PARTIAL UPDATE PNLMS ALGORITHM FOR NETWORK ECHO CANCELLATION

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ABSTRACT

The Proportionate Normalized Least Mean Square (PNLMS) algorithm has been proposed for network echo cancellation to take advantages of the sparseness of the echo path impulse responses. The PNLMS algorithm has fast initial convergence but slows down dramatically after the initial period. In this paper, a novel algorithm to combine the PNLMS algorithm with the technique of partial update is proposed. Simulation results show that the proposed algorithm can achieve faster overall convergence with less computation.

Index Terms— Network echo cancellation, PNLMS algorithm, partial update algorithm, sparse impulse response

1. INTRODUCTION

With the development of wireless communication and voice over IP (VoIP) communication, network echo canceller has been increasingly important voice enhancement component in the communication networks. Fig.1 shows a typical high level configuration of network echo cancellers. The core of the network echo canceller is the adaptive filter w, which estimates the impulse response of the echo path and generates an estimated echo y(k). By subtracting the estimated echo y(k) from the near-end input signal d(k), the echo gets cancelled and only the near-end speech is transmitted to the far end. x(k) is the far-end input signal and e(k) is the error signal.

The network echo path impulse responses are sparse in nature. Although the number of coefficients is large (1024 is the standard configuration today), only a small portion is significantly different from zero and these coefficients are called active coefficients. Other coefficients are just zero or unnoticeably small values and are called inactive coefficients. Fig.2 shows a typical network echo path impulse response. The total time span is 128ms. In order to model this echo path accurately, an adaptive filter with 1024 taps needs to be used for the 8kHz sampling frequency. It can be seen that among all the 1024 taps, only less than 80 coefficients (around 8ms) are active.

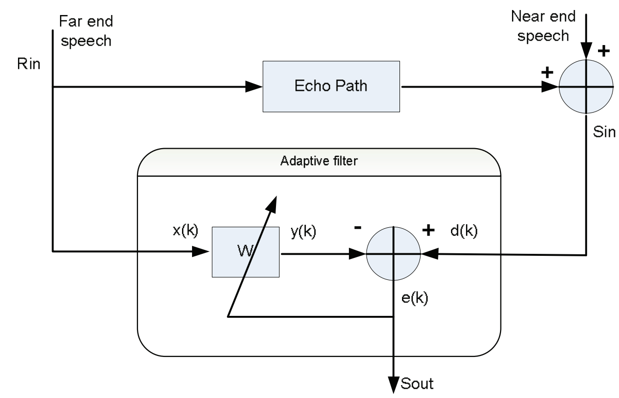


Fig. 1 High level diagram of an adaptive filter in a network echo canceller

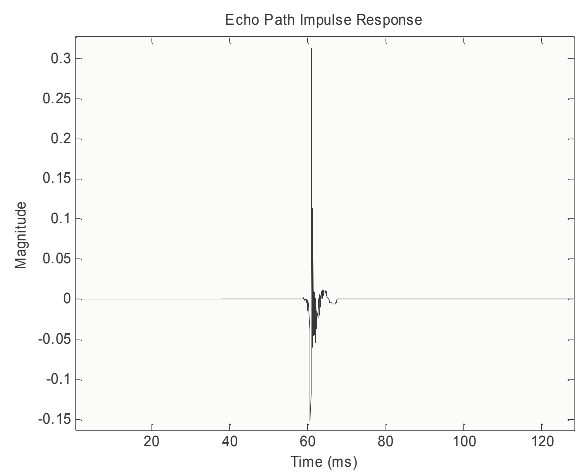


Fig. 2 Echo path impulse response example

Recently, several algorithms have been proposed [1] – [6] to take advantages of the sparseness of the echo path impulse responses to improve the adaptive filtering algorithm performance. In this paper, a novel algorithm to combine the proportionate algorithm with the technique of partial update is proposed to keep the fast convergence throughout the whole adaptation process with less computation. In Section 2, the Proportionate Normalized Least Mean Square (PNLMS) algorithm and μ-law PNLMS (MPNLMS) algorithm are introduced. The Partial update

PNLMS algorithm is described in Section 3. Simulation results in Section 4 demonstrate the performance of the proposed algorithm. Conclusions are in Section 5.

