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ANALYSIS OF BROADBAND MULTIPATH CHANNEL ESTIMATION ON A ZERO ATTRACTING PROPORTIONATE SYSTEM

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ABSTRACT

The proportionate normalized least mean square (PNLMS) algorithm, a popular tool for sparse system identification, achieves fast initial convergence by assigning independent step sizes to the different taps, each being proportional to the magnitude of the respective tap weight. However, once the active (i.e., non-zero) taps converge, the speed of convergence slows down as the effective step sizes for the inactive (i.e., zero or near zero) taps become progressively less. In this paper, we try to improve upon both the convergence speed and the steady state excess mean square error (EMSE) of the PNLMS algorithm, by introducing a l1 norm (of the coefficients) penalty in the cost function which introduces a so-called zero-attractor term in the PNLMS weight update recursion. The zero attractor induces further shrinkage of the coefficients, especially of those which correspond to the inactive taps and thus arrests the slowing down of the convergence of the PNLMS algorithm, apart from bringing down the steady state EMSE. We have also modified the cost function further generating a reweighted zero attractor which helps in confining the "Zero Attraction" to the inactive taps only.

1. INTRODUCTION

Broadband signal transmission is becoming a commonly used high-data-rate technique for next-generation wireless communication systems, such as 3 GPP long-term evolution (LTE) and worldwide interoperability for microwave access(WiMAX) [1].Thetransmission performance of coherent detection for such broadband communication systems strongly depends on the quality of channel estimation [2–5]. Fortunately, broadbandmultipath channels can be accurately estimated using adaptive filter techniques [6]such as the normalized least-mean-square (NLMS) algorithm, which has low complexity and can be easily implemented at the receiver. On the other hand, channel measurements have shown that broadband wireless multipath channels can often be described by only a small number of propagation paths with long delays [4]. Thus, a broadband multipath channel can be regarded as a sparse channel with only a few active dominant taps, while the other inactive taps are zero or close to zero. This inherent sparsity of the channel impulse response (CIR) can be exploited to improve the quality of channel estimation. However, such classical NLMS algorithms with a uniform step size across all filter coefficients have slow convergence when estimating sparse impulse response signals such as those in broadband sparse wireless multipath channels. Consequently, corresponding algorithms have recently received significant attention in the context of compressed sensing (CS) and were already considered for channel estimation prior to the CS era [5]. However, these CS channel estimation algorithms are sensitive to the noise in wireless multipath channels.

Inspired by the CS theory several zero-attracting (ZA) algorithms have been proposed and investigated by combining the CS theory and the standard least-meansquare (LMS) algorithm for echo cancellation and system identification, which are known as the zero-attracting LMS (ZA-LMS) and reweighted ZA-LMS (RZA-

VOLUME-1 ISSUE-3
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LMS) algorithms, respectively. Recently, this technique has been expanded to the NLMS algorithm and other adaptive filter algorithms to improve their convergence speed in a sparse environment. However, these approaches are mainly designed for nonproportionate adaptive algorithms. On the other hand, to utilize the advantages of the NLMS algorithm, such as stable performance and low complexity, the proportionate normalized least-mean-square (PNLMS) algorithm has been proposedand studiedtoexploit the sparsity innature and has been applied to echo cancellation in telephone networks.

Although the PNLMS algorithmcan utilize the sparsity characteristics of a sparse signal and obtain faster convergence at the initial stage by assigning independent magnitudes to the active taps, the convergence speed is reduced by even more than that of the NLMS algorithm for the inactive taps after the active taps converge. Consequently, several algorithms have been proposed to improve the convergence speed of the PNLMS algorithm which include the use of the l 1-norm technique and a variable step size. Although these algorithms have significantly improved the convergence speed of the PNLMS algorithm, they still converge slowly after the active taps converge. In addition, some of them are inferior to the NLMS and PNLMS algorithms in terms of the steady-state error when the sparsity decreases. From these previously proposed sparse signal estimation algorithms, we know that the ZA algorithms mainly exert a penalty on the inactive channel taps through the integration of the l 1-norm constraint into the cost function of the standard LMS algorithms to achieve better estimation performance, while the PNLMS algorithm updates each filter coefficient with an independent step size,which improves the convergence of the active taps.

