AN IMPROVED PROPORTIONATE AFFINE PROJECTION ALGORITHM FOR NETWORK ECHO CANCELLATION

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ABSTRACT

Recently, a fast converging algorithm for use in network echo cancellers called proportionate normalized least mean squares (PNLMS) has been proposed [1]. In comparison to the normalized least mean square (NLMS) algorithm, PNLMS has got fast initial convergence speed and tracking when the echo path is sparse. The idea behind PNLMS was to update each coefficient of the adaptive filter independently of the others by adjusting the adaptation step-size in proportion to the magnitude of the estimated filter coefficient. Unfortunately, when the echo path becomes dispersive, the PNLMS algorithm converges much slower than NLMS. In many simulations, it seems that PNLMS has an advantage only when the impulse response is close to a delta function. More recently, an improved PNLMS (IPNLMS) was proposed [2]. It performs better than both NLMS and PNLMS algorithms. In this paper, generalization of the reliable method from the IPNLMS algorithm to a proportionate affine projection algorithm (PAPA) [3] is presented. Simulations with real speech signals show that proposed algorithm (improved PAPA) is better than NLMS, PNLMS and IPNLMS and not dependent on the nature of the impulse response.

Index Terms— Adaptive filter, echo cancellation

1. INTRODUCTION

For line echo cancellers, it is reasonable to assume that the echo path is sparse (i.e. many coefficients are close to zero), and try to identify only non-zero active coefficients. This was the main idea behind the PNLMS and other proportionate algorithms. These approaches achieve higher convergence rate by using the fact that the active part of network echo path is usually much smaller (4-8ms) compared to 64-128 ms of the whole echo path that has to be covered by the adaptive filter. Unfortunately, when the impulse response is dispersive, the PNLMS converges slower than NLMS (see Fig.5a). This implies that the rule proposed in PNLMS is far from the optimal one.

PNLMS++ [4] and IPNLMS [2] a little bit later have been designed to improve the convergence rate for dispersive impulse responses so that these algorithms converge at least as fast as NLMS. For example, PNLMS++ solves the above mentioned problem by alternating the update process each sample period between NLMS and PNLMS algorithms. But, as it has been shown lately, this solution is far from general too.

IPNLMS presents more optimal way how to exploit the shape of the estimated echo path so as to have better performance (convergence speed) than NLMS with non-dispersive impulse responses and similar performance with highly dispersive impulse responses.

This paper combines the ideas of the proportionate step-size technique and method proposed in [2] with the Affine Projection Algorithm (APA) in order to achieve faster convergence for a wide range of echo paths.

2. THE NLMS AND PNLMS ALGORITHMS

In this section, the NLMS and PNLMS algorithms will be briefly explained. In derivations and descriptions, the following notation is used:

$x(n)$ = Far-end signal,
$y(n)$ = Echo and background noise,
$\mathbf{x}(n)$ = $[x(n)\dots x(n-L+1)]^T$, Excitation vector,
$\mathbf{h}$ = $[h_0 \dots h_{L-1}]^T$, True echo path,
$\hat{\mathbf{h}}(n)$ = $[\hat{h}_0(n)\dots \hat{h}_{L-1}(n)]^T$, Estimated echo path.

Here L is the length of the adaptive filter, and n is the time index.

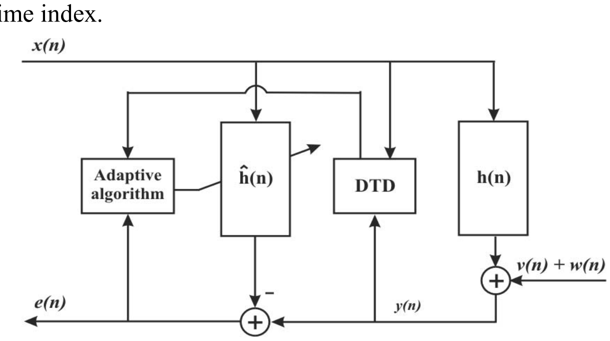


Figure 1: Block diagram of the echo canceller and double-talk detector.

According to Fig.1, the role of the adaptive filter is to estimate the echo path so that it can subtract a replica of the returned echo $y(n)$. Traditionally, the NLMS algorithm serves as a reference in echo canceller implementation. The error signal end the coefficient update equation of the NLMS algorithm are given by [5]

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1)\mathbf{x}(n), \quad (1)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu \mathbf{x}(n)e(n)}{\mathbf{x}^T(n)\mathbf{x}(n) + \delta_{NLMS}}, \quad (2)$$

where μ $(0 < \mu < 2)$ is the adaptation step and δ_{NLMS} is the regularization parameter.

