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A band-independent variable step size proportionate normalized subband adaptive filter algorithm

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ABSTRACT

Proportionate-type normalized subband adaptive filter (PNSAF-type) algorithms are very attractive choices for echo cancellation. To further obtain both fast convergence rate and low steady-state error, in this paper, a variable step size (VSS) version of the presented improved PNSAF (IPNSAF) algorithm is proposed by minimizing the square of the noise-free *a posterior* subband error signals. A noniterative shrinkage method is used to recover the noise-free *a priori* subband error signals from the noisy subband error signals. Significantly, the proposed VSS strategy can be applied to any other PNSAF-type algorithm, since it is independent of the proportionate principles. Simulation results in the context of acoustic echo cancellation have demonstrated the effectiveness of the proposed method.

1. Introduction

Over the past few decades, adaptive filtering algorithms have received great deal of development and been widely applied in practical fields such as system identification, channel equalization, echo cancellation and beamforming [1,2]. One of the popular algorithms is the normalized least mean square (NLMS) algorithm, due to its simplicity and easy implementation. However, it suffers from slow convergence when the input signal is colored, especially for speech signal in echo cancellation. Aiming to the colored input signal, affine projection algorithm (APA) and some of its variants can speed up the convergence (e.g., see [3,4,27,28] and the references therein) by utilizing the previous input vectors to update the tap-weight vector. Nevertheless, they require large computational cost due mainly to involving the matrix inversion operation. Another attractive approach is to use the subband adaptive filter (SAF) to deal with the colored input signal [5]. In SAF, the colored input signal is divided into almost mutually exclusive subband signals, and each subband signal is approximately white, thus improving the convergence. In [6], Lee and Gan proposed the normalized SAF (NSAF) algorithm based on the principle of the minimum perturbation, which has faster convergence rate than the NLMS for the colored input signal. Furthermore, for applications of long filter such as echo cancellation, the NSAF algorithm has almost the same computational complexity as the NLMS. In fact, the NSAF will be reduced to the NLMS when number of subbands is equal to one. In [7], Yin et al. studied the convergence models of the NSAF in the mean and mean-square senses by assuming that the analysis filter bank is paraunitary and using several hyperelliptic integrals. On another hand, to overcome the trade-off problem of the NSAF between the convergence rate and steady-state error, several variable step size (VSS) NSAF algorithms were presented [8–11,24].

In many realistic applications, sparse systems are often encountered (e.g., the impulse response of the echo paths), which have the property that only a fraction coefficients of impulse response (called *active coefficients*) have large magnitude while the rest coefficients (called *inactive coefficients*) are zero or very small. To improve the convergence rate of the classic adaptive filtering algorithms in sparse systems, several proportionate-type algorithms were developed [12–17]. The fundamental principle of this kind of algorithms is that each coefficient of the adaptive filter receives an independent step size in proportion to its estimated magnitude. The first proportionate algorithm is the proportionate NLMS (PNLMS) proposed by Duttweiler [12], which obtains faster initial convergence rate than the NLMS for a sparse case. However, the PNLMS shows a slow convergence when the unknown impulse response is dispersive. Moreover, its fast initial convergence is not maintained over the whole adaptation process. To solve the first problem of the PNLMS, the improved PNLMS (IPNLMS) algorithm was proposed by combining the proportionate (PNLMS)

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adaptation with non-proportionate (NLMS) adaptation [13]. To maintain fast initial convergence rate during the whole estimation process, the μ-law PNLMS (MPNLMS) algorithm was proposed in [14] by deriving the optimal step-size control rule. Recently, in order to enhance the convergence speed of the NSAF for sparse systems, Abadi et al. developed a class of proportionate NSAF algorithms by directly extending the existing proportionate ideas in the NLMS to the NSAF, e.g., the proportionate NASF (PNSAF), μ-law PNSAF (MPNSAF), improved PNSAF (IPNSAF), and so forth [16,17]. However, similar to the NSAF and/or the NLMS, the overall performance (including the convergence rate, tracking capability and steady-state error) of these PNSAF-type algorithms is dominated by a fixed step-size, i.e., a large step size results in faster convergence and tracking, while the steady-state error is reduced for a small step size. To address this problem, the set-membership IPNSAF (SM-IPNSAF) algorithm was proposed in [17], because it can be interpreted as a VSS algorithm. Inadequately, its convergence performance is sensitive to the selection of the error bound, and its improvement in the steady-state error is slight as compared to the IPNSAF.

To obtain both fast convergence rate and low steady-state error, this paper develops a VSS version of the IPNSAF. In this VSS algorithm, the individual time-varying step size for each subband is derived by minimizing the square of the noise-free *a posterior* subband error signal. Furthermore, the noise-free *a priori* subband error signal is obtained by using a noniterative shrinkage method reported in [18,19]. More importantly, the proposed VSS scheme can be applied to other existing PNSAF-type algorithms to improve their performance, due to the fact that it does not depend on the proportionate rules. Besides, the convergence condition of PNSAF-type algorithms in mean-square sense is provided in Appendix.

