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Short communication

Variable step-size sign subband adaptive filter with subband filter selection

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ABSTRACT

This letter proposes a novel sign subband adaptive filtering (SSAF) algorithm with a subset selection for subband filters, called the SS-SSAF. The proposed algorithm achieves the fast convergence performance and reduces the computational complexity by a proposed sufficient condition. The condition associated with each subband immediately ensures the decrease of the mean square deviation (MSD) value at every iteration. Furthermore, we suggest the variable step-size algorithm for SS-SSAF to achieve both fast convergence speed and small steady-state errors. Simulation results show that the proposed algorithm with fixed step-size performs better than the conventional SSAF and the other improved SSAF algorithms in terms of the convergence rate. In addition, the performance of proposed variable step-size algorithm is demonstrated in the system identification compared with recent variable step-size SSAFs.

1. Introduction

Adaptive filtering algorithms have been utilized in a wide variety of applications, such as system identification, acoustic echo cancellation, active noise control, channel equalization, and noise cancellation, because of their ability to deal with unknown and changing environments. The least-mean-squares (LMS) algorithm and its normalized version (NLMS) are the most widely used among various adaptive algorithms due to their low computational complexity and robustness [1,2]. However, they suffer from a poor convergence rate when the input signals are highly correlated, a case called colored input signals. To address this drawback, a normalized subband adaptive filter (NSAF) has been developed [3]. The NSAF improves the convergence rate for colored input signals with a “pre-whitening” procedure. Furthermore, to reduce the computational complexity of the NSAF, a simplified selective partial-update subband adaptive filter algorithm, a dynamic selection NSAF algorithm, and a flexible complexity variable step-size NSAF have been proposed [4–6]. Unfortunately, because of the nature of the $\mathcal{L}_2$-norm optimization, NSAF type algorithms suffer from performance degradations in impulsive noisy environments.

Recently, to overcome this drawback, several algorithms have been proposed using the $\mathcal{L}_1$-norm optimization. Representative algorithms include the affine projection sign algorithm (APSA) and the sign subband adaptive filter (SSAF) algorithm [7–11]. The APSA can achieve not only improved performance in impulsive noisy environments but also a fast convergence rate with colored input signals. As the projection order of the APSA increases, the computational complexity is getting high. The SSAF algorithm performs well in impulsive noisy environments with the lower computational complexity as compared to the APSA. However, this algorithm has a slow convergence speed. In order to improve the performance of SSAF, Jeong et al. proposed a novel SSAF algorithm (IS-SSAF) by using selection of subbands to obtain a fast convergence rate and save the computational cost [12]. In addition, Yu and Zhao proposed an individual-weighting-factor (IWF) SSAF algorithm that uses IWF for each subband instead of a common weighting factor as in the conventional SSAF. Although IS-SSAF and IWF-SSAF have fast convergence rate, IS-SSAF cannot improve the performance with large step size and IWF-SSAF has high computational complexity compared to the conventional SSAF.

This letter proposes a novel SSAF algorithm to improve the performance in terms of the convergence rate in impulsive noisy environments and to save the computational cost. The proposed algorithm selects a subset of subband filters through a criterion that guarantees the instant decrease of the MSD value in each iteration. Moreover, the variable step-size algorithm for the proposed SSAF is also presented to achieve both the fast convergence rate and small steady-state errors. The simulation results show that the proposed SSAF algorithm improves the performance as compared with the algorithms available in the literature.

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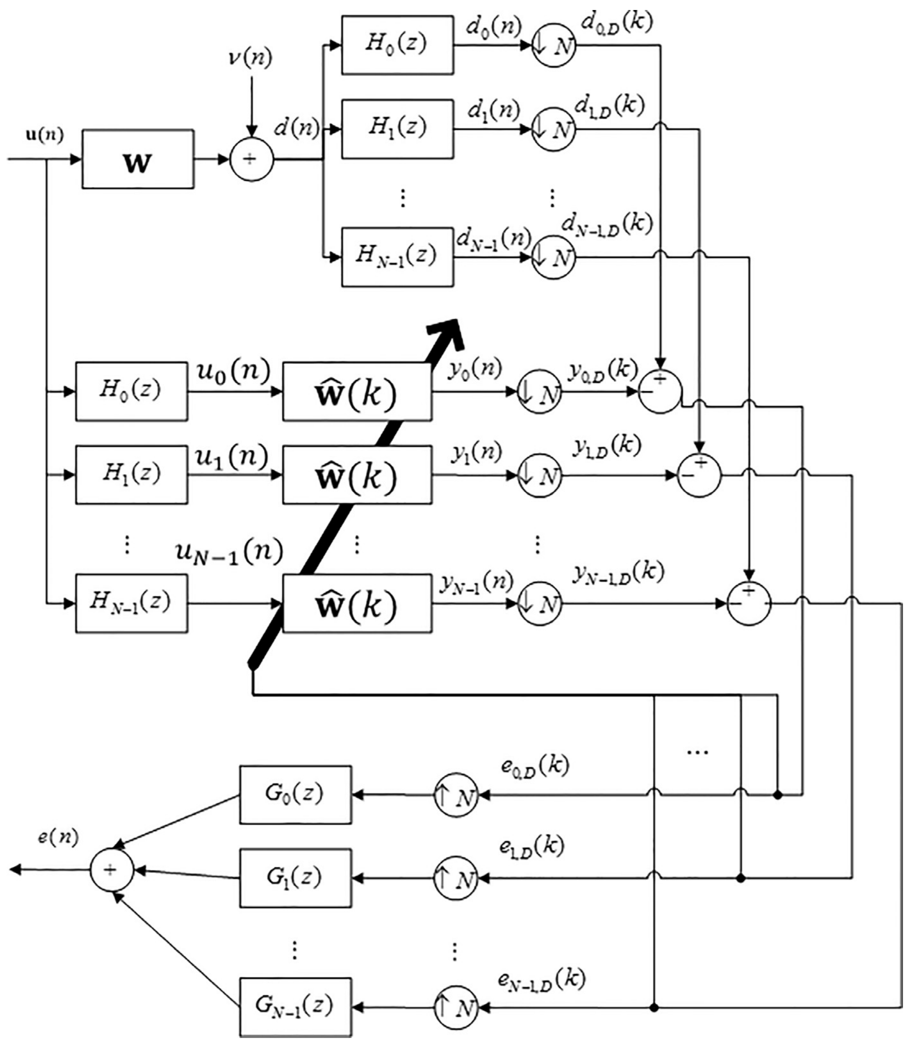

