Adaptive Affine Combination of Two IPNLMS Filters for Robust Sparse Echo Cancellation

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***Abstract*—Conventional adaptive filtering algorithms (LMS, NLMS) are widely used in system identification applications. However, the performance of these algorithms is degraded when the system echo path is sparse in nature as in network and acoustic echo cancellation scenarios. Proportionate-type filters (IPNLMS) are considered as suitable candidate to achieve better performance for sparse echo paths, but they fail to exploit the time varying system sparsity. Moreover, there exists some compromise between their convergence speed and steady-state error. To overcome these limitations, a combination approach of two adaptive filters that combines the output of individual filters through a mixing parameter has been developed. We propose an adaptive affine combination of two IPNLMS filters as a robust solution to alleviate the convergence speed vs steady-state error tradeoff, and to efficiently increase IPNLMS robustness to time varying sparsity of the system. Effectiveness of our proposed affine combination approach has been validated from the MATLAB simulations.**

***Index Terms*—System Identification; Echo Cancellation; Sparse Echo Path; Proportionate Adaptive Filters; Affine Combination; Convergence Speed; Steady State Error.**

I. Introduction

Adaptive filters are widely used in system identification applications, e.g., echo cancellation and channel estimation. In general, we often encounter systems with sparse impulse response like network and acoustic echo cancellation systems. A sparse system has only a few active coefficients while most of its coefficients are inactive [1]. Low complexity adaptive algorithms such as LMS and NLMS that are often used in echo cancellation tend to show slow performance as they apply uniform step size across all filter coefficients. Further, irrespective of the adaptive algorithm used, a tradeoff between convergence speed and steady-state error (MSE) always exists [2]. These conventional system identification algorithms are also incapable of utilizing the existing system sparse structure and their performance is reduced when estimating the sparse channels. Taking into account the time varying sparsity of echo path, it is essential to obtain a robust solution that is acceptable to perform effectively with different echo path channels [3].

In an echo cancellation set-up as shown in Figure 1, the adaptive filter w(n) estimates the echo path impulse response wo(n), and produces the output y(n) which is subtracted from the microphone signal, d(n) [2]. The goal of an echo canceller is to eliminate the undesired echo signal by replicating the echo signal and subtract the echo from the echo corrupted signal.

An echo canceller used to model a sparse echo channel usually requires long adaptive filters; hence the conventional adaptive algorithms suffer from slow convergence [4]. When the sparsity level increases, the traditional methods such as LMS and NLMS algorithms fail to exploit the system sparsity, whereas they perform well for non-sparse systems [5], [6]. To avoid these problems, proportionate adaptive algorithms are developed [7], [8], in which every coefficient is assigned different step size parameter. The convergence speed of Proportionate NLMS (PNLMS) filter [9] is faster than NLMS for sparse echo paths, but NLMS exhibits better performance when the system is not so sparse. Improved PNLMS (IPNLMS) algorithm was proposed in [10]. The update equation of IPNLMS is defined in Equation 1.

