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Short communication

A novel subband adaptive filter algorithm against impulsive noise and it's performance analysis

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ABSTRACT

The main drawback of the sign subband adaptive filter algorithm (SSAF) is its large steady-state error. To improve the performance, this paper proposes a novel normalized logarithmic subband adaptive filter algorithm (NLSAF), which is derived from a new normalized logarithmic cost function. Due to possess the advantages of the normalized subband adaptive filter (NSAF) and SSAF algorithms in the proposed NLSAF algorithm, it achieves a low steady-state error and the robustness performance against impulsive noise. Then, by using the energy conservation method, the mean-square convergence performance of the proposed NLSAF algorithm is presented. Simulations on system identifications demonstrate that the proposed subband adaptive filter performs better than the conventional SSAF algorithm in an impulsive-noise scenario.

1. Introduction

The adaptive filtering algorithms have been widely used in many practical areas such as system identification, channel estimation, and echo cancellation. The normalized least-mean-square (NLMS) algorithm is one of the simple algorithms because it is easy to implement and has low computational complexity [1]. However, it is well-known that the normalized least mean square algorithm converges slowly when the input signals are colored. In order to solve this problem, the affine projection algorithm (APA) and its variants (e.g., see [2,3] and the references therein) were developed to provide faster convergence rate than the NLMS algorithm. However, the APAs require large computational cost due to involving the matrix inversion operation in updating the tap-weight vector.

Recent years, an attractive approach is to use the subband adaptive filter (SAF), because it divides the colored input signal into almost mutually exclusive multiple subband signals and each subband signal is approximately white [4]. The NSAF algorithm had been proposed and studied by Lee and Gan in [5]. Because of the inherent decorrelating property of SAF [6], it converges faster than the NLMS for the colored input signals. Besides, the NSAF has almost the same computational complexity as the NLMS, especially for applications of long adaptive filter such as echo cancellation. However, similarly to the conventional NLMS algorithm, the performance of the NSAF algorithm will degrade when background noise includes impulsive noise. To maintain the robustness of filter performance against impulsive noise, the SSAF was derived by minimizing the l_1-norm of the subband a posteriori error vector of the filter [7,8], whereas it has a large steady-state error. Then Ni et al. proposed a variable regularization parameter SSAF (VRP-SSAF) algorithm to further reduce the steady state error [8].

In this paper, to improve the performance of the SSAF algorithm, we propose a new subband adaptive filter algorithm, which is derived by a normalized logarithm cost function. Because it inherits the advantages of the NSAF and SSAF algorithms, the proposed algorithm has good robustness performance against impulsive noise and small steady-state error. Then, the steady-state mean square derivation performance of the NLSAF is analyzed in this paper, which is based on the energy conservation relation [9], Price's theorem [10] and some reasonable assumptions such as the independent assumption. Simulation results show that the NLSAF algorithm achieves a lower the steady-state error compared to the SSAF algorithm with the same speed of convergence.

The paper is organized as follows. Section 2 provides a brief review and discussion of the SSAF algorithm. In Section 3, the proposed NLSAF is then presented. A convergence and steady state analysis of the proposed algorithm is carried out in Section 4. Section 5 contains simulation results. Finally, some conclusions are given in Section 6.

2. Review of conventional SSAF algorithm

Fig. 1 shows the structure of the subband adaptive filter [5]. Consider a desired signal

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$$d(n) = u^T(n)w_o + \eta(n) \tag{1}$$

where $u(n)=[u(n),u(n-1),\ldots,u(n-M+1)]^T$, w_o and $\eta(n)$ denote the input vector, the tap-weight vector of unknown channel with the length M and the background noise, respectively. The background noise $\eta(n)$ includes the white Gaussian background noise $\upsilon(n)$ and impulsive noise $\varsigma(n)$, which is independent of $u(n)$. The background measurement noise $\upsilon(n)$ is a zero-mean Gaussian process with variance σ_υ^2. In Fig. 1, the input signal $u(n)$ and desired signal $d(n)$ are decomposed into $u_i(n)$and $d_i(n)$ by the analysis filters $H_i(z)$ ($i = 0, 1\ldots N-1$), and the subband output signals $y_i(n)$ are obtained from $u_i(n)$ filtered by the adaptive filter $\hat{w}(k)$. N is the number of subbands. Note that we use the variable n to index the original sequences, and k to index the decimated sequences. Then, the signals $d_i(n)$ and $y_i(n)$ are decimated to $d_{i,D}(k)$ and $y_{i,D}(k)$ respectively. It is easy to note that

$$d_{i,D}(k) = u_i^T(k)w_o + \eta_i(k) \tag{2}$$

and

$$y_{i,D}(k) = u_i^T(k)\hat{w}(k) \tag{3}$$

where $u_i(k)=[u_i(kN),u_i(kN-1),\ldots,u_i(kN-M+1)]^T$ and $\eta_i(k)$ is a ith subband noise. The ith subband output error is defined as

$$e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k). \tag{4}$$

The original SSAF algorithm can be derived by minimizing the following cost function:

$$J(k) = \frac{\left\|e_D(k)\right\|_1}{\sqrt{\sum_{i=0}^{N-1} u_i^T(k)u_i(k)}} \tag{5}$$

where $e_D(k)=[e_{0,D}(k),e_{1,D}(k),\ldots e_{N-1}(k)]^T$.

