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An Improved Subband Adaptive Filter for Acoustic Echo Cancellation Application

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Abstract

Subband adaptive filters (SAFs) play an important role in digital signal processing field. We propose an improved subband adaptive filter which can be used to remove echo in telephone communication. The presented structure is based on polyphase decomposition of the filter to be integrated with Kalman filtering strategy. Compared to the Normalized Subband adaptive filter(NSAF) algorithm, the novel algorithm exhibits faster convergence when Kalman filtering algorithm is utilized for coefficient updating. Furthermore, with an increased number of subbands in the filter, the convergence rate improves considerably. The efficacy of the proposed algorithm is examined and validated by mathematical analysis and simulation.

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Keyword: adaptive filter; subband updates; convergence; Acoustic echo cancellation

1. Introduction

One problem encountered in telephone communication is the acoustic echo cancellation, which is produced when the signal passes through telephone channels. Removal of this echo requires accurate mathematic model of the channel. One scheme is adaptive estimation of the channel model where the impulse response involved is long.

In various adaptive filtering algorithms, the least mean square (LMS) algorithm of Widrow et al. [1]

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has been used widely in such applications. However, it suffers from slow convergence when the input signal to the adaptive filter is correlated. Adaptive filtering in subbands has been proposed to improve the convergence behavior of the LMS algorithm [2-7].In subband adaptive filters, the input signal and desired response are band-partitioned into almost mutually exclusive subband signals. This feature of the SAF permits the manipulation of each subband signal, and allows each subband to converge almost separately for various modes, and thus improving the overall convergence behavior.

Now, the adaptations are carried out in each subband, and updating method is adopted by the normalized LMS algorithm[3]. In our presentation, we consider the Kalman filtering as a novel updating algorithm in each subband in order to improve convergence of adaptive filter further.

This paper is organized as follows. Section II reviews the normalized subband adaptive filter, and proposes the improved subband adaptive filtering algorithm. In sections III, We illustrate our method by simulation. Finally, conclusion is derived in section V.

2. Improved subband adaptive filter

2.1. Normalized subband adaptive filter

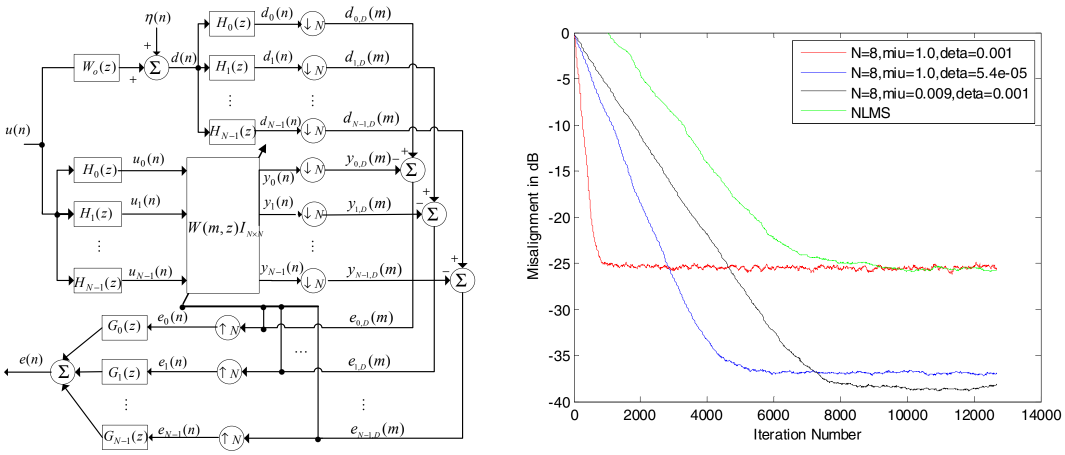


Fig. 1. (a) Structure of NSAF (b) Normalized misalignment learning curves for NSAF