In the PNLMS algorithm, an adaptive individual step-size is assigned to each coefficient. The step-sizes are calculated from the last estimate of the filter coefficients in such a way that a larger coefficient receives a larger increment, thus increasing the convergence rate of that coefficient. This has the effect that active coefficients are adjusted faster than non-active coefficients. Hence, PNLMS converges much faster than NLMS for sparse impulse responses (i.e., responses for which only a small amount of coefficients is significant).

The PNLMS algorithm is described by the following equations:

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1)\mathbf{x}(n), \quad (3)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu \mathbf{G}(n-1)\mathbf{x}(n)e(n)}{\mathbf{x}^T(n)\mathbf{G}(n-1)\mathbf{x}(n) + \delta_{PNLMS}}, \quad (4)$$

$$\mathbf{G}(n-1) = diag\{g_0(n-1), \ldots, g_{L-1}(n-1)\}, \quad (5)$$

where $\mathbf{G}(n-1)$ is a diagonal matrix that adjusts the step-sizes of the individual taps of the filter, μ is the overall step-size parameter (the same as in NLMS), and δ_{PNLMS} is the regularization parameter. The diagonal elements of $\mathbf{G}(n)$ are calculated as follows [1]:

$$\gamma_l(n) = \max\{\rho \max[\delta_p, |\hat{h}_0(n)|, \ldots, |\hat{h}_{L-1}(n)|], |h_l(n)|\} \quad (5)$$

$$g_l(n) = \frac{\gamma_l(n)}{\sum_{i=0}^{L-1}\gamma_i(n)}, \quad 0 \le l \le L-1. \quad (6)$$

Parameters δ_P and ρ are positive numbers with typical values $\delta_P = 0.01$, $\rho = 5/L$. The first term in (6), ρ, prevents $\hat{h}_l(n)$ from stalling when it is much smaller than the largest coefficient and δ_P regularizes the updating when all coefficients are zero at initialization.

A variant of this algorithm is the PNLMS++, [4]. In this algorithm, for odd-numbered time steps the matrix $\mathbf{G}(n)$ is derived as above, while for even-numbered steps it is chosen to be the identity matrix ($\mathbf{G}(n) = \mathbf{I}$), which results in an NLMS iteration. Alternating between NLMS and PNLMS iterations has the advantage of making the convergence rate not much worse than NLMS; as a result, the PNLMS++ algorithm is less sensitive to the assumption of a sparse impulse response than PNLMS. However, switching between the two algorithms works well only in the two extreme cases when the impulse response is sparse or highly dispersive. But if the impulse response is something between sparse and dispersive, PNLMS++ likely converges as fast as NLMS since the rule in PNLMS does not work for this case.

3. AN IMPROVED PNLMS (IPNLMS) AND PAPA (IPAPA) ALGORITHMS

3.1 IPNLMS Algorithm

An objective of the IPNLMS was to derive a rule that better exploits the "proportionate" idea than the original PNLMS. The fact that PNLMS is slower than NLMS with dispersive impulse responses means that (6) had to be modified [2]. The IPNLMS algorithm is given by

$$e(n) = y(n) - \hat{\mathbf{h}}^T(n-1)\mathbf{x}(n), \quad (7)$$

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \frac{\mu \mathbf{K}(n-1)\mathbf{x}(n)e(n)}{\mathbf{x}^T(n)\mathbf{K}(n-1)\mathbf{x}(n) + \delta_{IPNLMS}}, \quad (8)$$

$$\mathbf{K}(n-1) = diag\{k_0(n-1), \ldots, k_{L-1}(n-1)\}, \quad (9)$$

where

$$k_l(n) = \frac{1-\alpha}{2L} + (1+\alpha)\frac{|\hat{h}_l(n)|}{2\|\hat{h}_l(n)\|_1 + \varepsilon}, \quad (10)$$

$$\|\hat{h}_l(n)\| = \sum_{l=0}^{L-1}|\hat{h}_l(n)|, \quad (11)$$

$$\delta_{IPNLMS} = \frac{1-\alpha}{2L}\delta_{NLMS}. \quad (12)$$

where ε is a small positive number. For $\alpha = -1$, the IPNLMS is equal to NLMS. For α close to 1, the IPNLMS behaves like the PNLMS. In practice, good choices for α are 0 or –0.5 [2]. With those choices and in simulations, IPNLMS behaves better than both NLMS and PNLMS algorithms and does not dependent on the type of impulse response.

