AN IMPROVED IPNLMS ALGORTIHM FOR ECHO CANCELLATION IN PACKET-SWITCHED NETWORKS

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ABSTRACT

We present an improved adaptive echo cancellation algorithm designed for use with sparse echo path impulse responses such as arise from packet-switched networks. The new approach implicitly segments the impulse response into 'active' and 'inactive' regions, and employs different proportionate updating in each region. An efficient partial updating scheme is then formulated for the new algorithm. Evaluation results are presented to compare the new algorithm against three existing methods in terms of convergence and computational complexity. The results show that the new algorithm outperforms the best existing technique and has lower complexity.

1. INTRODUCTION

Telephony over packet-switched networks offers many advantages and is continuing to grow in interest for both end-users and network providers. Particular challenges arise in terms of network echo cancellation when traditional telephony equipment is connected to the packet-switched network using, for example, IP voice gateway interfaces [1]. The echo path impulse response in such cases typically exhibits an 'active' region and an unknown bulk delay due to encoding, network propagation and jitter buffer delays [2]. The 'active' region corresponds to the hybrid impulse response and is typically up to 12ms in duration. The presence of the unknown bulk delay due to the packet-switched network results in the need for cancellation of echoes up to typically 128ms duration. However, outside the 'active' region the impulse response is close to zero magnitude and therefore can be considered sparse. Classical adaptive algorithms such as the Normalized Least Mean Square (NLMS) algorithm [10] normally perform relatively poorly on such sparse echo paths impulse responses. This is caused by (i) slow convergence rate of such algorithms for long impulse responses and (ii) poor levels of final mean square error (MSE) due to coefficient noise in the 'inactive' region.

Several approaches to network echo cancellation for sparse echo paths have been proposed including the Proportionate Normalized Least Mean Square (PNLMS) algorithm [3] and improved versions (PNLMS++, IPNLMS) [4, 5]. Block-based partial update methods such as [9] have also been proposed. All these algorithms are well suited to operate on sparse echo path impulse responses and give improved performance compared to NLMS. Our aim here is to optimize adaptation further, exploiting the specific nature of the responses, by implicitly segmenting them into 'active' regions containing the hybrid response and 'inactive' regions representing pre- or post- delay.

In this paper, we begin by briefly reviewing PNLMS approaches in Sections 2.1 and 2.2. Section 2.3 describes our new algorithm, IIPNLMS, which uses an adaptation scheme based on PNLMS and modifies its tap-update operation depending on whether the tap in question is within the 'active' or 'inactive' (bulk delay) region of the echo path impulse response. The identification of the 'active' and 'inactive' regions is performed implicitly within the adaptation. Subsequently, we consider the efficient implementation of our algorithm and develop an efficient partial update version of IIPNLMS employing the recently proposed short-sort M-Max procedure [8]. Simulation results are presented to compare the performance of the new algorithm with three existing algorithms for echo cancellation using a sparse response from a real hybrid.

2. ADAPTIVE ESTIMATION OF SPARSE SYSTEMS FOR ECHO CANCELLATION

The PNLMS algorithm was proposed for echo cancellation of sparse systems in, for example, packet switched networks [3]. The update procedure is described by the following equations:

$$\hat{\mathbf{w}}(n+1) = \hat{\mathbf{w}}(n) + \frac{}{\|\mathbf{x}(n)\|^2 + \delta_{PNLMS}} \mathbf{G}(n)\mathbf{x}(n)e(n) \quad (1)$$