In the structure of normalized subband adaptive filter[4], the input signal $u(n)$ and the desired response $d(n)$ are partitioned into N subbands by means of analysis filters $H_0(z), \ldots, H_{N-1}(z)$. Each subband signal occupies a part of the original frequency band. Hence, the outputs of the diagonalized N-input N-output system $W(m,z)I_{N\times N}$ are essentially the responses of the transversal filter

$$W(m,z)=\sum_{k=0}^{M-1} w_n(m)z^{-k} \tag{1}$$

The time-varying feature of $W(m,z)$ is emphasized by the moment m. Note that $W(m,z)I_{N\times N}$ is basically a bank of parallel filters with identical transfer function $W(m,z)$, where $I_{N\times N}$ indicates the $N\times N$ identity matrix. These transversal filters are placed before the decimators, making the subband structure basically different from that of the conventional SAF in structural terms. The estimation error $e_i(m)$ measures how far the filter output $y_i(m) = w_T(m)u_i(m)$ is from the desired response $d_i(m)$ in each of the N bands, at the decimated rate indexed by m. Here, let

$$u_i(m)\equiv\left[u_i(mN),u_i(mN-1)\ ,\cdots,\ u_i(mN-M+1)\right] \tag{2}$$

which denotes the regression vector for the ith subband.

$$w(m)\equiv[w_0(m), w_1(m), \ldots, w_{M-1}(m)]^T \quad (3)$$

Which holds the fullband tap weights of the modeling filter $W(m,z)$. The estimation error in all the N subbands, and let

$$e(m)\equiv[e_0(m), e_1(m), \ldots, e_{N-1}(m)]^T \quad (4)$$

So the NSAF is summarized as

$$u_i(n) = h_i^T u(n), i = 0,1,\cdots,N-1$$
$$d_i(n) = h_i^T d(n)$$
$$e_{i,D}(m) = d_{i,D}(m) - w^T(m)u_{i,D}(m)$$
$$w(n+1) = w(n) + \mu\sum_{i=0}^{N-1} u_{i,D}(m)\left[u_{i,D}{}^T(m)u_{i,D}(m) + \theta\right]^{-1} e_{i,D}(m)$$
$$e(n) = \sum_{i=0}^{N-1} g_i^T e_i(n)$$

(5)

in which $n = 0,1,2,\cdots$, at $1/T_S$ processing rate, $m = 0,1,2,3\cdots$, at $1/NT_S$ processing rate. M is filter length, N is number of subbands, L is length of the analysis filters h_i and synthesis filters g_i, μ is step size, $0 < \mu < 2$, θ is a small positive constant to avoid possible division by zero. The Misalignment is shown in fig. 1 by comparing NLMS (μ=1)and NSAF, and this plot indicates that convergence performance of NSAF is better than that of NLMS.

2.2. Improved subband adaptive filter

In each subband, Kalman filtering is utilized to update the weight vector of adaptive filter, thus the improved SAF is noted as

$$u_i(n) = h_i^T u(n), i = 0,1,\cdots,N-1$$
$$d_i(n) = h_i^T d(n)$$
$$e_{i,D}(m) = d_{i,D}(m) - w^T(m)u_{i,D}(m)$$
$$K_i(m) = P_i(m)u_{i,D}^T(m)[u_{i,D}(m)P_i(m)u_{i,D}^T(m) + R_i(m)]^{-1}$$
$$P_i(m) = P_i(m-1) - K_i(m)u_i(m)P_i(m) + Q_i(m)$$
$$w(n+1) = w(n) + \sum_{i=0}^{N-1} K_i(m)e_{i,D}(m)$$
$$e(n) = \sum_{i=0}^{N-1} g_i^T e_i(n)$$

(6)

in which $n = 0,1,2,\cdots$, at $1/T_S$ processing rate, $m = 0,1,2,3\cdots$, at $1/NT_S$ processing rate. M is filter length, N is number of subbands, L is length of the analysis filters h_i, and synthesis filters g_i. K is the Kalman filter gain, P is the covariance matrix of the error. Q and R are the covariance matrices of the system and measurement noise, respectively.

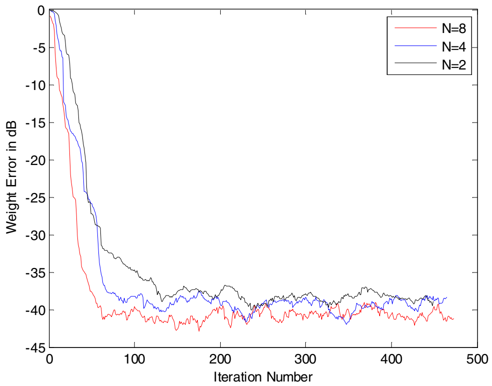
3. Simulation

In this section, we study the convergence performance of the SAF using simulations. This mathematical simulation is considered as the practical context of acoustic echo cancellation (represented in Fig. 1). The system to be identified is expressed by the acoustic response of a room with 300 ms reverberation time and truncated to 2048 taps. The length of the adaptive tap-weight vector M is 1024 taps. The residual tail of the acoustic response produces a disturbance to the system, which constrains the final misalignment to more than -40 dB. The adaptive identification system is excited with an AR(2) random process with coefficients (1.0, -0.1, -0.8). Cosine modulated filter banks for the subband structure are adopted. To maintain 40 dB stopband attenuation, the length of the prototype filter L is 16, 32, and 64, respectively, for N=2, 4, 8 subbands. High stopband attenuation ensures that the cross-correlation between nonadjacent subbands can be completely neglected.

