Variable Step Size Pre-Whitening Transform Domain LMS Adaptive Noise Canceller

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***Abstract*—In this paper, we propose a novel variable step size pre-whitening transform domain LMS algorithm for adaptive noise cancellation by introducing a new expression for updating the step size using a smoother gradient vector estimated by weighted averaging. The resulting algorithm presents a good tradeoff between performance and computational complexity and significantly outperforms the existing transform domain LMS algorithms in terms of the convergence speed, level of the steady state reached by the excess mean square error (EMSE), the steady state of the EMSE, misadjustment and output SNR.**

***Keywords*—Variable step size, Pre-whitening TDLMS, Noise cancellation.**

I. INTRODUCTION

The LMS algorithm is widely adopted in adaptive filtering for the reason of its simplicity, robustness and lower computational complexity [1]. The step size is a parameter playing a crucial role in the determination of the convergence performance of the LMS algorithm. A fast convergence speed can be obtained, at the expense of high misadjustment, using a large step size value, whereas smaller step size value can lead to smaller misadjustment at the expense of a slow convergence speed [2]. To overcome this problem and achieve a faster convergence rate with a smaller misadjustment, several variable step size LMS algorithms have been reported in the literature [2]-[8]. The variable step size is generally adjusted by employing the energy of the instantaneous estimated error. In [6], Hwang et al proposed a variable step size LMS algorithm using the weighted average of the gradient vector. In [9], Chergui and Bouguezel proposed a pre-whitening transform domain LMS (PW-TDLMS) adaptive noise canceller applied for speech denoising. This algorithm uses a fixed step size parameter, which limits its performance.

In this paper, we propose a new variable step size PW-TDLMS (VSSPW-TDLMS) algorithm, with its variable step size being adjusted using a modified formula based only on the weighted average of the gradient vector. The proposed algorithm outperforms the PW-TDLMS in terms of the convergence speed of mean square error (MSE) and the level of reached steady state. The rest of this paper is structured as follows. Section 2 briefly reviews the variable step size LMS algorithm with a weighted average of the gradient vector as well as the PW-TDLMS algorithm. Section 3 presents the proposed algorithm. The simulation results and discussions are shown in Section 4. Section 5 considers the computational complexities of different algorithms and finally, the conclusion is given in Section 6.

II. BRIEF LITERATURE REVIEW

In this section, we briefly review the algorithms reported in [6] and [9]. Even though the algorithm in [6] has been devoted for identification purposes, it is reviewed here to exploit, in the present work, its step size updating expression. The review of the algorithm in [9] is important due to the fact that the present work is based on it.

A. Variable step size LMS with a weighted average of the gradient vector

The variable step size LMS algorithm reported in [6], which uses a gradient-based weighted average, can be summarized as follows:

The instantaneous error e_k is given by

$$e_k = d_k - \mathbf{w}_k^T \mathbf{x}_k \tag{1}$$

where d_k is the desired signal, $\mathbf{x}_k = [x_k, x_{k-1}, \ldots, x_{k-N+1}]^T$ is the input signal of length N and $\mathbf{w}_k = [w_0, w_1, \ldots, w_{N-1}]^T$ is the filter vector updated according to the weight update recursion given by

$$\mathbf{w}_{k+1} = \mathbf{w}_k + \mu_k e_k \mathbf{x}_k \tag{2}$$

The step size μ_k in (2) is updated using the expression

$$\mu_{k+1} = \alpha\mu_k + \gamma_s \left\|\hat{\mathbf{p}}_k\right\|^2 e_k^2 \tag{3}$$

where $\gamma_s > 0$, $0 < \alpha < 1$, $\|\cdot\|^2$ denotes the squared Euclidean norm operation and $\hat{\mathbf{p}}_k$ is a smoother gradient vector estimated by weighted averaging as

$$\hat{\mathbf{p}}_k = \delta\hat{\mathbf{p}}_{k-1} + (1-\delta) e_k \mathbf{x}_k \tag{4}$$

with $0 < \delta < 1$ being a smoothing factor.

B. PW-TDLMS

The PW-TDLMS algorithm reported in [9] for adaptive noise cancellation can be summarized as follows:

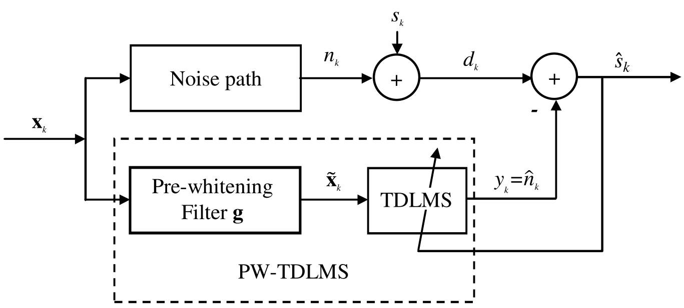

Fig. 1. PW-TDLMS adaptive noise canceller [9].

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