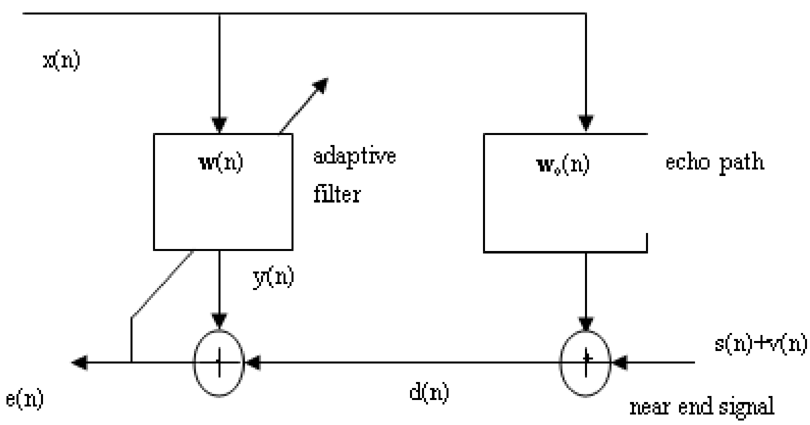

Figure 1: General echo canceller configuration

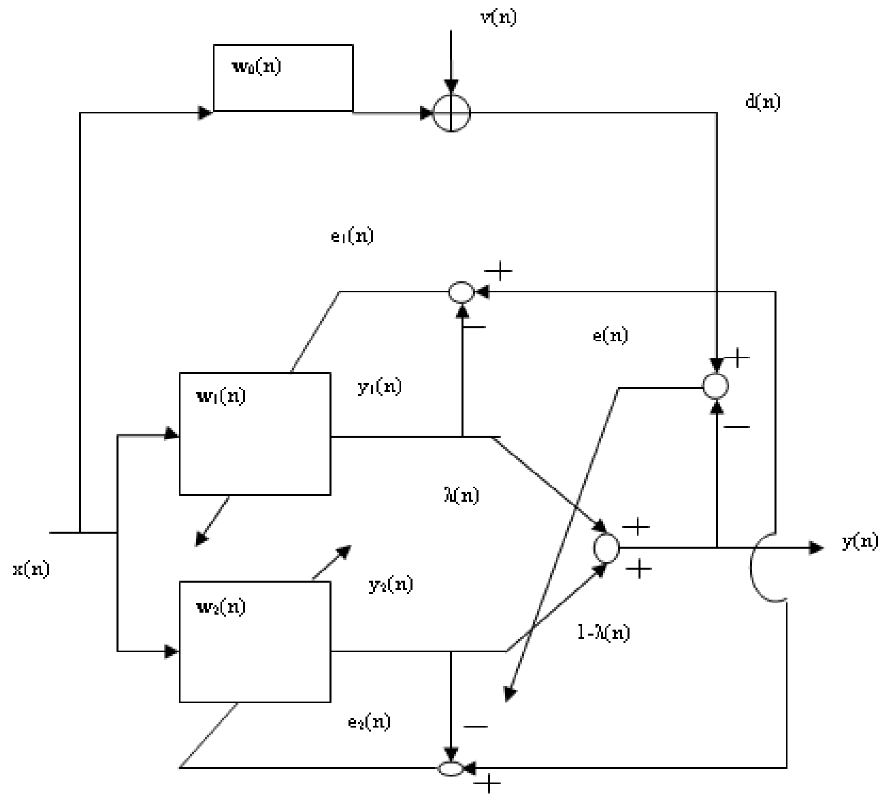

Figure 2: Affine combination of two adaptive filters

$$\overline{w}(n+1)=\overline{w}(n)+\frac{\mu\overline{Q}(n)\overline{x}(n)e(n)}{\overline{x}^{T}(n)\overline{Q}(n)\overline{x}(n)+\delta_{IPNLMS}} \tag{1}$$

where Q is a diagonal matrix, $\overline{Q}(n)=diag\{q_0(n),q_1(n),...q_{M-1}(n)\}$

$$q_l(n)=\frac{q_l(n)}{\|\overline{q}(n)\|_1}=\frac{1-k}{2M}+(1+k)\frac{|w_l(n)|}{2\|\overline{w}(n)\|_1+\varepsilon} \tag{2}$$
$$l=0,1,....M-1$$

The IPNLMS parameters μ and k must be properly chosen because,

i. IPNLMS algorithm exhibits faster convergence with larger step size and slower residual misadjustment with smaller step size μ.
ii. Selection of PNLMS filter with $k=1$ achieves faster convergence for strongly sparse channels, but has degraded performance for dispersive (non-sparse) channels.

Recently, the combination approach of adaptive filters has gained much importance for system identification applications [11], [12], as it provides robustness against systems with varying sparsity and also achieves better performance than each of the combining filters separately. Obtaining the mixing parameter, λ(n) through which the outputs of the individual adaptive filters are combined is crucial in this approach. In [11], the convex combination approach is used where λ(n) in defined by a sigmoid function, i.e., λ(n) is restricted to lie in the range [0, 1]. An approach based on the affine combination of two NLMS adaptive filters is proposed in [13], [14], where λ(n) is calculated from the two component filter output signals.

This paper is structured as follows. The proposed affine combination strategy of two IPNLMS filters is derived in Section 2. In Section 3, the effectiveness of the proposed affine combination scheme in terms of convergence vs steady state performance and robustness to variable sparsity system is verified through the simulation results. Finally, Section 4 concludes the paper and contains references.