2. PROPORTIONATE ALGORITHMS

The PNLMS algorithm is proposed in [1] for sparse impulse response estimation. The general idea consists of assigning different step size control factors to different coefficients based on their previous estimated magnitude values. In that way, large coefficients will gain more updating emphasis than small coefficients, which makes them converge faster. The algorithm is specified as follows:

$$\mathbf{w}(k+1) = \mathbf{w}(k) + \frac{\mu \mathbf{G}(k)}{\mathbf{x}^T(k)\mathbf{G}(k)\mathbf{x}(k)+\delta}\mathbf{x}(k)e(k)$$

$$\mathbf{G}(k) = diag\{g_0(k), g_1(k), \cdots, g_{L-1}(k)\}$$

$$\mathrm{L}_{\min} = \max\{\delta_p, |w_0(k)|, |w_1(k)|, ..., |w_{L-1}(k)|\}$$

$$\gamma_i = \max\{\rho L_{\min}, |\hat{w}_i(k)|\} \quad 0 \le i \le L-1$$

$$L_1 = \frac{1}{L}\sum_{i=0}^{L-1}\gamma_i$$

$$g_i(k) = \gamma_i / L_1 \quad 0 \le i \le L-1$$

where L is the length of the adaptive filter. The parameter δ is a small positive number to prevent overflow and δ_p is used to prevent the coefficients from stalling when all the coefficients are 0, especially in the beginning of adaptation. The typical value of δ_p is 0.01. ρ is a parameter used to prevent extremely small coefficients from freezing. $5/L$ is a good choice of ρ. The above updating equations indicate that active coefficients will get most of the update emphasis and dominate the convergence process.

The PNLMS algorithm converges fast in the initial period, usually marked by the convergence of active coefficients, but the adaptation rate slows down dramatically, even much slower than the NLMS algorithm, afterwards. The reason is that for small coefficients, they get smaller update emphasis than they get in the NLMS algorithm, thus making them converging slowly when they dominate the overall convergence process. In [2], the optimal solution of calculating the stepsize control factors is found and the μ-law PNLMS (MPNLMS) algorithm is proposed. It is demonstrated that the MPNLMS algorithm can keep the fast initial convergence through the adaptation process. However, the μ-law function used in the MPNLMS algorithm is expensive for computation. In addition to the computational load of the PNLMS algorithm, which needs approximately 50% more computations than the NLMS algorithm [1], it adds L logarithm calculations, L multiplications and L additions per iteration. Since calculation of the logarithm may be an expensive operation for a digital signal processor (DSP), the added computational overhead can be large.

3. PARTIAL UPDATE PNLMS ALGORITHM

3.1. Sparse Partial Update Algorithms

Partial update is a technique proposed to reduce computations for the long adaptive filter. The idea is to update only a portion of the adaptive filter's coefficients for each input sample (iteration). In general, there are two ways of partial update. One is to select the coefficients to be updated in a predefined way, either sequentially or periodically [3]. The other is to select the coefficients that correspond to input samples with large magnitudes to update [4]. The latter one has very close convergence performance to the full update algorithms with less computation.

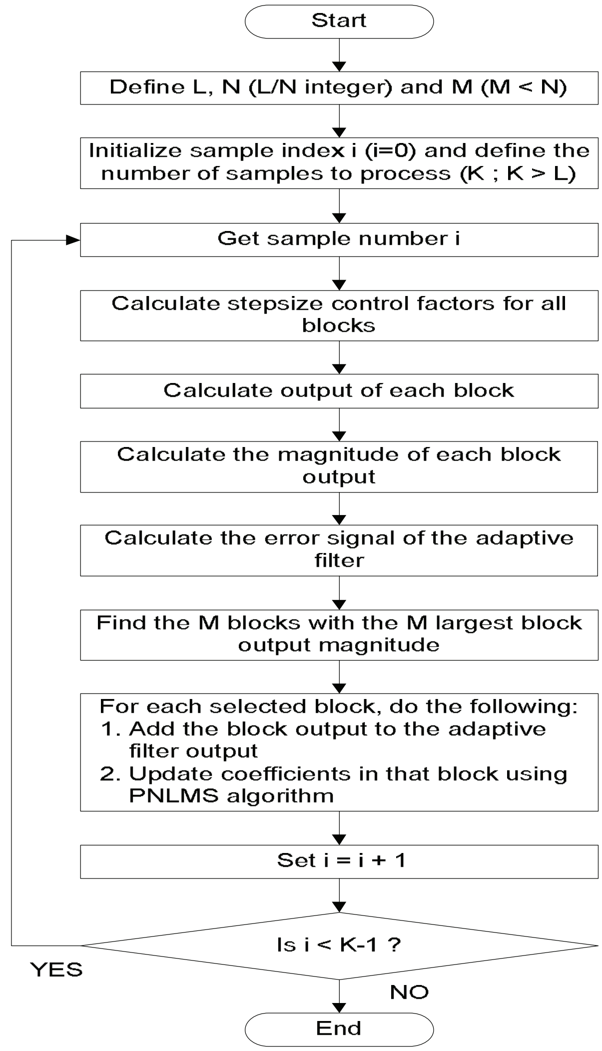
In [5], two sample-based Sparse Partial Update NLMS (SPNLMS) algorithms are proposed to take advantage of the sparseness of the network echo path impulse response and the partial update techniques. The coefficients to be updated are selected based on the product of the delayed input and the corresponding coefficient value (i.e., the filter tap output). It is shown that these two algorithms have faster convergence speed than the full rate NLMS algorithm with even less computational complexity. Note that these two algorithms are sample-based, which means that each coefficient is selected independently.