2. RELATED CHANNEL ESTIMATION ALGORITHMS

2.1. Normalized Least-Mean-Square Algorithm. In this section, we first consider the sparse multipath communication system shown in Figure 1 to discuss the channel estimation algorithms.The input signal $\mathbf{x}(n) = [x(n),x(n-1), . . . , x(n-N+1)]T$ containing the$N$most recent samples is transmitted over a finite impulse response (FIR) channel with channel impulse response (CIR) $\mathbf{h} = [h0, h1, . . . , hN-1]T$, where $(\cdot)T$denotes the transposition operation. Then the output signal of the channel is written as follows:

$$y(n) = \mathbf{h}^T \mathbf{x}(n),$$

where $\mathbf{h}$ is a sparse channel vector with K dominant active taps whose magnitudes are larger than zero and $(N-K)$
inactive taps whosemagnitudes are zero or close to zero with $K \ll N$. To estimate the unknown sparse channel $\mathbf{h}$, anNLMS algorithm uses the input signal $\mathbf{x}(n)$, the output signal $y(n)$, and the instantaneous estimation error $e(n)$, which is given by

$$e(n) = d(n) - \widehat{\mathbf{h}}^T(n)\mathbf{x}(n),$$

2.2. Proportionate Normalized Least-Mean-Square Algorithm.
The PNLMS algorithm, which is an NLMS algorithm improved by the use of a proportionate technique, has been proposed for sparse system identification and echo cancellation. In this algorithm, each tap is assigned an individual step size, which is obtained from the previous estimation of the filter coefficient. According to the gain allocation rule in this algorithm, the greater the magnitude of the tap, the larger the step size assigned to it, and hence the active taps converge quickly. The update function of the PNLMS algorithm is described by the following equation with reference to Figure 1:

VOLUME-1 ISSUE-3
ISSN : 2799-18

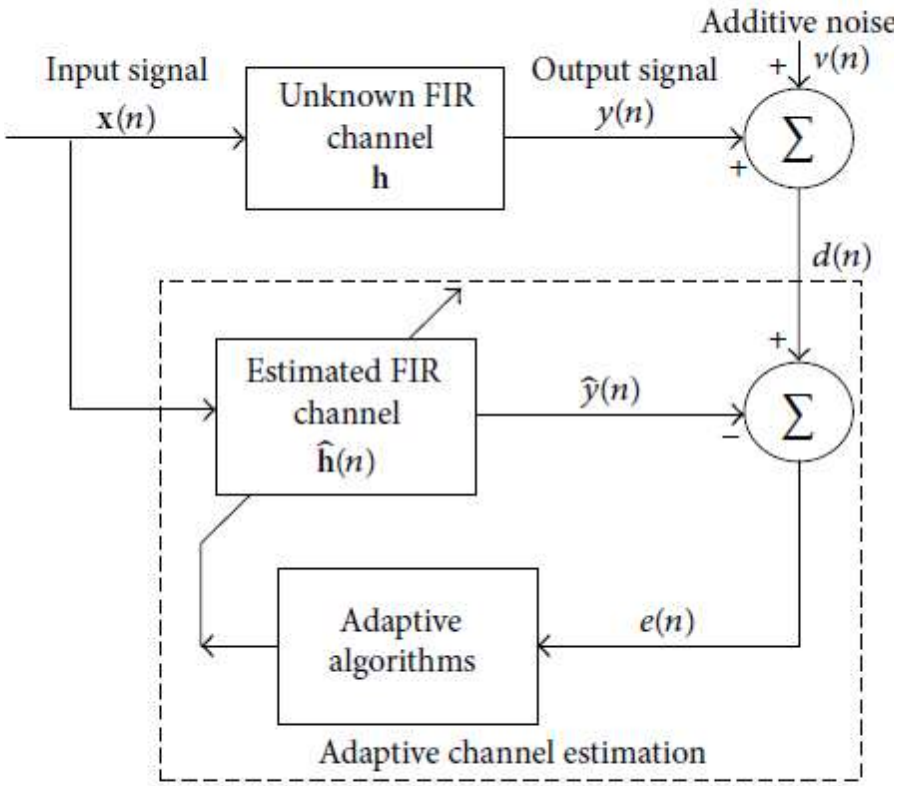

Figure 1: Typical sparse multipath communication system.

