Signal Processing 122 (2016) 14–23

Contents lists available at ScienceDirect

Signal Processing

journal homepage: www.elsevier.com/locate/sigpro

Novel sign subband adaptive filter algorithms with individual weighting factors

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ARTICLE INFO

Article history:
Received 19 May 2015
Received in revised form
17 September 2015
Accepted 7 November 2015
Available online 28 November 2015

Keywords:
Sign subband adaptive filter
Individual weighting factor
Proportionate sign subband adaptive filter
Impulsive interference
System identification
Acoustic echo cancellation

ABSTRACT

This paper presents a new sign subband adaptive filter (SSAF) algorithm with an individual-weighting-factor (IWF) for each subband, instead of a common weighting factor in the original SSAF algorithm, called the IWF-SSAF. Each individual weighting factor only depends on the corresponding subband input signal power. Compared with the SSAF algorithm, the proposed approach fully utilizes the inherent decorrelating property of subband adaptive filter for colored inputs, leading to a better convergence performance. After that, to further enhance the performance of the IWF-SSAF in a sparse system, an improved proportionate IWF-SSAF (IWF-IPSSAF) algorithm is proposed. The proposed algorithms not only inherit the good robustness of sign algorithm against impulsive interferences, but also obtain a significant improvement in the performance as compared to their counterparts (i.e., SSAF and IPSSAF), in terms of the convergence rate and tracking capability. Besides, the IWF-IPSSAF algorithm has faster convergence rate than the IWF-SSAF algorithm for sparse impulse responses. Finally, the performances of two proposed algorithms are demonstrated in the system identification and the acoustic echo cancellation with double-talk.

1. Introduction

Adaptive filtering techniques have been utilized in a wide variety of applications such as system identification, active noise control, channel equalization, and acoustic echo cancellation (AEC) [1]. The normalized least mean square (NLMS) is a very well-known and widely used algorithm because of its low complexity and robustness, but it converges slowly for colored input signals. In order to address this problem, one of the methods is to use the affine projection algorithm (APA) [1] as well as its modified versions [2,3]. However, they require large computational burden. Another wonderful way to speed up convergence is the multiband-structured subband adaptive filter, because it can whiten the colored input signals through analysis filter bank [4]. That is to say, it possesses the decorrelating property for colored inputs in the subband domain. Benefiting from the principle of minimum disturbance, Lee and Gan proposed the normalized subband adaptive filter (NSAF) algorithm by using subband input signals and subband output error signals to update the tap-weight vector [5]. In fact, it generalizes the NLMS algorithm along the subband axis, namely, it reduces to the NLMS algorithm when the number of subbands is equal to one. Apart from fast convergence for colored input signals, the computational complexity of the NSAF algorithm is comparable to that of the NLMS algorithm for a high-order adaptive filter, and is far less than that of the APA. Afterwards, the authors did analyze the inherent decorrelating and least perturbation properties of the NSAF algorithm [6]. Following their works, the statistical models of the NSAF algorithm (including the first and the

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http://dx.doi.org/10.1016/j.sigpro.2015.11.007
0165-1684/

second moments of the tap-weight error vector) were discussed in [7]. Furthermore, many modified versions have been developed to further improve the performance of the NSAF algorithm [8–12].

Unfortunately, the aforementioned algorithms suffer from large steady-state misalignment or even divergence when the impulsive interference is present in the environment, because they are derived based on the optimization of L_2-norm. In echo cancellation scenario with double-talk, moreover, the near-end speech signal can also be viewed as the impulsive interference. Although the sign algorithm (SA) [13] based on the L_1-norm optimization can efficiently suppress the impulsive interferences, its convergence rate is very slow for colored input signals. Inspired by the presented the affine projection sign algorithm (APSA) [14], Ni et al. proposed a sign subband adaptive filter (SSAF) algorithm by extending the SA to the multiband-structured subband adaptive filter, and then proposed a variable regularization parameter SSAF (VRP-SSAF) algorithm to further reduce the steady-state error [15]. Recently, many works from the following aspects have been devoted to improve the performance of the SSAF algorithm in terms of the convergence rate and the steady-state error. On the one hand, to overcome a trade-off problem between fast convergence and low steady-state error caused by the fixed step-size, several variable step size SSAF algorithms were proposed in [16–18]. On the other hand, in the light of the advantage of the APA for colored input signals, the affine projection SSAF (AP-SSAF) algorithm [19] was developed which provides faster convergence rate. Nevertheless, in many practical applications such as AEC, the impulse response of the echo path that is identified by an adaptive filter is usually sparse, i.e., only a small number of coefficients of the impulse response have large magnitude (called *active coefficients*) while the rest coefficients (called *inactive coefficients*) are close or equal to zero [2,3,20,21]. Aiming to this class of impulse responses, therefore, Ni and his co-authors proposed a class of proportionate SSAF (PSSAF) algorithms such as the improved proportionate PSSAF (IPSSAF) and the PSSAF with individual-activation-factors (IAF-PSSAF) [22]. In the SSAF, however, there is a key problem that all subbands are interconnected by a common weighting factor. This directly impacts its convergence performance, and some modified SSAF algorithms such as the IPSSAF also have the same problem.

