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REGULAR PAPER

A novel sign adaptation scheme for convex combination of two adaptive filters☆

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ABSTRACT

To improve the performance and reduce the computational complexity, a novel sign adaptation scheme for convex combination of adaptive filters is proposed. By using a sign adaptation scheme, the proposed scheme slightly reduces the computational complexity of the basic combination of mixing parameter, and improves the robustness of mixing parameter. Moreover, to obtain fast convergence property during the period of convergence transition in different environments, the instantaneous transfer scheme is applied to the proposed algorithm. The instantaneous transfer scheme has lower computational complexity than that of the basic combination of least mean square (basic-CLMS) algorithms. Simulation results in the context of system identification under time-invariant and time-variant systems demonstrate that the proposed algorithm based on the instantaneous transfer scheme has lower computational complexity and faster convergence rate than that of the basic-CLMS algorithm during period of convergence transitions.

1. Introduction

Adaptive algorithms play a major role in many signal processing fields [1,2]. One of the most popular adaptive filters is the normalized least-mean-square (NLMS) algorithm [3]. However, the NLMS algorithm reflects a tradeoff between fast convergence and good tracking ability. To solve this conflicting requirement, many schemes were proposed, such as the variable step size (VSS) NLMS algorithm [4,5] and the implementations of the affine projection algorithm (APA) [6,7].

In the past years, adaptively combining two least mean square filters (CLMS) scheme was developed to address the tradeoff in many signal processing applications, such as system identification, channel estimation, adaptive beamforming and acoustic echo cancelation. By paralleling two LMS filters with different step sizes, the scheme can improve the speed of convergence vs the residual error trade-off imposed by the selection of a certain value for the step size [8–12]. Following these works, García et al. presented a new plant identification method by using two or three LMS filters with large and small step sizes to gain fast convergence and low misadjustment [11]. Also, the convex combination strategy can be extended to the recursive least squares (RLS) [11], NLMS algorithm [13], APA [14], subband adaptive filter (SAF) [15], Shalvi–Weinstein algorithm (SWA) [16] and the constant-modulus algorithm (CMA) [16], etc. To achieve more strong robustness than the basic-CLMS algorithm, Ruiz et al. presented a new normalized rule of the CLMS algorithm when the signal-to-noise ratio (SNR) is time varying [17]. Consider the tap-length effect the identification precision of the filter [18,19], some algorithms were hybrid the convex combination scheme and variable tap-length scheme [20,21]. Both of these algorithms have effectively enhanced the performance of the filers (linear filter (LMS filter) and nonlinear filter (Volterra filter)). Besides, the convex combination scheme is not only used in linear structure but also nonlinear structure. The convex combination strategy has successfully used in the fields of nonlinear system identification under α-stable noise environment [22]. By using combination scheme, the two recursive least p-norm (RLMp) filters with different step sizes overcome the conflict between convergence rate and misadjustment in the presence of α-stable noise. Later, this scheme has extended in the field of the nonlinear acoustic echo cancelation (NLAEC) with Volterra filter [23]. It should be noted that for NLAEC the extension of the some adaptive algorithms have used to simplified Volterra filters [24]. These algorithms are numerically less complex than Volterra filter and superior performance. Moreover, recently, to improve the convergence speed and

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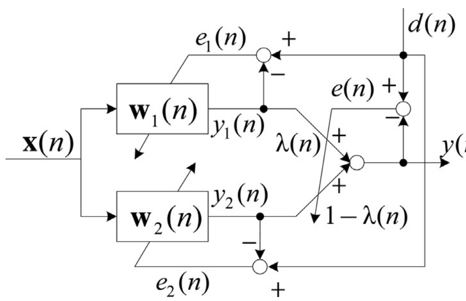

Fig. 1. Diagram of the basic-CLMS filter.

tracking capability, and to reduce the misadjustment of the traditional algorithm, some novel nonlinear neural networks were presented based on combination scheme [25–27]. Nevertheless, the convergence rate was still slow during the period of convergence transition. To solve this problem, a novel transfer of coefficients scheme is proposed, but its cost was relatively high [11]. To address this limitation, Nascimento et al. developed an instantaneous transfer scheme for the convex combination of adaptive filters which retains the convergence rate with low cost [28].

In this work, we propose a novel sign adaptation CLMS algorithm based on a coefficient transfer scheme to improve the filtering performance in different environments. By using a sign adaptation scheme, the proposed algorithm can slightly reduce the computational complexity and retain the robustness of the mixing parameter. Furthermore, a good convergence property during the period of convergence transition is obtained by using instantaneous transfer scheme. Compared with the basic-CLMS, the proposed algorithm has superior performance, but lower computations. In summary, the contribution of this paper is three-fold: (1) to develop a novel sign adaptation scheme that is well suited for the identification under time-invariant system and time-variant system, (2) to slightly reduce the computational complexity and memory usage, also retain the robustness of the CLMS filter, (3) to apply the instantaneous transfer scheme that is low computational complexity and effectiveness for increase convergence rate.

