see [8]). For filter dividing, we set $K = 2$, thus, a filter coefficient vector is divided into two sub-filters. The dividing points for even-energy filter divide scheme are $I_1^{(1)} = 165$, $I_1^{(2)} = 715$. For the copying process in the two-filter scheme, the forgetting factors α (for ξ_k) and β (for ψ_k) are set to 0.999 and 0.9983, respectively. The threshold for copying process η is set to -0.03.

5.1 Fixed Impulse Responses

First, we examine the performance of NLMS and two kinds of the two-filter scheme; one utilizes the proposed filter divide scheme as the guideline, and the other utilizes the conventional filter divide scheme [8] as the guideline. Simulation results are shown in Fig. 6, which compares system mismatch and ERLE.

It is observed that the proposed filter divide scheme achieves much accurate estimation than the NLMS and the conventional filter divide scheme in system mismatch, thus, the two-filter scheme which uses the proposed filter divide scheme shows better estimate performance than the other schemes. In ERLE, although both the filter divide schemes show poor performance, the proposed two-filter schemes show high level of performance equal to NLMS, in other words, introduction of *the guideline* can achieve good echo path estimate keeping the level of echo erasing performance equal to that of NLMS. From the viewpoint of convergence speed, the proposed two-filter scheme which utilizes the proposed filter divide scheme as the guideline achieves about six times as fast convergence as NLMS (in terms of the time when these schemes arrive at 4 dB in system mismatch). The number of multiplications in the proposed scheme is $3L+3I+3$, where L and I represent lengths of the adaptive filter and of the divided sub-filter, while the number of multiplications in NLMS is $2L + 1$. Assuming that $I = L/2$, the number of multiplications in the proposed scheme is $\frac{9}{2}L+3$, which is around twice as large as in NLMS. But, in other words, complexity of the proposed scheme is kept $O(L)$.

5.2 Time-Varying Impulse Responses of Receiving Room

Next, to inspect tracking performance of the proposed scheme for the echo path variation, and to confirm the effectiveness of the copying process in the two-filter scheme, we examine the performance of NLMS and four kinds of the two-filter scheme, which (i) utilize the proposed *or* the conventional filter divide scheme as the guideline, (ii) with *or* without copying process, thus, $2 \times 2 = 4$ kinds of the two filter scheme. The test was performed under the condition where the impulse responses of Receiving room (*estimudam*) are varied at iteration number 400,000.

One simulation result is shown in Fig. 7, which is the difference of the two kinds of smoothed residual echo of

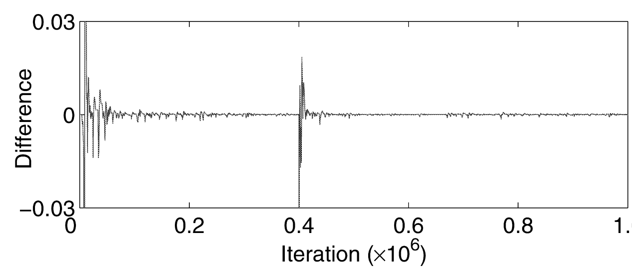

Fig. 7 Difference of two kinds of the smoothed residual echo of the main filter whose guideline is the proposed filter divide scheme.

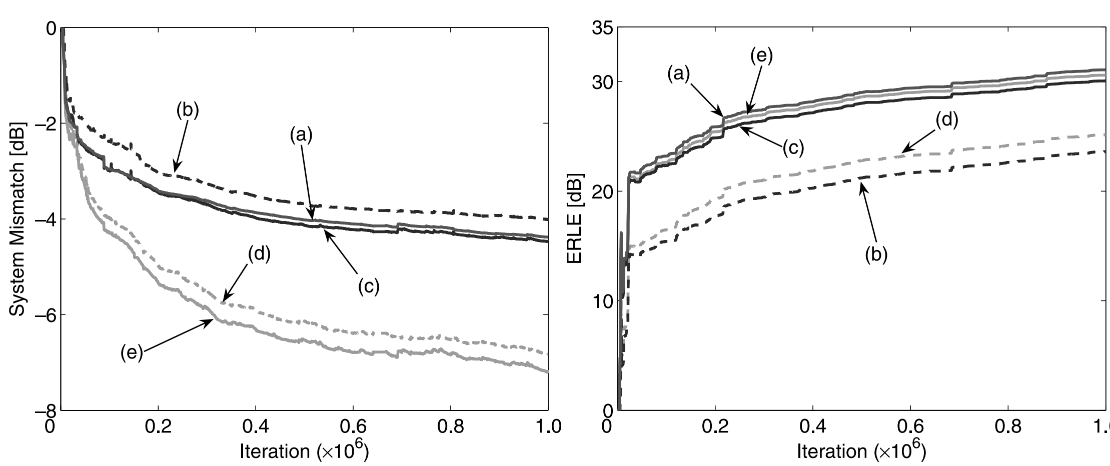

Fig. 6 Simulation results under SNR 30 dB. (a) NLMS, (b) conventional filter divide scheme, (c) proposed two-filter scheme utilizing (b) as the guideline, (d) proposed filter divide scheme, (e) proposed two-filter scheme utilizing (d) as the guideline.