II. Proposed Adaptive Affine Combination of IPNLMS Filters

Let us consider two adaptive filters (w_1 and w_2) combined in a manner as shown in Figure 2. $\overline{x}(n)$ is the input vector, common for both adaptive filters. The two filters are adapted using their own set of rules and the outputs are combined according to obtain an overall filter of improved performance and $\lambda(n)$ is called the mixing parameter. $y_1(n)$ and $y_2(n)$ denote the output of each of the combining filters i.e., $y_i(n)=w_i^T(n-1)\overline{x}(n)$, $i=1,2$.

$$y(n)=\lambda(n)y_1(n)+[1-\lambda(n)]y_2(n), \tag{3}$$

As we employ the IPNLMS as component filters, we consider the update equation (1) for their adaptation. The parameters $\{\mu_1,k_1\}$ and $\{\mu_2,k_2\}$ are selected in one of the following ways:

a) $\mu_1 > \mu_2$ and $k_1 = k_2$: With this configuration, the combined filter achieves faster convergence with filter having step size μ_1 and minimum steady-state error with filter having step size μ_2, simultaneously.
b) $\mu_1 = \mu_2$, $k_1 < 0$, $k_2 \approx 1$: With this setting, the

robustness against systems with varying sparsity and better convergence performance can be achieved.

In our affine combination approach, the mixing parameter λ(n) can be any real number. This is not the case in convex combination approach [11], where λ(n) lies between 0 and 1.

$$e_i(n) = d(n) - w_i^H(n-1)\bar{x}(n), \qquad (4)$$

The desired signal $d(n)$ is given by

$$d(n) = \bar{w}_0^T \bar{x}(n) + v(n) \qquad (5)$$

It is assumed that the noise $v(n)$ is zero mean Gaussian signal, and statistically independent of all other signals.

The *a priori* system error signal defined as difference between the output signal of the true system at time n, $y_0(n) = \bar{w}_0^T \bar{x}(n) = d(n) - v(n)$, and the output signal of our adaptive scheme $y(n)$ is

$$e_a(n) = y_0(n) - y(n) = y_0(n) - \lambda(n) y_1(n) - [1-\lambda(n)] y_2(n) \qquad (6)$$

$\lambda(n)$ is obtained by minimizing the mean square of the *a priori* system error. The derivative of $E[|e_a(n)|^2]$ with respect to $\lambda(n)$ is given by

$$\frac{\partial E[|e_a(n)|^2]}{\partial \lambda(n)} = 2E[\mathrm{Re}\{(y_0(n) - y_2(n))(y_2(n) - y_1(n))^*\} + \lambda(n)|(y_2(n) - y_1(n))|^2]$$
$$= 2E[\mathrm{Re}\{(y_0(n) - y_2(n))(y_2(n) - y_1(n))^*\} + \lambda(n)|(y_2(n) - y_1(n))|^2] \qquad (7)$$

Setting the derivative to zero results in

$$\lambda(n) = \frac{E[\mathrm{Re}\{(d(n) - y_2(n))(y_2(n) - y_1(n))^*\}]}{E[|(y_2(n) - y_1(n))|^2]} \qquad (8)$$

where the true system output signal, $y_0(n)$ is replaced by its observable noisy version, $d(n)$.

In order to obtain a practical algorithm, we replace the E[.] operators in (8) by exponential smoothing of the type

$$p_u(n) = (1-\gamma) p_u(n-1) + \gamma u^2(n), \qquad (9)$$

where u(n) is the signal to be averaged, $p_u(n)$ is the averaged quantity, and $\gamma = 0.01$. These averaged quantities were then used in (8) to obtain λ.

III. Simulation Results

In this section, we evaluate the performance of the proposed affine combination of two IPNLMS filters by considering the two parameter settings as discussed earlier. The simulations are done using MATLAB. The input signal $x(n)$ of 100000 samples is generated and is considered to be white Gaussian noise (WGN). The noise signal $v(n)$, with variance σ_0^2 is added to the reference signal to get an SNR of 70dB initially, and it is changed to SNR= 30dB at n= 80000. The impulse response of the echo path is generated synthetically using the method given in [15]. The adaptive filter coefficients were initialized to zero vectors. The length of the two component filters is set to M=512. A change in the echo path by circular shift operation is observed at n=50000 sample index to study the filter's reconvergence ability.

The following performance measures are used as the evaluation metric.

