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A band-dependent variable step-size sign subband adaptive filter

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ABSTRACT

This letter proposes a band-dependent variable step-size sign subband adaptive filter using the concept of mean-square deviation (MSD) minimization. Since it is difficult to obtain the value of the MSD accurately, the proposed step size is derived by minimizing the upper bound of the conditional MSD with given input. By assigning the different step size in each band, the filter performance can be improved. Moreover, we suggest the estimation method of the measurement-noise variance in an impulsive-noise environment, because the proposed algorithm needs the measurement-noise variance to calculate the step size. The reset algorithm is also applied for maintaining the filter performance when a system change occurs suddenly. Simulation results demonstrate that the proposed algorithm performs better than the existing algorithms in aspects of the convergence rate and the steady-state estimation error.

1. Introduction

Recently, the subband-type adaptive filters have received much intention due to their fast convergence rate for the correlated input signal, which is called as the colored input signal. One of the representative subband adaptive filters is a sign subband adaptive filter (SSAF) [1] that is not only robust against the impulsive noise, but also decorrelates the colored input signal using multiple subbands to improve the convergence rate. To enhance the performance for the SSAF, several algorithms [1–3] have been proposed. In this letter, we propose a band-dependent variable step-size SSAF (BDVSS-SSAF), which allots the different step size in each band, to achieve the fast convergence rate and the small steady-state error as compared to the existing algorithms. The following is the description of the conventional SSAF.

Consider the desired output data $d(n)$ obtained from an unknown system through $d(n)=\mathbf{u}^T(n)\mathbf{w_o}+v(n)$, where $\mathbf{w_o}$ is an M-dimensional column vector of the unknown system that we want to estimate, $v(n)$ denotes the measurement noise with zero mean and variance σ_v^2, and the input data vector is $\mathbf{u}(n)=[u(n)u(n-1)\cdots u(n-M+1)]^T$. Fig. 1 shows the structure of the SSAF, which is the same as that of the NSAF [4]. In Fig. 1, N is the number of subbands, $d_i(n)$ is the desired system output signal, and $y_i(n)$ is the filter output signal of the ith subband, respectively. L is length of the analysis and synthesis filters. Both $d_i(n)$ and $y_i(n)$ signals are divided into N subbands by the analysis filters, $H_0(z), H_1(z), \ldots, H_{N-1}(z)$. Then, both $d_i(n)$ and $y_i(n)$ for $i\in[0,N-1]$ are critically decimated to a lower sampling rate, one which corresponds to their reduced bandwidth. In this letter, variables n and k are used to index the original sequences and the decimated sequences, respectively. The decimated filter output signal is defined as $y_{i,D}(k)=\widehat{\mathbf{w}}^T(k)\mathbf{u}_i(k)$, where $\mathbf{u}_i(k)=[u_i(kN)u_i(kN-1)\cdots u_i(kN-M+1)]^T$. The output error of the ith subband is defined as $e_{i,D}(k)\triangleq d_{i,D}(k)-y_{i,D}(k)$, where $d_{i,D}(k)=d_i(kN)$.

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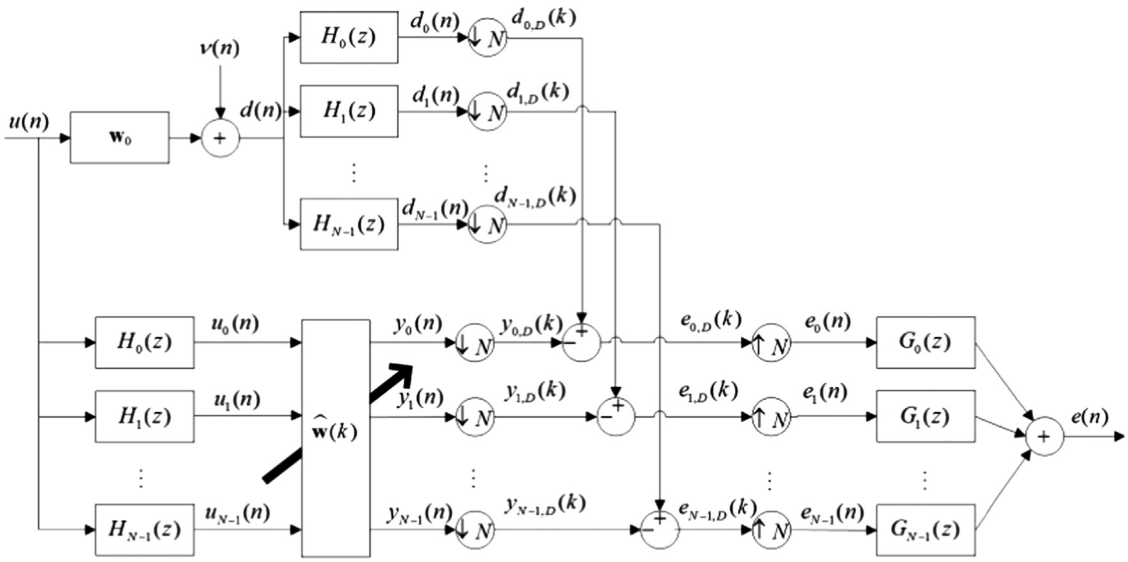

Fig. 1. Structure of the SSAF.