3.2 IPAP Algorithm

In this section, an improved Proportionate Affine Projection algorithm is introduced. The IPAPA applies the idea that was firstly introduced in the IPNLMS algorithm with the general Affine Projection Algorithm (APA) [6].

Let $\mathbf{y}(n) = [\mathbf{y}(n) \ldots \mathbf{y}(n-p+1)]^T$, be a vector of samples $\mathbf{y}(n)$ and $\mathbf{X}(n) = [\mathbf{x}(n) \ldots \mathbf{x}(n-p+1)]^T$ the excitation matrix, where p is the projection order. A residual echo vector $\mathbf{e}(n) = \mathbf{y}(n) - \mathbf{X}^T(n)\hat{\mathbf{h}}(n-1)$, a proportionate affine projection based algorithm (PAPA) is then given by

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu \mathbf{G}(n-1)\mathbf{X}(n)\left(\mathbf{X}^T(n)\mathbf{G}(n-1)\mathbf{X}(n) + \delta_{PAPA}\mathbf{I}\right)^{-1}\mathbf{e}(n), \quad (13)$$

where $\mathbf{G}(n)$ is as defined in equation (5) and $\mathbf{\Gamma} = (\mathbf{X}^T(n)\mathbf{G}(n)\mathbf{X}(n) + \delta_{PAPA})^{-1}$ is a weighted estimate of the inverse correlation matrix of the input signal. It "whitens" the input data, $\mathbf{X}(n)$, and thus the convergence rate is increased. With $\mathbf{G}(n) = \mathbf{I}$ and $\delta_{PAPA} = 0$, the equation (13) reduces to the standard APA.

An improved version of PAPA (and hence of APA) is obtained by applying the principles presented previously:

$$\hat{\mathbf{h}}(n) = \hat{\mathbf{h}}(n-1) + \mu \mathbf{K}(n-1)\mathbf{X}(n)\left(\mathbf{X}^{T}(n)\mathbf{K}(n-1)\mathbf{X}(n) + \delta_{IPAPA}\mathbf{I}\right)^{-1}\mathbf{e}(n) \tag{14}$$

where $\mathbf{K}(n-1)$ is calculated from equations (9) and (10), δ_{PAPA} is the same as defined in (12).

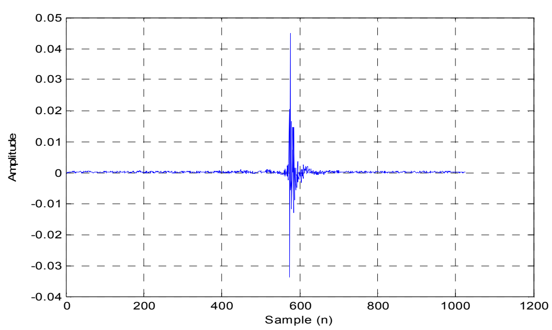
4. SIMULATIONS

In telephone networks that involve the connection of 4-wire and 2-wire links, an echo is generated at hybrid. This echo has a disturbing influence on the conversation and must therefore be cancelled. Figure 1 shows the principle of a network echo canceller (EC). During the simulations, the double-talk situation (it occurs when both the far-end and the near-end speakers speak simultaneously) was not considered, i.e. $v(n) = 0$.

In this section, the proposed IPAPA is compared to the NLMS, PNLMS and IPNLMS algorithms in context of a network echo cancellation. As shown in Fig.2, two different echo path were used ($\mathbf{h}$ of length $L = 1024$) to perform evaluation. The same length was set for the adaptive FIR filter $\hat{\mathbf{h}}(n)$. Recoded speech signals with the sampling rate of 8 kHz and 10 seconds in duration were used as input signals. The general parameter settings chosen for the simulations are: $\mu = 0.1$, $\delta_{NLMS} = 15 \cdot 10^{-5}$, $\delta_P = 0.01$, $\rho = 0.01$ (0.001), $\alpha = 0$ (0.5), p = 2 (for IPAPA).

Figure 3 compare the misalignment ratio, $\|\mathbf{h}-\hat{\mathbf{h}}\|/\|\mathbf{h}\|$, of the four algorithms when the echo path is sparse (Fig.2a). It could be seen that IPNLMS and IPAPA converge much faster than NLMS with a small advantage for IPAPA.

