Generalized Robust Multichannel Frequency-Domain LMS Algorithms for Blind Channel Identification

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Recently, several noise-robust adaptive multichannel LMS algorithms have been proposed based on the spectral flatness of the estimated channel coefficients in the presence of additive noise. In this work, we propose a general form for the algorithms that integrates the existing algorithms into a common framework. Computer simulation results are presented and demonstrate that a new proposed algorithm gives better performance compared to existing algorithms in noisy environments.

Keywords: Adaptive multichannel least-mean-square (LMS) algorithm, blind channel identification (BCI), noise robust.

I. Introduction

Blind channel identification has received a great deal of attention in various fields of science and engineering. A number of single and multichannel identification algorithms have been proposed in recent years. The inherent diversity of multichannel systems gives many advantages, which has led to multichannel identification schemes increasingly being preferred over their single channel counterparts.

Huang and Benesty proposed both the adaptive multichannel LMS (MCLMS) algorithm [1] and the adaptive multichannel frequency-domain LMS (MCFLMS) algorithm [2]. Since then, many variants have been proposed. The main drawback of Huang's algorithms is that they lack robustness to additive noise. Even under moderate noise conditions, the algorithms often do not converge. Several algorithms claiming robustness have been proposed. Some of them, however, require specific information on the acoustic impulse responses, such as the positions and amplitudes of direct path coefficients [3], and others show partial robustness [4]. Recently, Haque and Hasan proposed noise robust algorithms based on the spectral flatness of the estimated channel coefficients and showed through computer simulations that these algorithms converged for relatively high noise levels [5]-[7]. To the best of our knowledge, their algorithms are the only algorithms that converge under noisy environments without specific information.

In this letter, we propose a more general form for the update equations which gives better performance under the various environments.

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II. Robust MCFLMS Algorithms

In this section, we briefly present Haque's robust MCFLMS algorithms. We consider an M-channel system whose impulse responses are $\mathbf{h}_k = \left[h_{k,0}\ h_{k,1}\ \dots\ h_{k,L-1} \right]^T$, where k is the channel index, L is the length of the impulse responses, and ^{T} denotes transpose. To find an estimate $\hat{\mathbf{h}} = \left[\hat{\mathbf{h}}_1{}^T\ \hat{\mathbf{h}}_2{}^T \dots \hat{\mathbf{h}}_M{}^T \right]^T$ of the true channel impulse responses by solely using noise-corrupted observations $x_k(n),\ k = 1, 2, \dots, M$, that is, the signal received at the k-th sensor, we first define a cost function in the frequency domain, $J(m)$, as

$$J(m) = \sum_{i=1}^{M-1} \sum_{j=i+1}^{M} \underline{\mathbf{e}}_{i,j}^H(m)\underline{\mathbf{e}}_{i,j}(m), \tag{1}$$

where H denotes Hermitian transpose, $\underline{\mathbf{e}}_{i,j}(m)$ is the frequency-domain block error signal between the i-th and j-th channels, and m is the frame index. The update equation of the normalized MCFLMS (NMCFLMS) algorithm can be expressed as [2]

$$\underline{\hat{\mathbf{h}}}_k^{10}(m+1)=\underline{\hat{\mathbf{h}}}_k^{10}(m)-\rho\mathbf{P}_k^{-1}(m)\nabla_k^{10}J(m),\ \ k=1,2,\ldots,M,\quad(2)$$

where ρ is the step size for the update algorithm and $\underline{\hat{\mathbf{h}}}_k^{10}(m)=\mathbf{F}_{2L\times 2L}\left[\hat{\mathbf{h}}_k^T(m)\quad \mathbf{0}_{1\times L}\right]^T$, where $\mathbf{F}$ denotes the DFT matrix. $\mathbf{P}_k(m)=\sum_{i=1,i\neq k}^{M}\mathbf{D}_{x_i}^*(m)\mathbf{D}_{x_i}(m)$, where $*$ denotes the complex conjugate, $\mathbf{D}_{x_i}(m)=\mathrm{diag}(\mathbf{F}\{\mathbf{x}_i(m)\})$, and $\mathbf{x}_i(m)=[x_i(mL-L)\ x_i(mL-L+1)\ldots x_i(mL+L-1)]^T$. In (2), the unconstrained gradient vector $\nabla_k^{10}J(m)$ can be expressed as