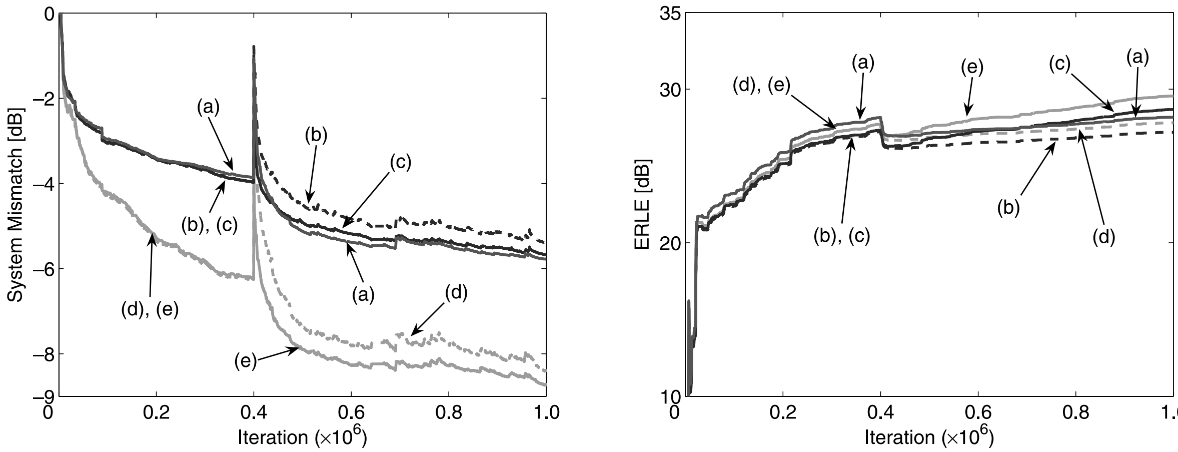

Fig. 8 Simulation results under the condition where the impulse responses of Receiving room are changed at the iteration number 400,000. (a) NLMS, (b) two-filter scheme utilizing the conventional filter divide scheme as the guideline without copying process, (c) two-filter scheme utilizing the conventional filter divide scheme as the guideline with copying processing, (d) two-filter scheme utilizing the proposed filter divide scheme as the guideline without copying process, (e) two-filter scheme utilizing the proposed filter divide scheme as the guideline with copying process (see Table 1).

Table 1 Symbols in Fig. 8

	Guideline	
	Conventional	Proposed
Without copy	(b)	(d)
With copy	(c)	(e)

the main filter whose guideline is the proposed filter divide scheme, i.e., $\xi_k - \psi_k$ (cf. (5), (6)). We see the two points, where the difference falls below the threshold η which is set to -0.03, at iteration number around 7,000 and 400,000. Also in the two-filter scheme which utilizes the conventional filter divide scheme as the guideline, the difference of the two kinds of smoothed residual echo shows similar behavior to Fig. 7, i.e., the same two points are detected as the point when the impulse responses are varied. The former detected point (i.e., iteration number around 7,000) is the start of convergence, and the latter (iteration number around 400,000) is the variation of the impulse responses. Since, at iteration number 0, both the main filter and the guideline filter are initialized zero vector, the copying at the former point hardly has effect on the convergence performance, but, at the latter point, the copying process may improve the estimate performance. Such improvements are shown in the other simulation results, which compare system mismatch and ERLE (see Fig. 8).

In system mismatch, we see that the two-filter scheme which utilizes the proposed filter divide scheme as the guideline achieves much better tracking of the impulse response variation than the other schemes, and we also see that the copying process somewhat improves the tracking performance of the impulse response variation, in the viewpoint both of accuracy and speed. Although, in this simulation, we could not say that the copying process has great effect on the estimate performance, it is possible that the change of impulse responses bring fell condition where the estimate performance of the two filter scheme become awful. In such a case, the copying process would achieve great effect. And, in ERLE, we see that the copying process has a some good effect on the two-filter schemes, as in system mismatch.

6. Conclusion

This paper has presented an efficient stereophonic acoustic echo canceling scheme without preprocessing. The proposed scheme utilizes two filters, of which one filter is updated by the devised scheme which aims at the point near to the optimum solution, and this filter is utilized as a guideline to improve the convergence performance of the other filter, the main filter. To improve the performance of the filter divide scheme, we have also proposed an efficient filter dividing technique based on a characteristic features of room impulse response. The proposed scheme which utilizes the proposed efficient filter divide scheme as the guideline shows good performance both in system mismatch and ERLE.

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