We define the subband input matrix, desired output signal vector, and output error vector as $\mathbf{U}(k)=[\mathbf{u}_0(k)\mathbf{u}_1(k)\cdots\ \mathbf{u}_{N-1}(k)]$, $\mathbf{d}_D(k)=\mathbf{U}^T(k)\mathbf{w}(k)+\mathbf{v}_D(k)$, $\mathbf{e}_D(k)=\mathbf{d}_D(k)-\mathbf{U}^T(k)\widehat{\mathbf{w}}(k)$, respectively, where $\mathbf{v}_D(k)=[v_{0,D}(k)\cdots v_{N-1,D}(k)]^T$, and $v_{i,D}(k)$ denotes the measurement noise with zero mean and variance $\sigma^2_{v_{i,D}}$. The weight coefficient vector of the conventional SSAF [1] is given recursively as

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

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

2. Band-dependent variable step-size SSAF (BDVSS-SSAF)

2.1. Derivation of the band-dependent variable step size

To assign the different step size in each band, the step size in (1) can be changed with a diagonal-matrix form. Therefore, the update equation for the SSAF is modified as

$$\widehat{\mathbf{w}}(k+1)=\widehat{\mathbf{w}}(k)+\frac{\mathbf{U}(k)\mathbf{\Lambda}(k)\mathrm{sgn}(\mathbf{e}_D(k))}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}},\tag{2}$$

where $\mathbf{\Lambda}(k)=\mathrm{diag}[\mu_0(k)\mu_1(k)\cdots\mu_{N-1}(k)]$ is the matrix-type step size. The SSAF update equation (2) can be expressed in terms of $\tilde{\mathbf{w}}$, where the weight-error vector is defined as $\tilde{\mathbf{w}}(k)\triangleq\mathbf{w_0}-\widehat{\mathbf{w}}(k)$, as follows:

$$\tilde{\mathbf{w}}(k+1)=\tilde{\mathbf{w}}(k)-\frac{\mathbf{U}(k)\mathbf{\Lambda}(k)\mathrm{sgn}(\mathbf{e}_D(k))}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}}.\tag{3}$$

Since the subband input matrix $\mathbf{U}(k)$ can be measured easily, it is assumed that the input is known. In this letter, the conditional expectation [5] with given $\mathbf{U}(k)$ is defined as $\mathrm{E}_u(\cdot)\triangleq\mathrm{E}(\cdot|\mathbf{U}(k))$. Squaring and taking the conditional expectation of both sides of (3), the update recursion of the conditional MSD with respect to $\mathbf{U}(k)$ is represented as

$$\begin{aligned}\mathrm{E}_u\left(\|\tilde{\mathbf{w}}(k+1)\|_2^2\right)&=\mathrm{E}_u\left(\|\tilde{\mathbf{w}}(k)\|_2^2\right)\\&-2\mathrm{E}_u\left(\frac{\mathrm{sgn}(\mathbf{e}_D^T(k))\mathbf{\Lambda}^T(k)\mathbf{U}^T(k)\tilde{\mathbf{w}}(k)}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}}\right)\\&+\mathrm{E}_u\left(\frac{\mathrm{sgn}(\mathbf{e}_D^T(k))\mathbf{\Lambda}^T(k)\mathbf{U}^T(k)\mathbf{U}(k)\mathbf{\Lambda}(k)\tilde{\mathbf{w}}(k)}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}}\right).\end{aligned}\tag{4}$$

Using the diagonal assumption $\mathbf{U}^T(k)\mathbf{U}(k)\approx\mathrm{diag}[\|\mathbf{u}_0(k)\|_2^2\ \|\mathbf{u}_1(k)\|_2^2\cdots\|\mathbf{u}_{N-1}(k)\|_2^2]$ [4], Eq. (4) can be rewritten as

$$\begin{aligned}\mathrm{E}_u\left(\|\tilde{\mathbf{w}}(k+1)\|_2^2\right)&=\mathrm{E}_u\left(\|\tilde{\mathbf{w}}(k)\|_2^2\right)\\&-2\frac{\mathrm{E}_u(\mathrm{sgn}(\mathbf{e}_D^T(k))\mathbf{\Lambda}^T(k)\mathbf{U}^T(k)\tilde{\mathbf{w}}(k))}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}}\\&+\frac{\sum_{i=0}^{N-1}\mu_i^2(k)\mathbf{u}_i^T(k)\mathbf{u}_i(k)}{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}\triangleq\mathrm{E}_u\left(\|\tilde{\mathbf{w}}(k)\|^2\right)\\&+P(\mu_i(k)),\end{aligned}\tag{5}$$

where $P(\mu_i(k))$ is a function of the step size for $i\in[0,N-1]$. To minimize the value of the MSD from iteration k to iteration $k+1$, the function $P(\mu_i(k))$ is minimized by deciding the step size reasonably. Then, the function $P(\mu_i(k))$ can be written as

$$\begin{aligned}P(\mu_i(k))=&-2\frac{\mathrm{E}_u(\mathrm{sgn}(\mathbf{e}_D^T(k))\mathbf{\Lambda}^T(k)\mathbf{U}^T(k)\tilde{\mathbf{w}}(k))}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}}\\&+\frac{\sum_{i=0}^{N-1}\mu_i^2(k)\mathbf{u}_i^T(k)\mathbf{u}_i(k)}{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)}.\end{aligned}\tag{6}$$

Because it is difficult to determine the $\mathrm{E}_u(\mathrm{sgn}(\mathbf{e}_D^T(k))\mathbf{\Lambda}^T(k)\mathbf{U}^T(k)\tilde{\mathbf{w}}(k))$ term, $P(\mu_i(k))$ cannot be obtained directly. Therefore, we find the lower bound of it as

$$\mathrm{E}_u(\mathrm{sgn}(\mathbf{e}_D^T(k))\mathbf{\Lambda}^T(k)\mathbf{U}^T(k)\tilde{\mathbf{w}}(k))$$