$$\nabla_k^{10}J(m)=\sum_{i=1}^{M}\mathbf{D}_{x_i}^*(m)\mathbf{F}_{2L\times 2L}\left[\mathbf{0}_{L\times L}\quad \mathbf{I}_{L\times L}\right]^T\mathbf{F}_{L\times L}^{-1}\underline{\mathbf{e}}_{ik}(m).\quad(3)$$

Using stacked vectors, (2) can be rewritten as [2]

$$\underline{\hat{\mathbf{h}}}^{10}(m+1)=\underline{\hat{\mathbf{h}}}^{10}(m)-\rho\mathbf{P}^{-1}(m)\nabla^{10}J(m),\quad(4)$$

where $\mathbf{P}(m)$ is a diagonal matrix with diagonal terms of $\mathbf{P}_k(m)$ in sequential order.

To cope with the NMCFLMS algorithm's lack of robustness to additive noise, Haque and Hasan proposed robust MCFLMS algorithms based on the fact that the Fourier domain energy of a channel impulse response is approximately uniformly distributed. First, they introduced an excitation function to the update equation to ensure robustness of the NMCFLMS algorithm as [5]

$$\underline{\hat{\mathbf{h}}}^{10}(m+1)=\underline{\hat{\mathbf{h}}}^{10}(m)-\rho\mathbf{P}^{-1}(m)\nabla^{10}J(m)+\rho\beta_1(m)\underline{\tilde{\mathbf{h}}}^{10}(m),\quad(5)$$

$$\beta_1(m)=\eta_1\left|\frac{\left\{\underline{\tilde{\mathbf{h}}}^{10}(m)\right\}^H\mathbf{P}^{-1}(m)\nabla^{10}J(m)}{\left\|\underline{\tilde{\mathbf{h}}}^{10}(m)\right\|^2}\right|,\quad(6)$$

where $\underline{\tilde{\mathbf{h}}}^{10}(m)$ is the excitation function in the frequency domain and $\|\ \|$ is the l_2 norm. Haque and Hasan showed that the update equation converges, provided that $\underline{\tilde{\mathbf{h}}}^{10}(m)$ resembles the true channel coefficients [5]. Since the true channel coefficients have a reasonably flat wide-band spectrum, they estimated the excitation function as

$$\begin{aligned}&\left|\underline{\tilde{h}}_{k,j}^{10}(m)\right|=1,\quad \angle\underline{\tilde{h}}_{k,j}^{10}(m)=\angle\underline{\hat{h}}_{k,j}^{10}(m),\\&k=1,2,\ldots,M,\quad j=0,1,\ldots,2L-1.\end{aligned}\quad(7)$$

We will refer to (5) to (7) as the RNMCFLMS-I algorithm.

Second, Haque and Hasan proposed another robust algorithm where a penalty function that ensures spectral flatness was introduced. The final update equation is given by [6]

$$\underline{\hat{\mathbf{h}}}^{10}(m+1)=\underline{\hat{\mathbf{h}}}^{10}(m)-\rho\mathbf{P}^{-1}(m)\nabla^{10}J(m)+\rho\beta_2(m)\nabla\tilde{J}_p(m),\quad(8)$$

$$\nabla\tilde{J}_p(m)=\mathbf{Q}_2(m)\underline{\hat{\mathbf{h}}}^{10}(m),\quad(9)$$

$$\beta_2(m)=\eta_2\left|\frac{\left\{\nabla\tilde{J}_p(m)\right\}^H\mathbf{P}^{-1}(m)\nabla^{10}J(m)}{\left\|\nabla\tilde{J}_p(m)\right\|^2}\right|,\quad(10)$$

where $\mathbf{Q}_2(m)$ is a ($2ML\times 2ML$) diagonal matrix whose diagonal elements are

$$\frac{2}{\left|\underline{\hat{h}}_{k,j}(m)\right|^2},\quad k=1,2,\ldots,M,\ \ j=0,1,\ldots,2L-1.\quad(11)$$