To overcome the disadvantages of the sample based SPNLMS algorithms, the Block based Sparse Partial update NLMS (BSPNLMS) algorithm is proposed in [6]. The idea is to segment the adaptive filter into N adjacent blocks with L/N coefficients per block. L is the length of the adaptive filter. Each block performs filtering of its corresponding input vector segment and produces a block output. Only the M ($M < N$) blocks with the largest magnitudes (absolute value) of the block outputs are selected to be updated at every iteration. Other blocks remain unchanged. In other words, the block output magnitudes are sorted into a vector in the decreasing order. If a block's output magnitude falls into the first M entries of this vector, the coefficients of this block will be updated; otherwise, they are unchanged for this iteration. The output of the adaptive filter is the sum of the block outputs of the selected blocks. Since only M out of N blocks (with $M < N$) are updated, computations can be reduced and convergence speed is greater because a shorter filter is actually used (it is known that shorter filter converges faster). The choice of N and M depends on the length and the sparseness of the echo path. In general, the sparser the echo path is, a smaller M can be chosen, which, in turn, leads to smaller computational cost and faster convergence.

3.2. Partial Update PNLMS Algorithm

From the analysis and simulation results, it is clear that the PNLMS algorithm boosts the convergence of the large coefficients by assigning them large stepsize control factors. But for the large amount of inactive coefficients, small stepsize control factors lead to slow convergence, thus making the overall convergence slow after the initial period. Because the values of most inactive coefficients should be zeros, ideally only the active coefficients need to be updated. The BSPNLMS algorithm provides a good way to identify the active coefficients dynamically throughout the adaptation process and only concentrate on these coefficients. Also the output of the adaptive filter only consists of the outputs of the selected blocks, therefore the coefficients within other blocks are effectively considered zero.

By combining the PNLMS algorithm with the BSPNLMS algorithm, the Proportionate Partial Update NLMS (PPNLMS) algorithm is proposed as in Flowchart 1. The PPNLMS algorithm possesses both the strength of fast initial convergence of the PNLMS algorithm and the strength of lower misalignment error of the BSPNLMS algorithm, thus making its overall performance better than of the PNLMS algorithm. Furthermore, because only a part of the coefficients is updated, the computational cost of the PPNLMS algorithm is even smaller than that of the PNLMS algorithm.



Flowchart 1 PPNLMS Algorithm

4. SIMULATION RESULTS

The echo path that is used in the simulations is the echo path model 1 specified in the ITU-T G.168 standard [7] with a 60 ms pure delay (see Fig.2). The total span of the impulse response is 128ms with the active coefficients only occupying less than 16ms. Therefore, an adaptive filter with 1024 taps is used to model it. The Echo Return Loss (ERL) of the echo path is set to 6dB.

The NLMS algorithm, the PNLMS algorithm and the PPNLMS algorithm are compared for the -15dBm0 white noise as the far-end input signal. For all the algorithms, the stepsize is set to 0.5. For the PPNLMS algorithm N is set to 8 and M is set to 2, which means only 2 blocks (256 coefficients) out of 8 blocks (1024 coefficients) are selected to be updated for every input sample. Fig.3 shows the output signals and Fig.4 shows the ERLE evolution trends. The PPNLMS algorithm converges as fast as the PNLMS algorithm in the initial period and keeps the fast convergence throughout the adaptation process. Fig.5 shows the output signals of all the three algorithms for CSS signal [7] with the far-end input signal at -15dBm0. Fig.6 shows the comparison results for different configurations of the PPNLMS algorithm, for the white noise input. One setting has $N = 8$ blocks with $M = 2$ and the other one has