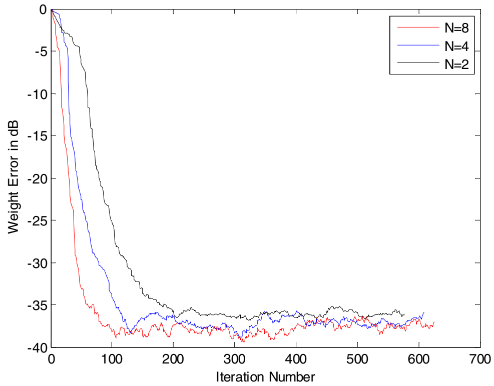
The normalized misalignment is defined as the norm of the weight-error vector $\|\varepsilon(n)\|$ normalized by the norm of the optimum tap-weight vector $\|\mathbf{w}_o\|$.

$$\|\varepsilon(n)\| = 10\log_{10}\frac{\mathbf{w}^T(n)\mathbf{w}(n)}{\mathbf{w}_o^T\mathbf{w}_o} \tag{7}$$

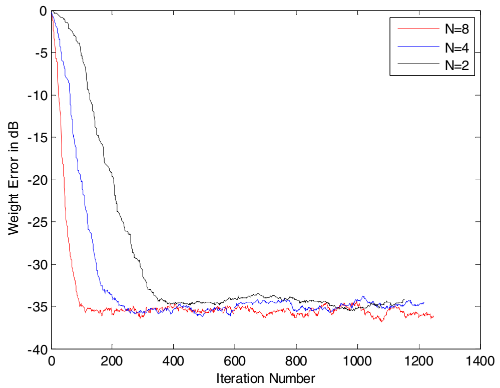
In order to verify the validation of the proposed filter, first of all we calculate the convergence performance of this adaptive filter with different lengths (for M=64, 128 and 256) and different subband (for N=2, 4 and 8). Fig.2 is the learning curves of the improved SAF algorithms by simulation. Furthermore, the comparison of the NSAF and the improved SAF (length of adaptive filter M=1024, subband N=8) is plotted in Fig.3.



(a) M=64



(b) M=128



(c) M=256

Fig. 2. Performance comparison for Improved SAF with different subband

The plots of Fig. 2 (a)-(c) are the simulation results of weight error of adaptive filters with different lengths and subband, which clearly shows that the convergence performance goes up with subband number N. Fig.3 indicates the learning curves of the NSAF and the improved SAF with length M=1024. From this plot, it can be seen that the improved SAF has faster convergence performance than the NSAF.

Regarding computational complexity, the improved NSAF requires many numbers of multiplications per sampling period because of the Kalman updating. The computational time of the proposed SAF algorithm will be longer than that of the NSAF. In fact, the convergence of the presented algorithm is improved at the cost of the computational complex, so reducing the computational complex is our next goal.

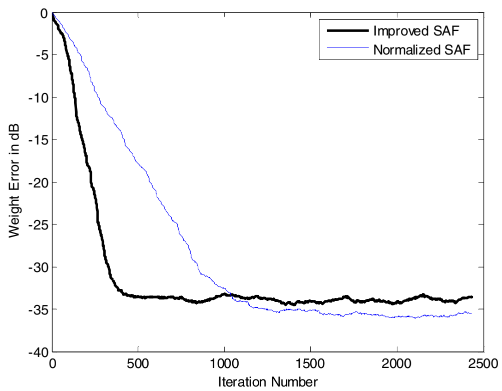


Fig. 3. Normalized misalignment learning curves for the NSAF and improved SAF(M=1024)

4. Conclusion

An improved SAF is proposed by integrating the SAF with the Kalman filtering. Compared to the NSAF algorithm, the improved subband adaptive filtering algorithm derived from this scheme exhibits faster convergence under colored excitation. The simulation results support the theoretical predictions. It will be our future target to reduce the computational complex of the subband adaptive filters.

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