We will refer to (8) to (11) as the RNMCFLMS-II algorithm.

Meanwhile, in the original RNMCFLMS-I and RNMCFLMS-II algorithms, the coupling factors $\beta_1(m)$ and $\beta_2(m)$ do not include the proportional constant parameters, η_1 and η_2, respectively, that is, η_1 and η_2 are fixed to 1. However, in [8], the authors implied the necessity of the proportional constant parameters by defining the coupling factor as

$$\beta(m)=\eta\,\mathrm{Re}\left\{\frac{\left\{\nabla\tilde{J}_p(m)\right\}^H\mathbf{P}^{-1}(m)\nabla^{10}J(m)}{\left\|\nabla\tilde{J}_p(m)\right\|^2}\right\},\quad(12)$$

where they used Re{ }, which denotes the real part, instead of | |. However, they did not mention its role or effect on convergence, nor did they suggest its proper values. Our experiment revealed that the coupling factors affected convergence behavior significantly; therefore, they should be properly determined. We can say empirically that these values can be set to 1 for random source signals except for η_2 under high SNR, which shows poor performance, and should be greater than 1 for speech or colored source signals.

III. Generalized Robust MCFLMS Algorithms

Since the RNMCFLMS-I and the RNMCFLMS-II algorithms were derived from different starting points—one from the introduction of the excitation function and the other from the minimization of the penalty function—these two algorithms look ostensibly different. (See (7), (9) and (11).) However, it can be shown that the two algorithms can be integrated into a general form. Equation (7) is equivalent to

$$\underline{\tilde{h}}_{k,j}^{10}(m)=\frac{\underline{\hat{h}}_{k,j}^{10}(m)}{\left|\underline{\hat{h}}_{k,j}^{10}(m)\right|},\quad k=1,2,\ldots,M,\ \ j=0,1,\ldots,2L-1.\ (13)$$

Expressing this in the form of (9), we obtain

$$\underline{\tilde{\mathbf{h}}}^{10}(m)=\mathbf{Q}_1(m)\underline{\hat{\mathbf{h}}}^{10}(m),\quad(14)$$

where $\mathbf{Q}_1(m)$ is a ($2ML\times 2ML$) diagonal matrix whose diagonal elements are

$$\frac{1}{\left|\hat{h}_{k,j}(m)\right|},\quad k=1,2,\ldots,M,\ j=0,1,\ldots,2L-1. \tag{15}$$

With some manipulation over the terms inside the absolute operations in $\beta_1(m)$ and $\beta_2(m)$, and using (11) and (15), we can integrate the two algorithms into one general update equation as

$$\underline{\hat{\mathbf{h}}}^{10}(m+1)=\underline{\hat{\mathbf{h}}}^{10}(m)-\rho\mathbf{P}^{-1}(m)\nabla^{10}J(m)+\rho\beta(m)\underline{\tilde{\mathbf{h}}}_{\gamma}^{10}(m), \tag{16}$$

$$\underline{\tilde{\mathbf{h}}}_{\gamma}^{10}(m)=\mathbf{Q}(m)\underline{\hat{\mathbf{h}}}^{10}(m), \tag{17}$$

$$\beta(m)=\eta\left|\frac{\left\{\underline{\tilde{\mathbf{h}}}_{\gamma}^{10}(m)\right\}^{H}\mathbf{P}^{-1}(m)\nabla^{10}J(m)}{\left\|\underline{\tilde{\mathbf{h}}}_{\gamma}^{10}(m)\right\|^{2}}\right|, \tag{18}$$

where $\mathbf{Q}(m)$ is a $(2L\times 2L)$ diagonal matrix whose diagonal elements are

$$\frac{1}{\left|\hat{h}_{k,j}(m)\right|^{\gamma}},\quad k=1,2,\ldots,M,\ j=0,1,\ldots,2L-1. \tag{19}$$

