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An improved mean-square weight deviation-proportionate gain algorithm based on error autocorrelation

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ABSTRACT

This paper presents an alternative approach to the gain distribution policy used in the z^2-proportionate algorithm. The gain policy of the z^2-proportionate uses a rule that combines the mean-square weight deviation-proportionate gain and a uniform one to obtain the whole algorithm gain distribution, leading to very good convergence characteristics. However, such a gain combination law is dependent on the knowledge of the measurement noise variance in the system, which in practice is not always readily available. Here, aiming to circumvent such dependence, a new strategy of gain distribution based on error autocorrelation is introduced. The proposed approach makes the use of the mean-square weight deviation-proportionate gain more attractive for real-world applications. Simulation results show that the proposed algorithm outperforms the z^2-proportionate in terms of convergence characteristics for cases in which the measurement noise variance is either unknown or poorly estimated.

1. Introduction

In many real-world applications, such as echo cancellation, channel equalization, and seismic processes, the plant impulse response is sparse [1–5]. For this class of responses, the well-known least-mean-square (LMS) and normalized LMS (NLMS) algorithms (which use the same adaptation step size for all filter coefficients) exhibit poor convergence characteristics [6–9]. To exploit the sparse nature of the plant impulse response, Duttweiler in [10] has proposed an algorithm, called proportionate NLMS (PNLMS), in which each filter coefficient is updated proportionally to its magnitude, resulting in an algorithm with improved convergence characteristics. However, the PNLMS fast initial convergence is not preserved over the whole adaptation process [9,11]. Furthermore, the PNLMS algorithm provides slow convergence when the plant exhibits medium and low sparseness [6,7]. To circumvent these problems, several versions of the PNLMS algorithm have been proposed in the open literature [7,9,12–14]. For instance, the improved PNLMS (IPNLMS) algorithm allows controlling its performance for convergence speed according to the plant sparseness, resulting in better convergence characteristics than the PNLMS for a wide range of plant sparseness [7]. Two versions of the PNLMS algorithm, termed sparseness-controlled PNLMS (SC-PNLMS) and sparseness-controlled IPNLMS (SC-IPNLMS), which take into account the sparseness variation of the plant are presented in [15] and [16], respectively; these algorithms perform well for both very high and medium sparseness levels, however at the expense of a high computational burden. Aiming to provide fast convergence during the whole adaptation

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process, μ-law PNLMS (MPNLMS) and adaptive MPNLMS (AMPNLMS) algorithms are given, respectively, in [11] and [17]; however, such algorithms are computationally much more complex than the PNLMS.

In [17,18], a new proportionate-type algorithm is presented. Such an algorithm, termed water-filling, is based on minimizing the mean-square error with respect to the algorithm gains for white input data. Also in [18], seeking to reduce computational complexity, the z^2-proportionate algorithm is derived from the water-filling one. To deal with colored input data, a colored-water-filling (CWF) algorithm is discussed in [19,20]. This algorithm exhibits very good convergence characteristics; however, its computational load is too high. To circumvent such a drawback, two suboptimal versions of the CWF algorithm [suboptimal gain allocation version 1 (Suboptimal 1) and suboptimal gain allocation version 2 (Suboptimal 2)] are given in [19]. In contrast to the PNLMS-type algorithms that take into account the magnitude of the coefficients to compute the gain allocation, the algorithms discussed in [17–20] use an estimate of the mean-square weight deviation. Among the latter, the z^2-proportionate algorithm is the one that exhibits lower computational complexity and, for this reason, we concentrate here our study on this algorithm.

The z^2-proportionate uses a gain distribution that combines the mean-square weight deviation-proportionate gain and a uniform one, such that the algorithm gain in steady state is uniform. This mixture of gains is controlled by a parameter that depends on the measurement noise variance, requiring therefore its estimate. Moreover, the z^2-proportionate algorithm performance is degraded when such a variance value is not accurately estimated.

In this research work, a novel approach to obtain the algorithm gain distribution is proposed aiming to circumvent the dependence on the knowledge of the measurement noise variance. Thus, a new strategy to carry out the migration from the mean-square weight deviation-proportionate gain to uniform one is here introduced. Such a strategy, which does not require the knowledge of the measurement noise variance, is based on the autocorrelation between adjacent samples of the error signal. The proposed algorithm outperforms the z^2-proportionate algorithm in terms of convergence characteristics for cases in which the measurement noise variance is either unknown or poorly estimated. Through numerical simulations, using a real-world echo path as plant impulse response, the effectiveness of the proposed algorithm is assessed for different operating scenarios.