2. PNSAF-type algorithms

Consider the desired signal $d(n)$ that arises from the unknown system,

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

where $(\cdot)^T$ indicates transpose of a vector or a matrix, $\mathbf{w}_o$ is the unknown M-dimensional vector to be identified with an adaptive filter, $\mathbf{u}(n) = [u(n), u(n-1), \ldots, u(n-M+1)]^T$ is the input signal vector, and $\eta(n)$ is the system noise with zero-mean and variance σ_η^2. Fig. 1 shows the block diagram of multiband-structured SAF, where

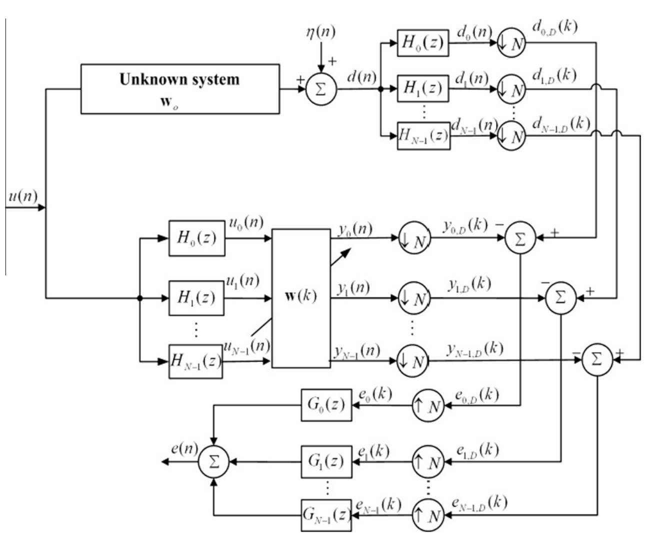

Fig. 1. Block diagram of multiband-structured SAF.

N denotes number of subbands. The desired signal $d(n)$ and the input signal $u(n)$ are partitioned into multiple subband signals $d_i(n)$ and $u_i(n)$ through the analysis filter bank $\{H_i(z), i \in [0, N-1]\}$, respectively. The subband output signals $y_i(n)$ are obtained from $u_i(n)$ filtered by the adaptive filter given by $\mathbf{w}(k) = [w_1(k), w_2(k), \ldots, w_M(k)]^T$. Then, $y_{i,D}(k)$ and $d_{i,D}(k)$ are generated by critically decimating $y_i(n)$ and $d_i(n)$. Here, n and k are used to indicate the original sequences and the decimated sequences, respectively. It is easy to note that $y_{i,D}(k) = \mathbf{u}_i^T(k)\mathbf{w}(k)$, where $\mathbf{u}_i(k) = [u_i(kN), u_i(kN-1), \ldots, u_i(kN-M+1)]^T$. Accordingly, the ith subband error signal is given by

$$e_{i,D}(k) = d_{i,D}(k) - y_{i,D}(k) = d_{i,D}(k) - \mathbf{u}_i^T(k)\mathbf{w}(k) \tag{2}$$

where $d_{i,D}(k) = d_i(kN)$.

For all the PNSAF-type algorithms [16,17], the update formula of the tap-weight vector is expressed as

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \mu\sum_{i=0}^{N-1}\frac{\mathbf{G}(k)\mathbf{u}_i(k)e_{i,D}(k)}{\mathbf{u}_i^T(k)\mathbf{G}(k)\mathbf{u}_i(k) + \delta} \tag{3}$$

where μ is the step-size, δ is the regularization constant to avoid division by zero, and $\mathbf{G}(k) = \text{diag}\{g_1(k), g_2(k), \ldots, g_M(k)\}$ is an $M \times M$ diagonal matrix (called the proportionate matrix) whose role is to assign an individual step size for each filter coefficient (i.e., a filter coefficient $w_m(k)$ with larger magnitude receives a larger step size $\mu g_m(k)$, thus improving the convergence rate of that coefficient). Evidently, different strategies to calculate the proportionate matrix $\mathbf{G}(k)$ can generate different PNSAF algorithms, e.g., [17]. In particular, the NSAF algorithm is obtained when $\mathbf{G}(k) = \mathbf{I}_{M\times M}$ with $\mathbf{I}_{M\times M}$ being the identity matrix (i.e., when all the filter coefficients receive the same increment).

3. Proposed VSS-IPNSAF

Now, we start to derive a VSS scheme which is suitable for any PNSAF-type algorithm, whose inspiration arises from the presented shrinkage NLMS (SHNLMS) algorithm in [18].

3.1. Derivation of VSS scheme

Replacing the fixed step size μ with an individual time-varying step size $\mu_i(k)$ for each subband and neglecting δ for the convenience of derivation, (3) becomes

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \sum_{i=0}^{N-1}\mu_i(k)\frac{\mathbf{G}(k)\mathbf{u}_i(k)e_{i,D}(k)}{\mathbf{u}_i^T(k)\mathbf{G}(k)\mathbf{u}_i(k)}. \tag{4}$$

Before deriving this VSS scheme, we define the noise-free *a priori* subband error and noise-free *a posterior* subband error as follows

$$\varepsilon_{i,a}(k) = \mathbf{u}_i^T(k)[\mathbf{w}_o - \mathbf{w}(k)] \tag{5}$$

$$\varepsilon_{i,p}(k) = \mathbf{u}_i^T(k)[\mathbf{w}_o - \mathbf{w}(k+1)]. \tag{6}$$

Then, (2) can be rewritten as

$$e_{i,D}(k) = \varepsilon_{i,a}(k) + \eta_{i,D}(k) \tag{7}$$

where $\eta_{i,D}(k)$ is the ith subband noise with zero-mean and variance $\sigma^2_{\eta_{i,D}} = \sigma^2_\eta/N$, which is obtained by partitioning the system noise $\eta(n)$ [10].

Subtracting (4) from $\mathbf{w}_o$ and pre-multiplying $\mathbf{u}_i^T(k)$, we have

$$\varepsilon_{i,p}(k) = \varepsilon_{i,a}(k) - \mu_i(k)e_{i,D}(k) - \sum_{\substack{j=0\\ i\neq j}}^{N-1}\mu_i(k)\frac{\mathbf{u}_i^T(k)\mathbf{G}(k)\mathbf{u}_j(k)e_{j,D}(k)}{\mathbf{u}_j^T(k)\mathbf{G}(k)\mathbf{u}_j(k)}. \tag{8}$$