Fig. 1. Structure of the SSAF.

2. Sign subband adaptive filter (SSAF)

Consider a desired signal $d(n)$ that is derived from an unknown linear system

$$d(n) = \mathbf{u}^T(n)\mathbf{w} + v(n), \tag{1}$$

where $\mathbf{w}$ is an unknown m-dimensional vector to be identified with an adaptive filter, $v(n)$ represents the measurement noise assumed with zero mean and variance σ_v^2, and $\mathbf{u}(n)$ denotes an m-dimensional input vector. Fig. 1 shows the structure of a typical SSAF, which is the same as that of the NSAF, where N is the number of subbands. The desired system output signal of the ith subband is $d_i(n)$, and the filter output signal of the ith subband is $y_i(n)$. Both signals are divided into N subbands by analysis filters $H_0(z), \ldots, H_{N-1}(z)$. Then, $d_i(n)$ and $y_i(n)$ for $i \in [0, N-1]$, are critically decimated to a lower sampling frequency, one which matches to their reduced bandwidth. In this letter, n is used to index the original sequences, and k is used to index the decimated sequences, respectively. The filter output signal of the ith subband is defined as $y_{i,D}(k) = \hat{\mathbf{w}}^T(k)\mathbf{u}_i(k)$, where $\mathbf{u}_i(k) = [u_i(kN)\ u_i(kN-1)\ \ldots\ u_i(kN-m+1)]^T$. The output error of the ith subband is defined as $e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k)$, where $d_{i,D}(k) = d_i(kN)$. Then, we define the subband input matrix, desired output signal vector, output error vector, and *a posteriori* output error vector as follows:

$$\mathbf{U}(k) = [\mathbf{u}_0(k)\ \mathbf{u}_1(k)\ \ldots\ \mathbf{u}_{N-1}(k)], \tag{2}$$

$$\mathbf{d}_D(k) \triangleq [d_{0,D}(k)\ \ldots\ d_{N-1,D}(k)]^T = \mathbf{U}^T(k)\mathbf{w} + \mathbf{v}_D(k), \tag{3}$$

$$\mathbf{e}_D(k) = \mathbf{d}_D(k) - \mathbf{U}^T(k)\hat{\mathbf{w}}(k), \tag{4}$$

$$\mathbf{e}_p(k) = \mathbf{d}_D(k) - \mathbf{U}^T(k)\hat{\mathbf{w}}(k+1), \tag{5}$$

where $\mathbf{v}_D(k) = [v_{0,D}(k)\ \ldots\ v_{N-1,D}(k)]^T$, and $v_{i,D}(k)$ denotes the measurement noise with zero mean and variance $\sigma_{v_{i,D}}^2$.

The conventional SSAF is derived by minimizing the $\mathcal{L}_1$-norm of $\mathbf{e}_p(k)$ with a constraint on the weight coefficient vectors [8]. Then, the update equation of the SSAF can be expressed as

$$\hat{\mathbf{w}}(k+1) = \hat{\mathbf{w}}(k) + \mu \frac{\mathbf{U}(k) sgn(\mathbf{e}_D(k))}{\sqrt{\sum_{i=0}^{N-1} \mathbf{u}_i^T(k)\mathbf{u}_i(k)}}, \tag{6}$$

where $sgn(\cdot)$ denotes the sign function, $sgn(\mathbf{e}_D(k)) \triangleq [sgn(e_{0,D}(k))\ \ldots\ sgn(e_{N-1,D}(k))]^T$, and μ is the step size.