(a)



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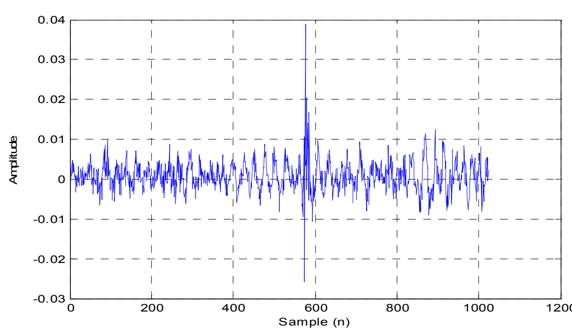
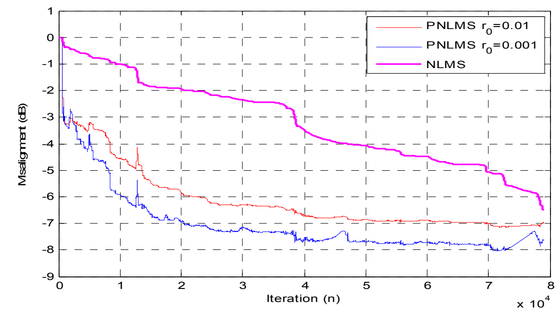


Figure 2: Two different impulse responses used in simulations: (a) sparse echo path, (b) dispersive echo path.

(a)



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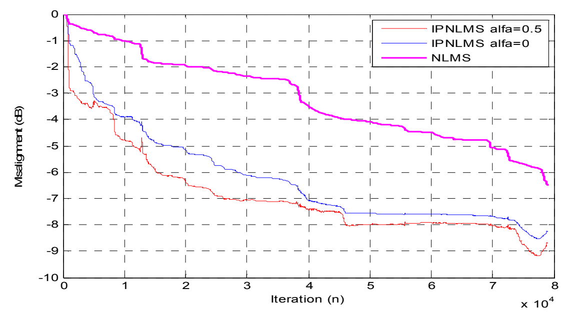

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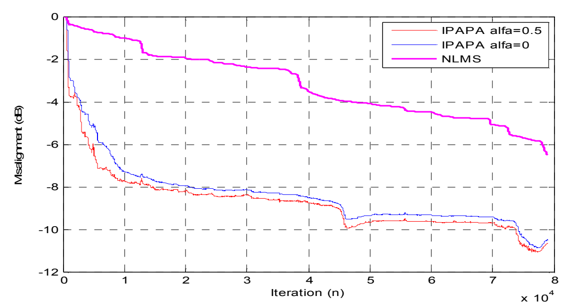


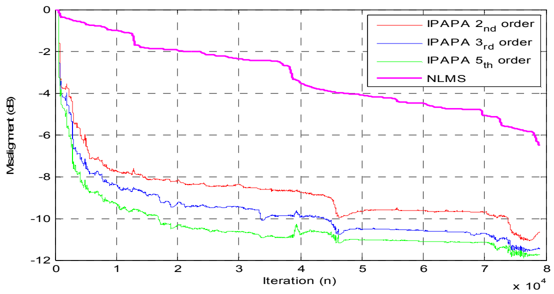
Figure 3: Misalignment of (a) PNLMS, (b) IPNLMS and (c) IPAPA, with a sparse impulse response.

It is also shown how the main control parameters of the algorithms affect adaptation process: (a) for the PNLMS, (b) for the IPNLMS, and (c) is relied to the IPAPA. Figure 5 represents simulations in the same way for the case when network impulse response has dispersive character. While PNLMS diverges and IPNLMS has the same behavior as NLMS, IPAPA achieves the highest results. Figure 4 and Figure 6 compare the misalignment of the IPAPA algorithm with different projection order.

5. CONCLUSION

While the PNLMS algorithm behaves very well and has a fast initial convergence rate compared to the NLMS when the impulse response is sparse, it has no advantages when the echo path is not sparse enough. It means that the principle used in the PNLMS is not adequate and does not fully exploit the structure of the impulse response. The IPNLMS recently proposed may overcome this problem. For very sparse impulse responses, it converges as well as the PNLMS and behaves in the same way as the NLMS algorithm for dispersive paths.