$$\mathbf{G}(n) = diag\{g_0(n) \cdots g_{L-1}(n)\} \quad (2)$$

$$l_\infty(n) = \max\{|\hat{w}_0(n)| \cdots |\hat{w}_{L-1}(n)|\} \quad (3)$$

$$l'_\infty(n) = \max(\delta, l_\infty(n)) \quad (4)$$

$$g_k(n) = \max\{\rho l'_{\infty}(n), |\hat{w}_k(n)|\} \quad (5)$$

$$\bar{g}(n) = \frac{1}{L}\sum_{0}^{L-1} g_k(n) \quad (6)$$

$$g_k(n) = \frac{g_k(n)}{\bar{g}(n)} \quad (7)$$

where, $\mathbf{x}(n)$ denotes the L-by-1 excitation vector of the tap inputs $\left[x(n)\ x(n-1)\ldots x(n-L+1)\right]^T$, in which $x(n)$ is far-end signal, L is the length of the adaptive filter and n is the time index. The vector $\hat{\mathbf{w}}(n)$ denotes the estimated echo path $\left[\hat{w}_0(n)\ldots\hat{w}_k(n)\ldots\hat{w}_{L-1}(n)\right]^T$, in which k is the coefficient number. The PNLMS update differs from the NLMS update only in the presence of **G**, so that the adaptive step size varies for each tap and is effectively proportional to the coefficient absolute magnitude. It has been shown in [3, 4], that the advantage of the PNLMS algorithm is that it exhibits fast initial convergence compared to the NLMS algorithm for sparse impulse responses. However, the rate of convergence can slow down after an initial period as illustrated in Fig. 2 and Fig. 3 because of the effective scaling of by the coefficient absolute magnitude.

An enhancement of this algorithm, IPNLMS, was proposed in [5]. IPNLMS is a combination of the PNLMS and NLMS update terms with the relative significance of each controlled by a parameter α. The difference from PNLMS in the update procedure is:

$$g'_k(n) = \max\left(\rho l'_{\infty}(n), |\hat{w}_k(n)|\right) \quad (8)$$

$$g_k(n) = \frac{1-\alpha}{2} + \frac{1+\alpha}{2} g'_k(n) \quad (9)$$

The update is equivalent to the NLMS update when $\alpha = -1$ and the PNLMS update when $\alpha = 1$. In practice, good choices for α are 0 or –0.5 [5]. It has been shown in [5] that the IPNLMS algorithm has faster initial convergence than NLMS and at the same time, it has the same benefit in terms of final MSE and misalignment performance after the initialization period. However, IPNLMS fails to match the fast initial convergence of the PNLMS algorithm for typical choices of the value of α.

Here, we introduce an improved IPNLMS (IIPNLMS) algorithm. The objective is to derive a rule to locate the 'active' portion of the echo path in order to further improve performance. In IPNLMS, the parameter α is fixed for the whole echo path. In our improved version, we allow α to vary as:

$$\alpha_k = \begin{cases} \alpha 1, & \text{when } g'_k(n) > \gamma \times g'(n)_{\max} \\ \alpha 2, & \text{when } g'_k(n) < \gamma \times g'(n)_{\max} \end{cases} \quad (10)$$

where, $g'(n)_{\max}$ is the maximal value of all the weights of coefficients calculated from the PNLMS algorithm and γ is the parameter to control the threshold in order to locate the 'active' portion. When the weight $g'_k(n)$ corresponding to the k^{th} coefficient is larger than the threshold $\gamma \times g'(n)_{\max}$, this coefficient is determined to be in the 'active' portion and α_k is equal to $\alpha 1$. Contrarily, the coefficient is considered to be in the 'inactive' portion if its weight is less than the threshold and α_k is then set equal to $\alpha 2$. The parameters γ, $\alpha 1$ and $\alpha 2$ can be determined experimentally. It can be observed that α_k classifies the echo path as 'active' or 'inactive' as shown in Fig. 1.