Normalized Weight Misalignment (NWM) evaluates the convergence of the adaptive algorithm. It is defined by

$$\mathrm{NWM(n)} = 20\log_{10} \frac{\|W_o - W(n)\|_2^2}{\|W_o\|_2^2} (dB) \qquad (10)$$

Echo Return Lossless Enhancement (ERLE) measures the attenuation of the echo path. A higher ERLE corresponds to higher reduction in echo.

$$\mathrm{ERLE(n)} = \frac{E[d(n) - v(n)]^2}{E[e(n) - v(n)]^2} \qquad (11)$$

A. *With $\mu_1 > \mu_2$ and $k_1 = k_2$:*

The step size values for each component filter are selected as $\mu_1 = 1$ and $\mu_2 = 0.2$ and the constant k parameter is fixed to $k_1 = k_2 = -0.5$. By using this setting in our combination approach we try to alleviate the convergence speed vs steady-state error tradeoff. The channel echo path with sparse impulse response is shown in Figure 3.

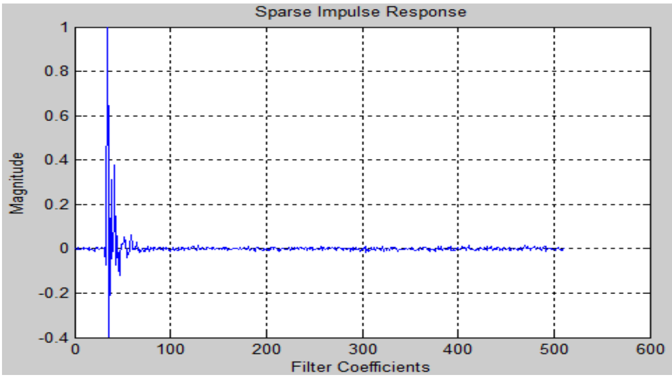

Figure 3: Echo path with sparse impulse response

Figure 4 illustrates the convergence performance of our proposed combination approach to which we will refer hereafter as CIPNLMS. The misalignment curves for the component filters are also displayed for comparison. From the figure, it is observed that the IPNLMS filter with step size μ_1 achieves faster convergence and the filter with step size μ_2 achieves smaller steady-state error. Thus, our CIPNLMS filter keeps the best property of each of the component filter at each time instant i.e. faster convergence and lower steady-state error. This fact is clear even when the echo path is changed (at n=50000). Further, the CIPNLMS filter follows μ_2 - filter steady state value when SNR decreases to 30dB (at n=80000) showing its robust performance.

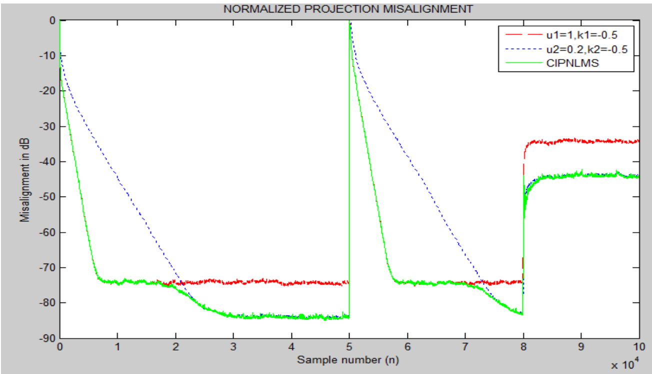

Figure 4: Misalignment performance evaluation of the proposed CIPNLMS filter

From Figure 5, it is evident that the ERLE value of filter 1 is high during the start of the iteration and after a sudden change in the echo path. But filter 2 dominates filter 1 after a period of time and even at low SNR conditions (n=80000). The ERLE of the CIPNLMS filter always attains the highest value. Thus, our proposed filter achieves higher reduction in echo at every time instant.

Figure 6 shows the evolution of mixing parameter, λ(n) for the proposed affine combination filter. It can be concluded that the mixing parameter λ(n) is not restricted to lie between 0 and 1as in the convex combination approach [11] and it can take any real number.