If $\gamma=1$ and $\eta=\eta_1$, the above equations reduce to the RNMCFLMS-I algorithm, and if $\gamma=2$ and $\eta=\eta_2$, they reduce to the RNMCFLMS-II algorithm. From the viewpoint of the excitation function, the estimated excitation function must resemble the true channel coefficients. In (7), the spectra of the true channel coefficients are assumed to be perfectly flat. However, since the spectra of the true channel coefficients are not completely flat, some modification is needed. One observation is that the proposed algorithm gives flexibility for controlling the shape of the spectrum through the parameter γ. However, when the parameter γ is not an integer, the computational complexity of the algorithm is increased due to an exponential operation. We will refer to the proposed algorithm as GRNMCFLMS and show through computer simulation that this modification improves performance in section IV.

IV. Simulations Results

In this section, we demonstrate the performance of the proposed algorithm by carrying out computer simulations using acoustic multichannel systems, and also compare the performance of the proposed GRNMCFLMS algorithm with the RNMCFLMS algorithms. For consistent comparisons, we used the same experimental setup as reported in previous work [6]. The dimensions of the room were chosen to be (5 m× 4 m×3 m). A linear array consisting of M=5 microphones with uniform separation of d=0.2 m along the y-axis was used in the simulation. The first microphone and source were placed at (1.0 m, 1.5 m, 1.6 m) and (2.0 m, 1.2 m, 1.6 m), respectively.

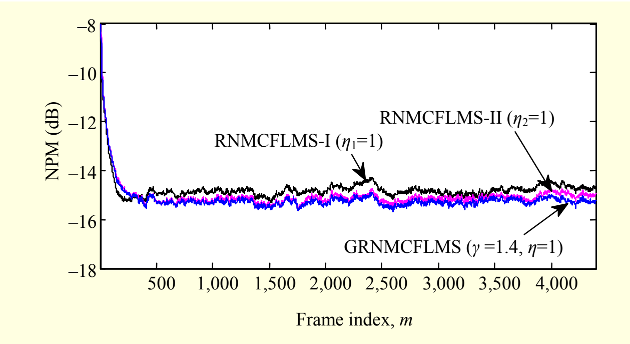

Fig. 1. Comparison of convergence behaviors of GRNMCFLMS and RNMCFLMS algorithms for M=5 channels, L=512, and T_{60}=0.1 s acoustic channel coefficients with white Gaussian input at SNR=10 dB.

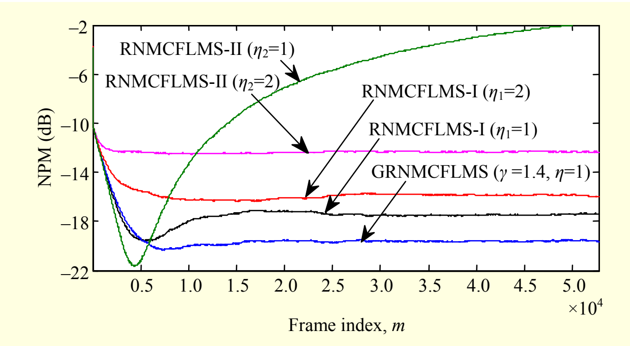

Fig. 2. Comparison of convergence behaviors of GRNMCFLMS and RNMCFLMS algorithms for M=5 channels, L=512, and T_{60}=0.1 s acoustic channel coefficients with white Gaussian input at SNR=25 dB.