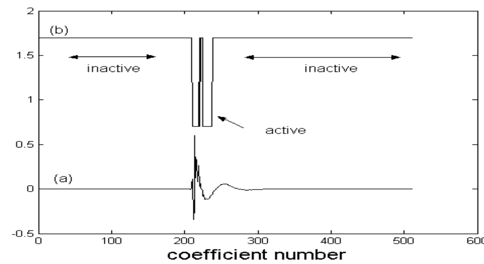

Fig. 1. A sparse hybrid echo path (a) the sparse impulse response (b) the value of α_k

Given this classification, IIPNLMS appears a weighted combination of NLMS and PNLMS such that PNLMS is more strongly weighted on the 'inactive' portion of the echo path and NLMS is chiefly responsible for convergence on the 'active' portion. The motivation for this approach is to exploit the advantages of both algorithms according to the nature of different regions of the impulse responses. Hence, the update term for weights is done with $\alpha 1$ of negative value and $\alpha 2$ of positive value so that:

$$g_k(n) = \frac{1-\alpha_k}{2} + \frac{1+\alpha_k}{2} g'_k(n) \quad (11)$$

We wish to compare the NLMS, PNLMS, IPNLMS and IIPNLMS algorithms. In simulations, we use the sparse hybrid echo path with length 512 as shown in Fig. 1 (a) and Gaussian white noise input signal with signal-to-noise ratio of 30 dB. The parameter settings are chosen as in [5]: =0.2, ρ =0.01, δ =0.01, $\delta_{NLMS} = \sigma_x^2$, $\delta_{PNLMS} = \delta_{NLMS}/L$, $\delta_{IPNLMS} = \delta_{NLMS}/2L$, $\delta_{IIPNLMS} = \delta_{NLMS}/2L$, α=0. Good choices for the parameters $\gamma, \alpha 1$ and $\alpha 2$ are: γ=0.1, $\alpha 1$=-0.5 and $\alpha 2$=0.5. Fig. 2 and Fig. 3 compare the normalized MSE (NMSE) and misalignment of the four algorithms respectively.

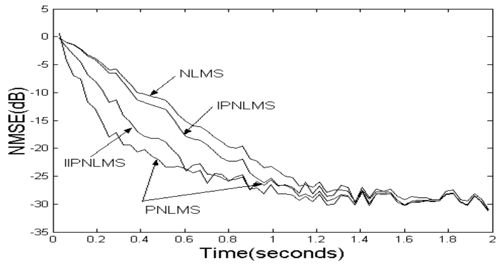

Fig. 2. NMSE of NLMS, PNLMS, IPNLMS and IIPNLMS with a white noise input

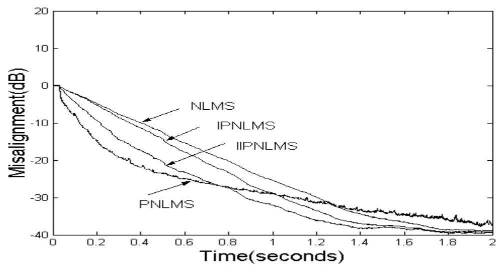

Fig. 3. Misalignment of NLMS, PNLMS, IPNLMS and IIPNLMS with a white noise input

It can be observed that NLMS and IPNLMS converge slower than PNLMS by, at some times more than 10dB, while IPNLMS has better performance and takes more advantage of PNLMS for initialization period. After this period, PNLMS converges more slowly than NLMS and IPNLMS while IIPNLMS still sustains a faster convergence rate and final MSE and misalignment performance. Hence, IIPNLMS has achieved a superior performance for echo cancellation with sparse echo path impulse responses.

3. EFFICIENT PARTIAL UPDATING

In the M-MAX NLMS (MMNLMS) algorithm [6, 7], the adaptive filter only adjusts the coefficients associated with the M largest value of $\left|\mathbf{x}(n)\right|$. The update equation is:

$$\hat{w}_k(n+1)=\begin{cases}\hat{w}_k(n)+\dfrac{}{\left\|\mathbf{x}(n)\right\|^2+\delta_{MMNLMS}}x(n-k)e(n) \\ \qquad \text{if } k \text{ corresponds to one of the} \\ \qquad \text{first } M \text{ maxima of} \left|\mathbf{x}(n)\right| \\ \hat{w}_k(n) \quad \text{otherwise}\end{cases} \tag{12}$$

In has been shown [6, 7] that the MMNLMS algorithm has almost as good performance as the NLMS algorithm in terms of convergence rate, final MSE and misalignment with $M=\dfrac{L}{2}$. However it suffers from a sorting process computational overhead that reduces the advantages of partial updating.