Applying the gradient descent method, the conventional SSAF algorithm for updating the tap-weight vector is expressed as

$$\hat{w}(k+1) = \hat{w}(k) + \mu\frac{U(k)\mathrm{sgn}\left[e_D(k)\right]}{\sqrt{\sum_{i=0}^{N-1} u_i^T(k)u_i(k)}} \tag{6}$$

where μ is the step-size, $U(k) = [u_0(k), u_1(k), \ldots, u_{N-1}(k)]$. In the following, we define

$$A(k) = \sum_{i=0}^{N-1} u_i^T(k)u_i(k). \tag{7}$$

3. The normalized logarithmic subband adaptive filter (NLSAF) algorithm

3.1. The proposed algorithm

Although the SSAF is robustness against impulsive noise, it has a large steady-state error. To improve the performance of the SSAF, the new cost function combining the NSAF and SSAF algorithms is proposed in this section.

To derive the proposed algorithm, the novel cost function using the logarithm function in [11] is firstly defined by

$$J(k) = \sum_{i=0}^{N-1} J\left(e_{i,D}(k)\right) \tag{8}$$

where

$$J\left(e_{i,D}(k)\right) = \frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}} - \frac{1}{\alpha}ln\left(1+\alpha\frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}}\right) \tag{9}$$

and $\alpha > 0$ is the design parameter. When $\left|e_{i,D}(k)\right|/\sqrt{A(k)} < 1$, we expand (9) with a Taylor series for small perturbations of the error

$$\begin{aligned} J\left(e_{i,D}(k)\right) &= \frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}} - \frac{1}{\alpha}\left(\alpha\frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}} - \frac{\alpha^2}{2}\left(\frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}}\right)^2 + \ldots\right) \\ &= \frac{\alpha}{2}\left(\frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}}\right)^2 - \frac{\alpha^3}{2}\left(\frac{\left|e_{i,D}(k)\right|}{\sqrt{A(k)}}\right)^3 + \ldots. \end{aligned} \tag{10}$$

We note that the expand cost function includes the higher-order measures of the error. Thus, the proposed algorithm can achieve smaller steady-state mean square errors through the use of the higher-order statistics for small perturbations of the error. Taking the derivative of (9) with respect to the tap-weight vector $\hat{w}(k)$

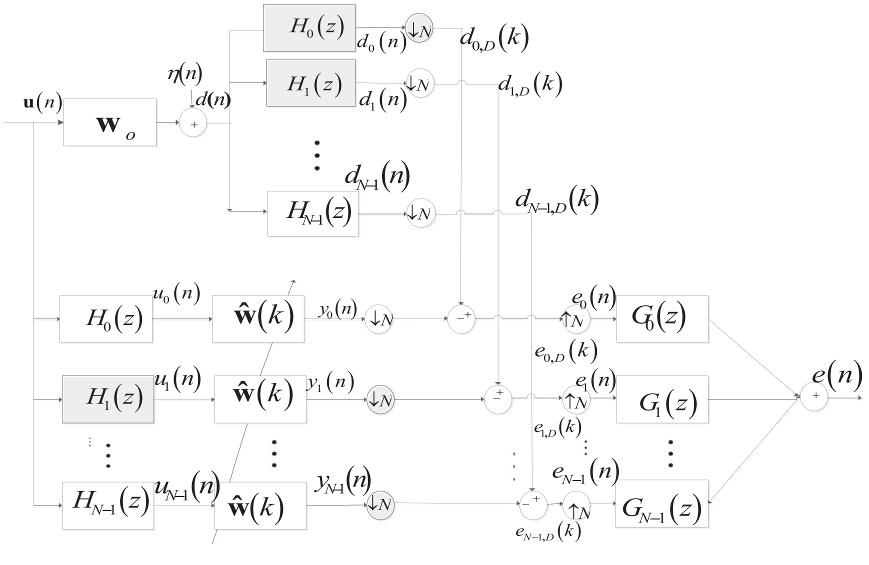

Fig. 1. structure of SSAF.