3. IMPROVED PROPORTIONATE NORMALIZED LEAST-MEAN-SQUARE ALGORITHMS

3.1. IPNLMS Algorithm.

The IPNLMS algorithm is a type of PNLMS algorithmused to improve the convergence speed of the PNLMS algorithm. It is a combination of the PNLMS and NLMS algorithms with the relative significance of each coefficient controlled by a factor α. The IPNLMS algorithm [20] adopts the l 1-norm to enable the smooth selection of (7), and the update equation of the IPNLMS algorithm is expressed as

$$\hat{\mathrm{h}}(n+1) = \hat{\mathrm{h}}(n) - \mu_{\mathrm{IPNLMS}} \frac{e(n)\mathrm{K}(n)\mathrm{x}(n)}{\mathrm{x}^T(n)\mathrm{K}(n)\mathrm{x}(n) + \delta_{\mathrm{IPNLMS}}}$$

where $\mathbf{K}(n) = \mathrm{diag}(k0(n), k1(n), \ldots, kN{-}1(n))$ is a diagonal matrix used to adjust the step size of the IPNLMS algorithm, where

$$k_j(n) = \frac{1-\alpha}{2N} + (1+\alpha)\frac{\left|\hat{h}_j(n)\right|}{2\left\|\hat{\mathrm{h}}(n)\right\|_1 + \varepsilon},$$

$$0 \le j \le N-1$$

3.2. MPNLMS Algorithm. The μ-law PNLMS algorithm

(MPNLMS) is another enhancement of the PNLMS algorithm that utilizes the logarithm of the magnitudes of the filter coefficients instead of using the magnitudes directly in the PNLMS algorithm [21]. The update equation is the same as that in the PNLMS algorithmgiven by (4). In theMPNLMS algorithm,

VOLUME-1 ISSUE-3
ISSN : 2799-18

$$\gamma_l(n) = \max \left[\rho_g \max\left[\delta_p F\left(\left|\hat{h}_0(n)\right|\right), F\left(\left|\hat{h}_1(n)\right|\right), \ldots F\left(\left|\hat{h}_{N-1}(n)\right|\right)\right], F\left(\left|\hat{h}_l(n)\right|\right)\right]$$

4. RESULTS AND DISCUSSIONS

In this section,we present the results of computer simulations carried out to illustrate the channel estimation performance of the proposed LP-PNLMS algorithm over a sparse multipath communication channel and compare it with those of the previously proposed IPNLMS, MPNLMS, PNLMS, and NLMS algorithms. Here, we consider a sparse channel **h** whose length N is 64 or 128 and whose number of dominant active taps K is set to three different sparsity levels, namely, K = 2,4 and 8, similar to previous studies [6, 22, 25, 26]. The dominant active channel taps are obtained from a Gaussian

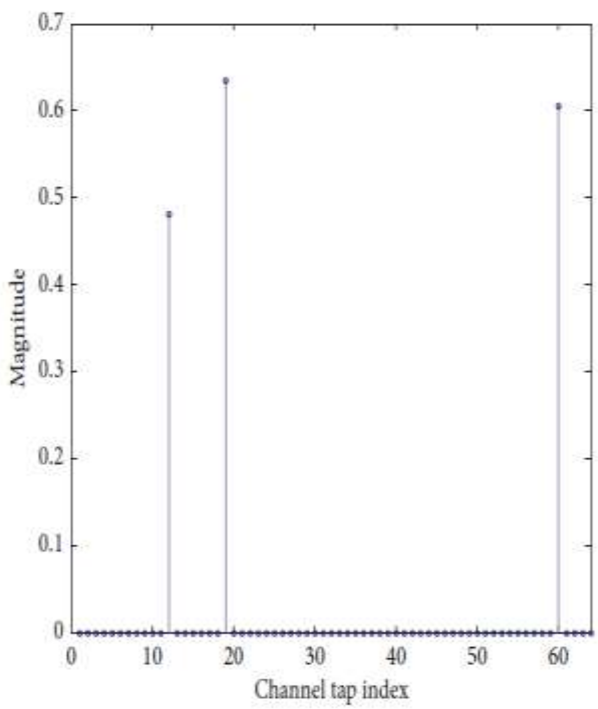

Figure 2: Typical sparse multipath channel.