The Short-sort M-MAX NLMS (SMNLMS) algorithm addresses this problem by introducing the short-sort procedure [8]. This algorithm divides the echo path into two regions. In region 1, the number of the taps is equal to S ($<L$) and all the taps are updated. In region 2, the number of taps is equal to L-S and a partial update is performed using an efficient approximation of the MMNLMS algorithm [8].

$$\hat{w}_k(n+1)=\begin{cases}\hat{w}_k(n)+\dfrac{}{\left\|\mathbf{x}(n)\right\|^2+\delta_{SMNLMS}}x(n-k)e(n) \\ \qquad \text{if } f_k(n)=1 \\ \hat{w}_k(n) \quad \text{otherwise}\end{cases} \tag{13}$$

$k=S,S+1,\ldots L-1$

where $f_k(n)$ is updated if (n mod S) =0 using

$$f_k(n)=\begin{cases}1, \quad \text{if } x(n-k) \text{ is one of the } A \text{ largest} \\ \quad\ \text{values of } \mathbf{x}_n \\ 0, \quad \text{otherwise}\end{cases} \tag{14}$$

$k=0,1,\ldots S-1$

It has been shown that SMNLMS has successfully maintained the advantages of MMNLMS but with very low computational overhead in sorting procedure [8].

The IIPNLMS algorithm has achieved good performance for sparse echo cancellation but increases the computational complexity by about a factor of 2 compared to NLMS. Hence, we introduce the short-sort partial update procedure into the IIPNLMS algorithm to reduce its complexity. The update structure for the combined algorithm IIP-SMNLMS is:

$$\boxed{\text{IIP}} \longrightarrow \boxed{\text{SMNLMS}}$$

meaning that first the weight matrix $\boldsymbol{G}$ is updated as in IIPNLMS and then SMNLMS is responsible for selecting the subset of the coefficient of the echo path followed by the updating. The update equation corresponding to (13) is modified to give

$$\hat{w}_k(n+1) = \begin{cases}\hat{w}_k(n)+\dfrac{}{\left\|\mathbf{x}(n)\right\|^2+\delta_{SMNLMS}}g_k(n)x(n-k)e(n) \\ \qquad \text{if } f_k(n)=1 \\ \hat{w}_k(n) \quad \text{otherwise}\end{cases} \tag{15}$$

We now wish to compare the NLMS, IPNLMS, IIPNLMS and IIP-SMNLMS algorithms. In simulations, we use the sparse hybrid echo path as shown on Fig. 1 (a) with length 512 and a real speech input signal with signal-to-noise rate of 39 dB. The parameter settings chosen are the same with the above simulation but with of 0.5. Fig. 4 and Fig. 5 compare the NMSE and misalignment of the four algorithms respectively.

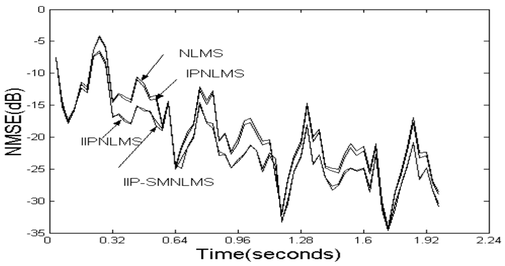

Fig. 4. NMSE of NLMS, IPNLMS, IIPNLMS and IIP-SMNLMS with speech signal input

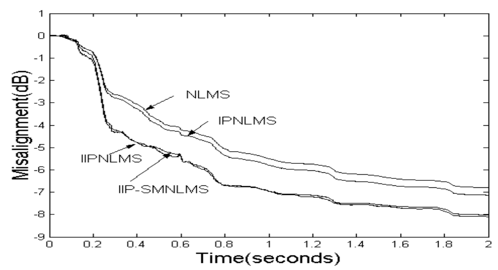

Fig. 5. Misalignment of NLMS, IPNLMS, IIPNLMS and IIP-SMNLMS with speech signal input

It can be observed that the IIP-SMNLMS algorithm has maintained the advantage of IIPNLMS over NLMS and IPNLMS while it reduces the computational complexity of IIPNLMS by about 25% due to the partial updating.