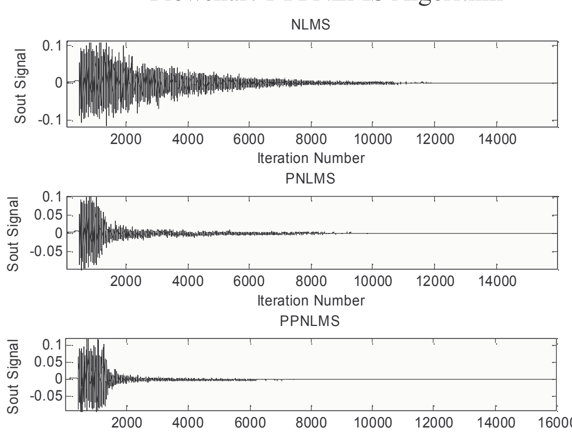


Fig. 3 Error signal of NLMS, PNLMS and PPNLMS algorithm for white noise

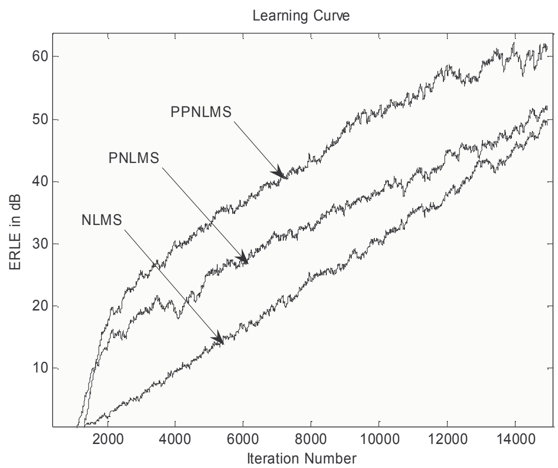


Fig. 4 ERLE of NLMS, PNLMS and PPNLMS algorithm for white noise

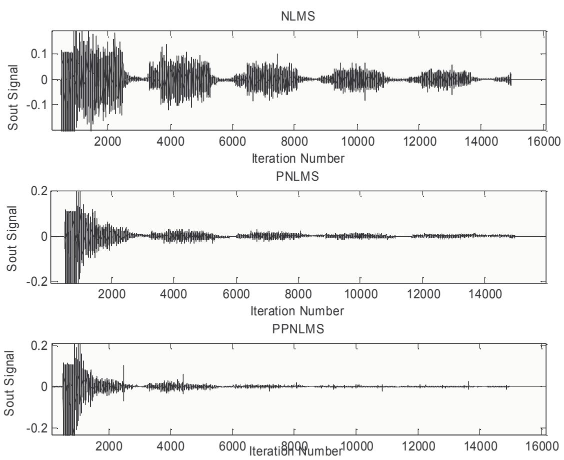


Fig. 5 Error signal of NLMS, PNLMS and PPNLMS algorithm for CSS signal

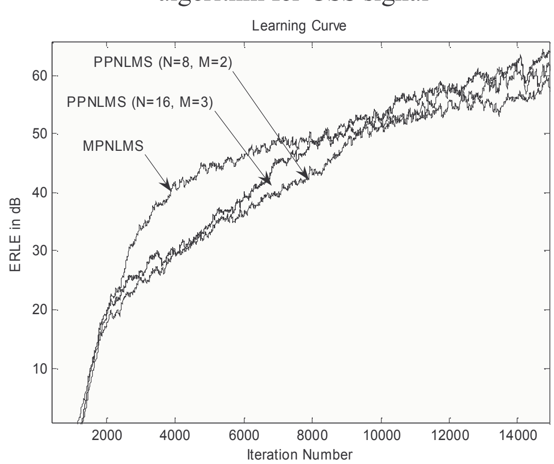


Fig. 6 ERLE of PPNLMS (N=8, M=2), PPNLMS (N=16, M=3) and MPNLMS algorithm for white noise

N = 16 blocks with M =3. The performance is very close for these two configurations. The result of the MPNLMS algorithm is also shown in Fig.6 as the optimal solution. It is observed that the proposed PPNLMS algorithm's performance is in the middle of the PNLMS algorithm and the MPNLMS algorithm. It is worth noting that the computational cost of the PPNLMS algorithm is much smaller than the MPNLMS algorithm and the PNLMS algorithm. Thus, the PPNLMS algorithm is a preferred solution for practical implementations on DSP platforms.

5. CONCLUSIONS

In this paper, a novel PPNLMS algorithm is proposed to take advantages of the fast initial convergence speed of the PNLMS algorithm and the deep convergence of the partial update NLMS algorithm. The PPNLMS algorithm has fast convergence throughout the whole adaptation process with even less computations than the PNLMS algorithm. It can be used for network echo cancellation when the echo path span is long and impulse response is sparse.

6. REFERENCES

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