VLSI Implementation for the MPDSAP Adaptive Filter

Hun Choi*, Young-Min Kim*, Hong-Gon Ha*

Abstract

A new implementation method for MPDSAP(Maximally Polyphase Decomposed Subband Affine Projection) adaptive filter is proposed. The affine projection(AP) adaptive filter achieves fast convergence speed, however, its implementation is so expensive because of the matrix inversion for a weight-updating of adaptive filter. The maximally polyphase decomposed subband filtering allows the AP adaptive filter to avoid the matrix inversion, moreover, by using a pipelining technique, the simple subband structured AP is suitable for VLSI implementations concerning throughput, power dissipation and area. Computer simulations are presented to verify the performance of the proposed algorithm.

Keywords : Affine Projection, Subband Filtering, VLSI implementation, Pipelining, Acoustic echo cancellation

Ⅰ. Introduction

It is well-known that affine projection (AP) adaptive filter is a generalized version of the normalized least mean square (NLMS) adaptive filter, and in application such as noise cancellation, system identification, channel equalization, etc[1-10]. Recently, a new subband AP (SAP) adaptive filter was suggested in [9],[10]. The new SAP algorithm is based on the subband structure[12] that uses sufficiently decomposed adaptive sub-filters with the polyphase decomposition and the noble identity[13]. It can result in RLS-like performance with LMS-like computational complexity. In hardware implementation of SAP adaptive filter, however, computational complexities for the weight updating is still big a burden.

In this paper, we present a new design technique based on a hardware-efficiency and implementation flexibility for the SAP adaptive filter. As adaptive sub-filters are decomposed sufficiently into polyphase components, the weights of adaptive sub-filters can be updated by a simple weight-updating formula without a matrix inversion. In addition, by using a pipelining technique, the MPDSAP is suitable for VLSI implementations. The pipelining of shorter sub-filters will require a smaller number of delays for weight-updating and then they will not be much affected by the performance degradation due to pipelining delays. To evaluate the performance of the proposed pipelined MPDSAP(PIPMPDSAP), computer simulations are performed for the system identification in acoustic echo cancellation scenario.

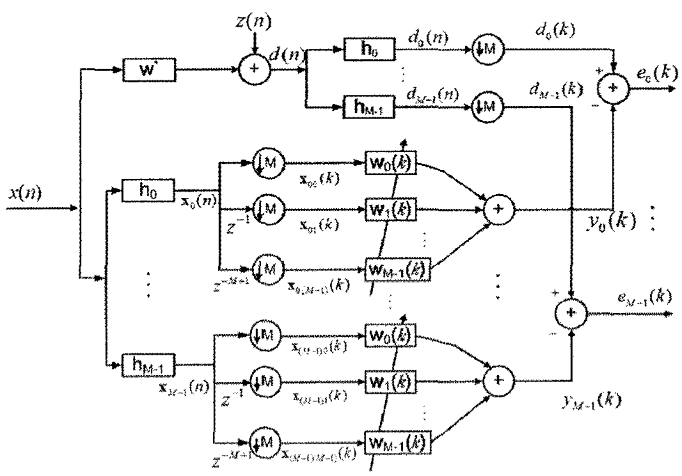

Fig.1. System identification model with subband adaptive filter [12]

Ⅱ. MPDSAP Adaptive Filter

Consider the subband adaptive acoustic echo cancellation (SAEC) system and the block diagrams of system identification for the SAEC in M-subband structure [12] as shown in Fig. 1. In [14], the excellency of this subband structure has been fully analyzed. This subband structure is always alias-free and stable. It is, and also, reasonable for implementation.