(a)



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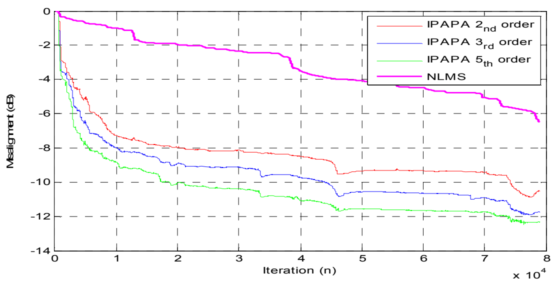
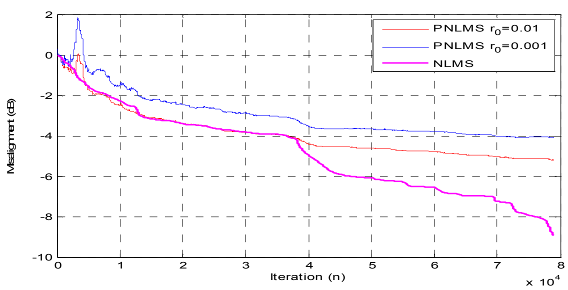
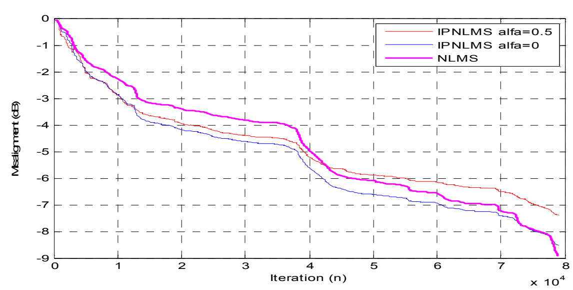


Figure 4: Misalignment of (a) IPAPA α = 0.5 and (b) IPAPA α = 0.

(a)



(b)



(c)

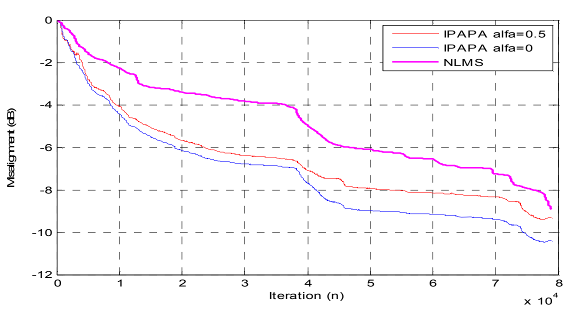
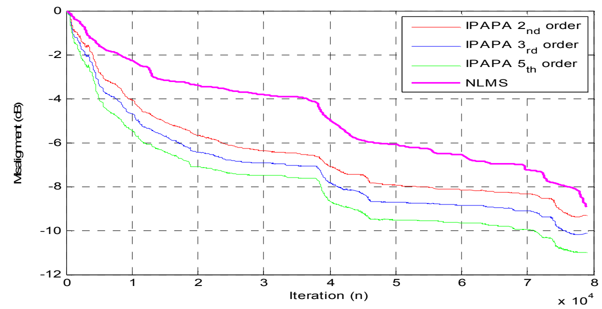


Figure 5: Misalignment of (a) PNLMS, (b) IPNLMS and (c) IPAPA, with a dispersive impulse response.

(a)



(b)

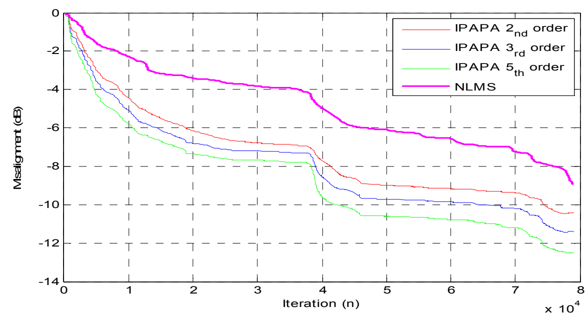


Figure 6: Misalignment of (a) IPAPA α = 0.5 and (b) IPAPA α = 0.

In this paper, generalization from the IPNLMS algorithm to the proportionate affine projection algorithm has been presented. IPAPA of the second order easily outperforms all the above mentioned algorithms and its performance does not dependent on the type of impulse response. It is clear that with growing order complexity and performance of the IPAPA are growing up exceeding the IPNLMS algorithm. It must be also mentioned that the choice of a proper value for α has no any significant impaction on the IPAPA tracking properties comparing to the IPNLMS.

6. REFERENCES

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