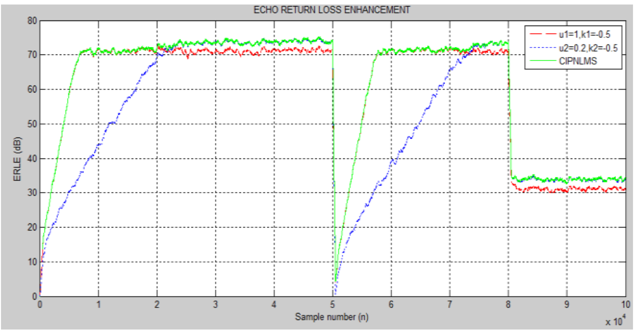

Figure 5: ERLE performance evaluation of the proposed CIPNLMS filter

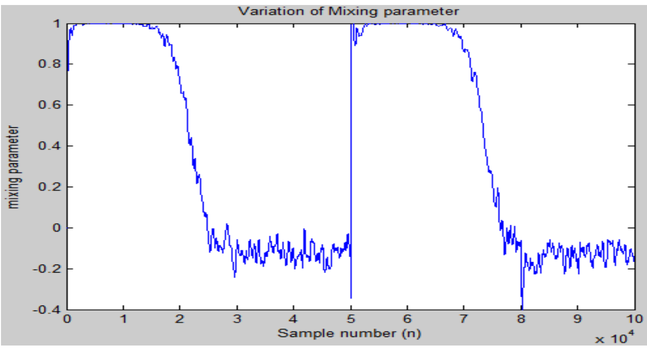

Figure 6: Mixing parameter, $\lambda(n)$ for the proposed affine combination

B. With k1 < 0, k2 ≈ 1 and μ1 = μ2:

We consider selecting the step size value of individual filters as $\mu_1 = \mu_2 = 0.5$; and for parameter k, $k_1 = -0.5$ and $k_2 = 0.9$. With this setting we evaluate the robustness of the proposed combination filter to systems with variable sparsity. The impulse response of the non sparse and sparse echo channels is represented in Figure 7. We carried our simulations assuming that the system echo path is non-sparse initially and later it has changed to a completely sparse system at n= 50000. The WGN noise $v(n)$, is added to get an SNR of 20dB in the reference signal.

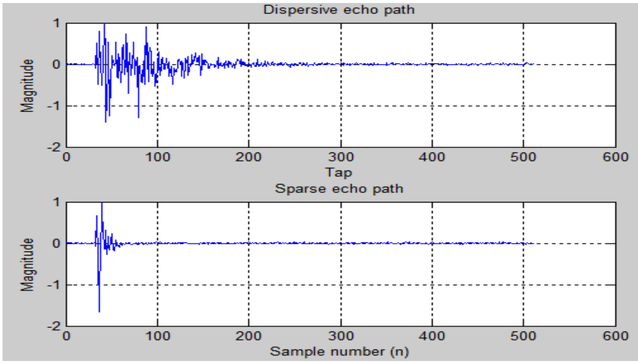

Figure 7: Echo path impulse responses: Dispersive (top), Sparse echo path (bottom)

In Figure 8, when the echo path is non sparse, the filter with $k_1 = -0.5$ guarantees fast convergence and for sparse systems the filter with $k_2 = 0.9$ provides good convergence properties and the CIPNLMS filter always inherits the best component filter performance at each time instant. Thus, we conclude that the combination filter is robust to channels with different degrees of sparsity.

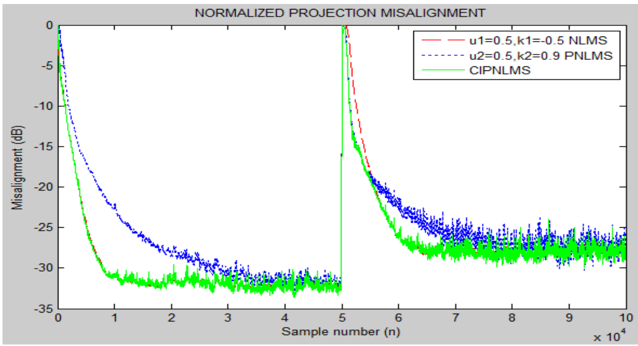

Figure 8: Misalignment performance evaluation of the proposed CIPNLMS filter

From Figure 9, the CIPNLMS filter maintains the high ERLE value at each iteration by choosing the best of the two component filters depending on the sparsity of the system.

Figure 9: ERLE performance evaluation of the proposed CIPNLMS filter.

IV. CONCLUSION

In this paper, we have presented an adaptive affine combination of two IPNLMS filters that achieves better steady state performance at each iteration and attains robustness to systems with varying degrees of sparsity. From our simulation results, the proposed combination approach with different parameter settings has improved the robustness of proportionate filters to systems with varying degrees of sparsity and also alleviated the convergence speed vs steady state error tradeoff of adaptive filters.

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