In Fig. 1, $x(n)=a^T g(n)+f(n)$ where the input

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투고 일자 : 2010. 6. 16 수정 일자 : 2010. 7. 22
게재확정일자 : 2010. 7. 29
※ This work was supported by Dong-eui University Grant.(2008AA170)

sequence $\{x(n)\}$ is assumed to have zero mean with variance σ_x^2, $a=[a_{(0)}\ a_{(1)}\ \ldots\ a_{(P-1)}]^T$, where P is order of autoregressive (AR) process. $g=[g(n)\ g(n-1)\ \ldots\ g(n-L+1)]^T$ are L samples from an underlying zero mean and unit variance i.i.d random sequence $\{g(n)\}$ and $f(n)$ is a WSS white process with variance σ_f^2. $d(n)=w^{*T}x(n)+r(n)$ are input signal and desired signal, respectively. w^* is the echo path that we wish to estimate and r(n) is measurement noise that is the independent identically distributed (iid) random signal with zero mean and variance σ_r^2. Using orthonormal analysis filters $h_0 \ldots h_{M-1}$, the input signal u(k) and the desired signal d(n) are partitioned into new signals denoted by $x_i(n)=h_i^T x(n)$ and $d_i(n)=h_i^T d(n)$ for $x(n)=[x(n)\,x(n-1)\ \ldots\ x(n-P+1)]^T$ and $d(n)=[d(n)\,d(n-1)\ \ldots\ d(n-P+1)]^T$, respectively.

In Fig. 1, the decimated signal $x_{ij}(k)=x_i(Mk-n)$ is the subband polyphase components of $x_i(k)$. The polyphase component vectors of the subband inputs can be presented by $x_{ij}(k)=[x_{ij}(k)\ x_{ij}(k-1)\ \ldots\ x_{ij}(k-P_s)]^T$. The subscript ij is the subband decomposed polyphase index (i and j = 0, 1, ..., M-1) and P_s is both the order of the subband-partitioned AR process and the order of projection in each subband. The adaptive sub-filters $w_i(k)$ attempt to estimate a subband desired signals $d_i(k)$ which are linearly related to the subband-partitioned input signals $x_i(k)$. In M-subband structure, the adaptive filter can be represented in terms of polyphase components [13] as

$$W(z)=W_0(z^M)+z^{-1}W_1(z^M)+\ldots+z^{-i}W_i(z^M) \tag{1}$$

and its weight-updating formula is given by [9],[10]

$$w_s(k+1)=w_s(k)+\mu X(k)\Pi^{-1}(k)E_s(k) \tag{2}$$

where

$$w_s(k)=[w_0^T(k)\ w_1^T(k)\ \cdots\ w_{M-1}^T(k)]^T \tag{3}$$

$$X(k)=\begin{bmatrix} X_{00}(k) & X_{10}(k) & \cdots & X_{(M-1)0}(k) \\ X_{01}(k) & X_{11}(k) & \cdots & X_{(M-1)1}(k) \\ \vdots & \vdots & \ddots & \vdots \\ X_{0(M-1)}(k) & X_{0(M-1)}(k) & \cdots & X_{(M-1)(M-1)}(k) \end{bmatrix} \tag{4}$$

$$X_{ij}(k)=[x_i(k)\ x_i(k-1)\cdots x_i(k-P_s)] \tag{5}$$

$$\Pi(k)=\begin{bmatrix} A_0(k) & 0 & \cdots & 0 \\ 0 & A_1(k) & & \vdots \\ \vdots & & \ddots & 0 \\ 0 & \cdots & 0 & A_{(M-1)(k)} \end{bmatrix} \tag{6}$$

$$A_i(k)=\sum_{n=0}^{M-1}X_{ij}^T(k)X_{ij}(k) \tag{7}$$

$$E(k)=\begin{bmatrix} e_0(k) \\ e_1(k) \\ \vdots \\ e_{M-1}(k) \end{bmatrix} \tag{8}$$

$$e_i=d_i(k)-\sum_{n=0}^{M-1}X_{ij}^T(k)w_j(k) \tag{9}$$

III. Pipelined MPDSAP Adaptive Filter

A. MPDSAP Adaptive Filter

In the conventional AP (fullband AP), AR(P) input signal is decorrelated by the P times projection operations with the corresponding past P input vectors. In SAP, whereas, the lower order of projection is sufficient for the signal-decorrelating.