The comparison in computational complexity among the NLMS, SMNLMS, PNLMS, IPNLMS, IIPNLMS and IIP-SMNLMS algorithm is shown in Table 1, in which Cc means computational complexity based on the number of multiplications in a direct implementation. It can be seen that IIP-SMNLMS is 50% more complex than NLMS but with faster convergence rate and lower complexity than IPNLMS.

Algorithm	**Cc**	**Algorithm**	**Cc**	**Algorithm**	**Cc**
NLMS	2L	SMNLMS	1.5L	PNLMS	3L
IPNLMS	4L	IIPNLMS	4L	IIP-SMNLMS	3L

Table 1. Comparison in computational complexity

4. DISCUSSIONS AND CONCLUSION

This paper has presented the new IIPNLMS algorithm for echo cancellation with sparse echo path impulse responses as found typically in telephony systems employing packet-switched networks. The new algorithm uses proportionate tap updates as in PNLMS and IPNLMS but also makes use of different updating schemes depending on whether the tap in question is within the ‘active’ or ‘inactive’ regions of the echo path impulse response, where these regions are determined implicitly within the adaptation. An efficient short-sort partial updating scheme has also been presented for IIPNLMS. Evaluation results for echo cancellation with a real sparse echo path have shown that IIPNLMS outperforms IPNLMS in terms of convergence for both noise and speech input signals. The efficient partial updating scheme has been shown to effectively reduce the computational complexity of IIPNLMS without any significant degradation in performance.

5. REFERENCES

[1] Krishna, V. V., Rayala, J. and Slade, B., “Algorithmic and Implementation Apsects of Echo Cancellation in Packet Voice Networks,” in *Proc. Thirty-Sixth Asilomar Conference on Signals, Systems and Computers*, vol. 2, 2002, pp. 1252 –1257.

[2] Radecki, J., Zilic, Z. and Radecka, K., “Echo cancellation in IP networks,” in *Proc. 45th Midwest Symposium on Circuits and Systems*, vol. 2, pp. 219-222, 2002.

[3] Duttweiler, D. L., “Proportionate normalized least mean square adaptation in echo cancellers,” *IEEE Trans. Speech and Audio Processing*, vol. 8, pp. 508-518, 2000.

[4] Gay, S. L., “An efficient, fast converging adaptive filter for network echo cancellation,” in *Proc. 32nd Asilomar Conf. on Signals and System for Computing*, vol. 1, 1998, pp. 394-398.

[5] Benesty, J. and Gay S. L., “An improved PNLMS algorithm,” in *Proc. IEEE Int. Conf. Acoustics*, *Speech*, *Signal Processing*, vol. 2, 2002, pp. 1881-1884.

[6] Aboulnasr, T. and Mayyas, K., “Complexity reduction of the NLMS algorithms via selective coefficient update,” *IEEE Trans. Signal Processing*, vol. 47, pp.1421-1424, 1999.

[7] Douglas, S. C., “Adaptive filters employing partial updates,” *IEEE Trans. Circuits Syst.2*, vol. 44, no. 3, pp. 209-216, 1997.

[8] Naylor, P. A. and Sherliker, W., “A short-sort M-max NLMS partial-update adaptive filter with applications to echo cancellation,” in *Proc. IEEE Int. Conf. Acoustics, Speech, Signal Processing*, vol. 5, 2003, pp. 373-376.

[9] Tanrikulu, O. and Dogancay, K. “Selective-partial-update proportionate normalized least-mean-squares algorithm for network echo cancellation,” in *Proc*. *IEEE Int*. *Conf. Acoustics*, *Speech*, *Signal Processing*, vol. 2, 2002, pp.1889- 1892.

[10] Haykin, S.*, Adaptive Filter Theory*, Englewood Cliffs, NJ: Prentice Hall, 1991.