In this paper, we propose a new SSAF algorithm, called the individual-weighting-factors SSAF (IWF-SSAF), by re-examining the way to compute the weighting factor in the SSAF algorithm, aiming to improve the filter's performance. In addition, the mean-square transient behavior of the IWF-SSAF algorithm is analyzed. In contrast to the original SSAF algorithm, the new algorithm has the following characteristics:

1) an individual weighting factor is used for each subband;
2) each weighting factor is computed only using the corresponding subband input signal power. Moreover, the subband with larger input signal power receives lower weight, vice versa.

As a result, the proposed algorithm is of significant improvement in the convergence performance. For sparse systems, we also develop an improved proportionate IWF-SSAF (IWF-IPSSAF) algorithm by incorporating the proportionate idea into the IWF-SSAF, which speeds up the convergence rate.

The remainder of this paper is organized as follows. Section II briefly reviews the original SSAF algorithm. In Section 3, we firstly discuss the problem of the SSAF algorithm, and then develop the IWF-SSAF algorithm and its mean-square analysis. In Section 4, the proportionate idea is introduced into the IWF-SSAF algorithm. In Section 5, computer simulations in the context of the system identification and AEC verify the excellent performance of the proposed algorithms. Finally, Section 6 gives our conclusions.

2. Review SSAF algorithm

Let us consider that the observed output data $d(n)$ from the unknown system is given by

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

where $\mathbf{w}_o$ denotes an unknown M-dimensional vector that we want to estimate with an adaptive filter, the superscript T indicates transpose operator, $\mathbf{u}(n)=[u(n),u(n-1),\ldots,u(n-M+1)]^T$ is the input signal vector, and $\vartheta(n)$ is the additive noise. In many practical situations, the additive noise consists of the background noise $v(n)$ and the impulsive interference $\eta(n)$, i.e., $\vartheta(n)=v(n)+\eta(n)$. Fig. 1 shows the multiband-structure of subband adaptive filter [4] which has been used to design the NSAF and SSAF algorithms, where N represents the number of subbands. The observed output data $d(n)$ and the input signal $u(n)$ are partitioned into N subband signals $d_i(n)$ and $u_i(n)$ through analysis filter bank $\{H_i(z), i\in[0,N-1]\}$, respectively. Then, subband signals $y_i(n)$ and $d_i(n)$ for $i\in[0,N-1]$ are critically decimated to yield $y_{i,\mathrm{D}}(k)$ and $d_{i,\mathrm{D}}(k)$, respectively, where n and k indicate the original sequences and the decimated sequences. Thereby, the subband output error signals can be calculated by

$$e_{i,D}(k)=d_{i,D}(k)-\mathbf{u}_i^T(k)\mathbf{w}(k)\text{for} i\in[0,N-1] \tag{2}$$

where $\mathbf{w}(k)=[w_1(k),w_2(k),\ldots,w_M(k)]^T$ denotes the tap-weight vector of the adaptive filter, $d_{i,D}(k)=d_i(kN)$ and $\mathbf{u}_i(k)=[u_i(kN),u_i(kN-1),\ldots,u_i(kN-M+1)]^T$.

Rewriting (2) in matrix form yields

$$\mathbf{e}_\mathrm{D}(k)=\mathbf{d}_\mathrm{D}(k)-\mathbf{U}^T(k)\mathbf{w}(k)\triangleq\left[e_{0,D}(k),e_{1,D}(k),\ldots,e_{N-1,D}(k)\right]^T \tag{3}$$

where $\mathbf{d}_\mathrm{D}(k)=\left[d_{0,\mathrm{D}}(k),\ d_{1,\mathrm{D}}(k),\ \ldots,\ d_{N-1,\mathrm{D}}(k)\right]^T$ and $\mathbf{U}(k)=\left[\mathbf{u}_0(k),\ \mathbf{u}_1(k),\ \ldots,\ \mathbf{u}_{N-1}(k)\right]$.

As reported in [15], the tap-weight vector of the original SSAF algorithm is updated as

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\mu\frac{\mathbf{U}(k)\mathrm{sign}(\mathbf{e}_\mathrm{D}(k))}{\sqrt{\sum_{i=0}^{N-1}\mathbf{u}_i^T(k)\mathbf{u}_i(k)+\varepsilon}} \tag{4}$$

where μ is the step size, ε is a small positive number to avoid division by zero, and $\mathrm{sign}(\cdot)$ indicates the sign function and $\mathrm{sign}(\mathbf{e}_\mathrm{D}(k))$ takes the sign operation of each element of $\mathbf{e}_\mathrm{D}(k)$.