This paper is organized in the following manner. Section 2 introduces a brief description of the basic-CLMS. In Section 3, the proposed algorithm is presented, and analysis of computational complexity, data memory usage and mixing parameter is provided. In Section 4, we show the advantages of the proposed algorithm through some simulation results. Finally, some conclusions are given in Section 5.

2. Brief description of the basic-CLMS algorithm

Fig. 1 shows the diagrams of the basic-CLMS filter [8–11], where $d(n)$ represents the desired response signal. Outputs $y_1(n)$ and $y_2(n)$ of two filters with different step sizes are combined as an overall output $y(n)$ of the basic-CLMS filter, as shown in the following:

$$y(n) = \lambda(n)y_1(n) + [1 - \lambda(n)]y_2(n) \tag{1}$$

where $\lambda(n) \in [0, 1]$ is a mixing scalar parameter. By adjusting $y(n)$, adaptively combining two independent LMS filters with large and small step sizes can obtain fast convergence with the low steady-state error. Moreover, in order to make the value of $\lambda(n)$ be in the [0,1], $\lambda(n)$ is defined by using a sigmoid function with the parameter $a(n)$

$$\lambda(n) = \frac{1}{1 + e^{-a(n)}} \tag{2}$$

where the update rule for $a(n)$ to the minimize the quadratic error of the combined filter [11]

$$\begin{aligned} a(n+1) &= a(n) - \frac{\mu_a}{2}\frac{\partial e^2(n)}{\partial a(n)} \\ &= a(n) + \mu_a e(n)[y_1(n) - y_2(n)]\lambda(n)[1 - \lambda(n)] \end{aligned} \tag{3}$$

where the step-size μ_a is a positive constant, and the overall filter error $e(n)$ is calculated by $e(n) = d(n) - y(n)$. To avoid stagnation when $\lambda(n)$ equal to 0 or 1, $a(n)$ is restricted in $[-a^+, a^+]$, which limits the permissible range of $\lambda(n)$ to $[1 - \lambda^+, \lambda^+]$. Note that the parameters a^+ and λ^+ are the positive constants. Later, Gredilla et al. proposed a nonlinear function based on a sigmoid to include the bounds of $a(n)$ [29]. This weight transfer scheme has more robustness capability than (3).

For ith filter ($i = 1, 2$), the update rule of the weight vector $\mathbf{w}_i(n)$ is given as

$$\mathbf{w}_i(n+1) = \mathbf{w}_i(n) + \mu_i \mathbf{x}(n)e_i(n) \tag{4}$$

where μ_i denotes the step size of ith adaptive filter, $\mathbf{x}(n)$ is an input signal vector of two filters in n moment. Thus, the overall weight vector $\mathbf{w}(n) = [w_1(n), w_2(n), \ldots, w_M(n)]^T$ with length M can be calculated by

$$\mathbf{w}(n) = \lambda(n)\mathbf{w}_1(n) + [1 - \lambda(n)]\mathbf{w}_2(n). \tag{5}$$

Consequently, by adjusting the mixing parameter, the basic-CLMS algorithm has good balance between the convergence speed and steady-state error. However, since the basic-CLMS algorithm requires the accurately setting parameters, these would not guarantee its best performance in different noise environment. Moreover, it has high computational complexity due to the increasing computational burden of the parameter $a(n)$.

3. The proposed CLMS algorithm

3.1. The proposed algorithm

To solve these problems, we proposed a novel CLMS algorithm. By using a sign adaptation scheme, the update rule of the parameter $a(n)$ is modified to reduce the squared estimation error

$$J(n) = \frac{1}{2}e^2(n). \tag{6}$$

In this proposed strategy, the gradient $\nabla_a J(n)$ with respect to $a(n)$ is normalized by its norm. Then, the parameter $a(n)$ is recursively updated by

$$a(n+1) = a(n) - \mu_a \frac{\nabla_a J(n)}{||\nabla_a J(n)||} \tag{7}$$

where the step-size μ_a is a small positive constant, and $\nabla_a J(n)$ can be calculated as

$$\nabla_a J(n) = -e(n)[y_1(n) - y_2(n)]\lambda(n)[1 - \lambda(n)]. \tag{8}$$

Then, $\frac{\nabla_a J(n)}{||\nabla_a J(n)||}$ in (8) can be written as

$$\frac{\nabla_a J(n)}{||\nabla_a J(n)||} = sgn(\nabla_a J(n)) \tag{9}$$

where $\mathrm{sgn}(\cdot)$ is a sign function which is expressed by

$$sgn(x) = \frac{x}{||x||} = \begin{cases} 1, & \text{if} x > 0 \\ 0, & \text{if } x = 0 \\ -1, & \text{if } x < 0 \end{cases} . \rightarrow \tag{10}$$

Consequently, (7) can be rewritten as

$$a(n+1) = a(n) + \mu_a sgn(e(n)[y_1(n) - y_2(n)]\lambda(n)[1 - \lambda(n)]). \tag{11}$$