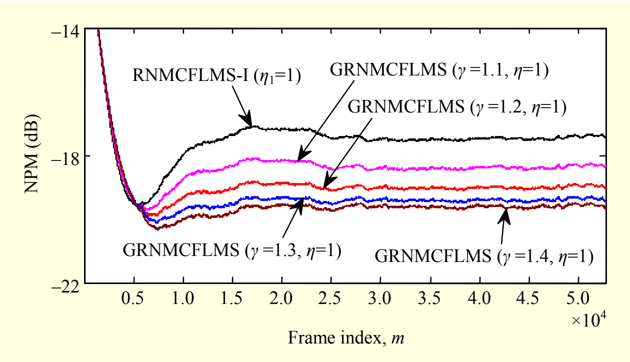

Fig. 3. Effect of variation in γ on convergence of GRNMCFLMS algorithm for M=5 channels, L=512, and T_{60}=0.1 s acoustic channel coefficients with white Gaussian input at SNR=25 dB.

All of the impulse responses were generated using the well-known image method with reverberation times T_{60}=0.1 s for a white Gaussian source, and T_{60}=0.55 s for a speech source. The length of each channel impulse response is 512 for a white Gaussian source and 4,400 for a speech source. The sampling

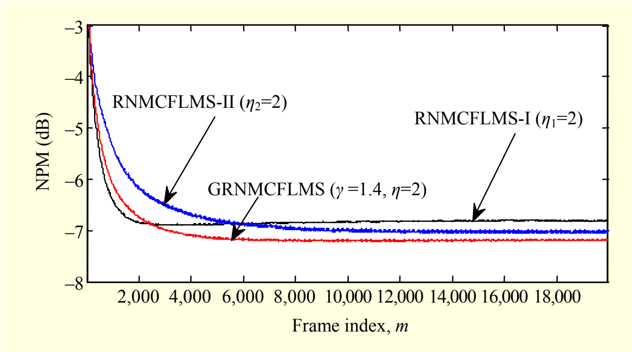

Fig. 4. Comparison of convergence behaviors of GRNMCFLMS and RNMCFLMS algorithms for M=5 channels, L=4,400, and T_{60}=0.55 s acoustic channel coefficients with speech input at SNR=25 dB.

frequency was 8 kHz. In all cases, the step size ρ was fixed at 0.5. Figures 1 and 2 show the simulation results for the white Gaussian source at SNR=10 and SNR=25, respectively. Normalized projection misalignment (NPM) [9] was used as a performance metric. These figures indicate that the GRNMCFLMS algorithm outperforms both RNMCFLMS algorithms, though the improvement is not significant at low SNR. In this simulation, parameter γ was found to be suitable at 1.4. Figure 3 shows the performance improvement of the GRNMCFLMS algorithm for various values of γ. With values of γ greater than 1.4, the performance no longer improved and, in fact, deteriorated as the value approached 2, which showed the same performance as that of the RNMCFLMS-II at γ=2. Figure 4 shows the performance comparison of the GRNMCFLMS algorithm with the RNMCFLMS algorithms for speech source signals. It can be also seen that the GRNMCFLMS algorithms shows best performance over the other algorithms at γ=1.4. Through simulations under various experimental settings, we determined that values of γ=1.3 to 1.5 were suitable for random signals at both low and high SNRs, and speech or colored signals at relatively high SNR. Smaller values of γ=1.0 to 1.2 were suitable for speech or colored signals at low SNR.

V. Conclusion

In this work, we proposed a generalized robust multichannel frequency domain algorithm integrating the existing algorithms. The flexibility of the proposed method obtained by generalization leads to performance improvement over these existing algorithms. We carried out comparisons of the proposed algorithm with other robust algorithms for acoustic multichannel. It was shown that the proposed algorithm presents good convergence characteristics for both random source signals and speech source signals under the various noise conditions.

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