distribution with ‖h‖22= 1, and the positions of the dominant channel taps are randomly spaced along the length of the channel. The input signal x(n) of the channel is a Gaussian random signal while the output of the channel is corrupted by an independent white Gaussian noise V(n). An example of a typical sparse multipath channel with a channel length of N = 64 and a sparsity level of K = 3 is shown in Figure 2. In the simulations, the power of the received signal is Eb= 1, while the noise power is given by δ2V and the signal -to-noise ratio is defined as SNR = 10 log(Eb/δ2V). In all the simulations, the difference between the actual and estimated channels based on the sparsity-aware algorithms and the sparse channel mentioned above is evaluated by the MSE defined as follows:

$$\mathrm{MSE}(n) = 10\log_{10} \mathrm{E}\left\{\left\|\mathbf{h} - \hat{\mathbf{h}}(n)\right\|_2^2\right\} (\mathrm{dB}).$$

The convergence behavior of the proposed algorithms is also sensitive to the choice of the parameter ρg. We demonstrate this in Fig. 3 by considering the ZA-PNLMS algorithm (we do not consider the RZA-PNLMS algorithm here in order to avoid crowding, after noting from above that its performance is almost identical to that of the ZA-PNLMS algorithm) for ρg = 0.01, 0.05, 0.1. For comparison, we also plot the learning curve (EMSE-vs-iteration index n) of the PNLMS algorithm for ρg = 0.01. It is seen that the steady state EMSE of the ZA-PNLMS algorithm decreases as ρg increases. This can be easily explained by first noting from (4) that in the steady state, as the inactive tap weights attain values very close to zero, the corresponding γl(n) is given by ρg times the maximum tap weight magnitude. From this and the fact that �N−1i=0 gl(n) = 1, it follows that as ρg increases, the gain gl(n) and thus the effective step sizes for the active taps decrease. As a result, their contribution to the EMSE decreases (for the inactive taps, however, the marginal increase in the EMSE that an increasing ρg could give rise to is offset by the zero attractors). Of course, the reduction in the effective step sizes for the active taps tries to slow down the initial fast convergence somewhat. However, as can be seen from Fig. 3, such slowing down effect is marginal.

VOLUME-1 ISSUE-3
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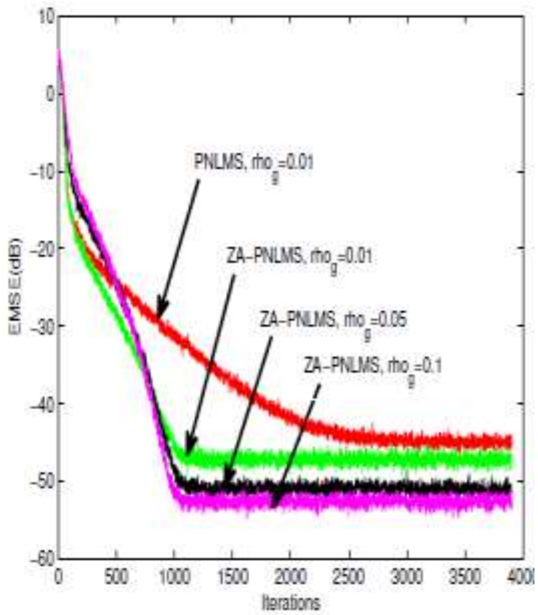

Fig. 3. The effect of ρg on the steady state EMSE of the ZA-PNLMS algorithm.

CONCLUSION

In this paper, we have proposed an LP-PNLMS algorithm to exploit the sparsity of broadband multipath channels and to improve both the convergence speed and steady-state performance of the PNLMS algorithm.This algorithm was mainly developed by incorporating the gain-matrix-weighted $l\ p$-norm into the cost function of the PNLMS algorithm, which significantly improves its convergence speed and steady-state performance. The simulation results demonstrated that our proposed LP-PNLMS algorithm, which has an acceptable increase in computational complexity, increases the convergence speedand reduces the steady-state error comparedwith the previously proposed PNLMS algorithms.

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