This paper is organized as follows. Section 2 revisits the z^2-proportionate algorithm. In Section 3, the impact of the measurement noise variance estimate error on the z^2-proportionate algorithm behavior is briefly discussed. Section 4 presents the proposed algorithm as well as describes in detail its operation principle. In Section 5, numerical simulation results attest the performance of the new algorithm. Finally, Section 6 presents concluding remarks.

2. Revisiting the z^2-proportionate algorithm

In this section, we start reviewing the general expressions of the PNLMS-type algorithms and next a brief description of the z^2-proportionate algorithm is presented.

2.1. General expressions of the PNLMS-type algorithms

The PNLMS-type adaptive algorithms are formulated by the following set of equations [7,9]:

Coefficient update vector

$$\mathbf{w}(k+1)=\mathbf{w}(k)+\frac{\beta\mathbf{G}(k)\mathbf{x}(k)e(k)}{\mathbf{x}^{\mathrm{T}}(k)\mathbf{G}(k)\mathbf{x}(k)+\xi} \tag{1}$$

Error signal

$$e(k)=d(k)+v(k)-y(k) \tag{2}$$

Adaptive filter output

$$y(k)=\mathbf{w}^{\mathrm{T}}(k)\mathbf{x}(k)=\mathbf{x}^{\mathrm{T}}(k)\mathbf{w}(k) \tag{3}$$

Gain distribution matrix

$$\mathbf{G}(k)=\mathrm{diag}[g_1(k)\; g_2(k)\cdots g_L(k)] \tag{4}$$

where $\mathbf{w}(k)=[w_1(k)\; w_2(k)\cdots w_L(k)]^{\mathrm{T}}$ is the L-dimensional adaptive coefficient vector, $\mathbf{x}(k)=[x(k)\; x(k-1)\cdots x(k-L+1)]^{\mathrm{T}}$ denotes the input vector with variance σ_x^2, $d(k)$ represents the desired signal, $v(k)$ denotes a zero-mean independent and identically distributed (i.i.d.) measurement noise with variance σ_v^2 and uncorrelated with any other signal in the system, and β is the step-size control parameter. Constant $\xi>0$ is a regularization parameter that prevents division by zero in (1) and stabilizes the solution. The diagonal matrix $\mathbf{G}(k)$ distributes individual gains among the filter coefficients according to a specific rule. It should be noted that by setting the matrix $\mathbf{G}(k)$ equal to the identity matrix, the proportional adaptive algorithm becomes the NLMS algorithm. For the sake of clarity, we illustrate in Fig. 1 the block diagram of a typical adaptive filtering scheme showing the variables used here.

2.2. Brief description of the z^2-proportionate algorithm

Let us define the weight deviation vector as

$$\mathbf{z}(k)=\mathbf{w}^{\mathrm{o}}-\mathbf{w}(k) \tag{5}$$

where $\mathbf{w}^{\mathrm{o}}=[w_1^{\mathrm{o}}\; w_2^{\mathrm{o}}\cdots w_L^{\mathrm{o}}]^{\mathrm{T}}$ is an L-dimensional vector representing the plant impulse response. Thus, the gain of the z^2-proportionate algorithm, obtained from the simplification of the water-filling algorithm, is given by [18]

$$g_i^{\mathrm{o}}(k)=\frac{\mathrm{E}[z_i^2(k)]}{(1/L)\sum_{j=1}^{L}\mathrm{E}[z_j^2(k)]},\qquad i=1,2,\ldots,L \tag{6}$$

with

$$\mathrm{E}[z_i^2(k)]=\mathrm{E}\{[w_i^{\mathrm{o}}-w_i(k)]^2\} \tag{7}$$

where $\mathrm{E}[z_i^2(k)]$ represents the mean-square weight deviation of the ith coefficient.

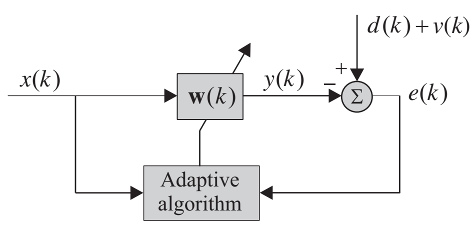

Fig. 1. Typical setup of adaptive filtering.