That is, $P_s < P$. Because the input signal is pre-whitened by the subband partitioning and then, the spectral dynamic range of the subband input is decreased.

Moreover, the length of the adaptive sub-filter becomes $N_s=N/M$ by applying the polyphase decomposition and the noble identity to the maximally decimated adaptive filter.

The projection order is typically much smaller than the length of the adaptive filter. Therefore, the SAP algorithm can be simplified by partitioning the P-order fullband AP into P-subbands.

Consequently, the projection order for the shortened adaptive sub-filter can become $P_s \approx P/M$. When the size of the data matrix is $N\times(P+1)$ in the conventional AP, it can become $N_s\times(P_s+1)\approx(N/M)\times(P/M)$ in SAP. When the projection order is 2 (P=2), by partitioning into two-subbands, the projection order for SAP becomes unit (Ps=1).

From eq. (2), therefore, each adaptive sub-filter is simply rewritten as

$$w_i(k+1)=w_i(k)+\mu\sum_{j=0}^{M-1}\left[\frac{X_{ji}(k)e_j(k)}{\sigma_{x_j}^2(k)}\right] \text{ for } i=0,1,\ldots M-1 \tag{10}$$

where $\sigma_{x_j}^2(k)$ is the variance of input signal in each subband.

This MPDSAP updates the weights of adaptive sub-filters with $N/P\times 1$ data vectors instead of data matrices[12].

B. Pipelined MPDSAP Adaptive Filter

The MPDSAP algorithm as shown in eq. (10) has very simple forms.

Since its weight-updating is the first-order recursion form, the MPDSAP algorithm can be easily realized by pipelining.

Applying K-stage look-ahead [15, 16] to eq. (2), we can get

$$w(k+1) = w(k-K+1) + \mu \sum_{t=0}^{K-1} X(k-K+t+1) \times \Pi^{-1}(k-K+t+1) E(k-K+t+1) \quad (11)$$

In eq. (11), the pipelined SAP maintains the functionality of input-output behavior. For implementation, however, it has a difficult problem that is the increment of hardware cost. The relaxed look-ahead [17] is proposed for reducing the hardware cost. First, by applying the delay and sum relaxations to eq. (11), we obtain

$$w(k+1) = w(k-K+1) + \frac{\mu}{LA} \sum_{t=0}^{LA-1} X(k-D_1+t+1) \times \Pi^{-1}(k-D_1+t+1) E(k-D_1+t+1) \quad (12)$$

where $LA \ll K$.

In eq. (12), if step size μ is replaced by β including the term LA, we can obtain the pipelined MPDSAP (PIPMPDSAP) following as

$$w(k+1) = w(k-K+1) + \beta \sum_{t=0}^{LA-1} X(k-D_1+t+1) \times \Pi^{-1}(k-D_1+t+1) E(k-D_1+t+1) \quad (13)$$

where $1 \le LA \ll K$.

By applying the relaxation technique to eq. (9), the subband error vector of eq. (8) is represented as

$$\begin{aligned} E(k) &= D(k) - X^T(k) w(k) \\ &= D(k) - X^T(k)[w(k-K) + \beta \sum_{t=0}^{LA-1} X^T(k-D_1+t) \\ &\quad \times \Pi^{-1}(k-D_1+t) E(k-D_1+t)] \\ &\cong D(k) - X^T(k) w(k-K+1) \end{aligned} \quad (14)$$

where $\beta \ll 1$ and $w(k-K+1) \cong w(k-K)$.

From eq. (13), the D_2-stage relaxed look-ahead pipelined MPDSAP adaptive filters are updated by eq. (15), and the architecture of eq. (15) is shown in Fig. 2. D_1 and D_2 are the delay factors.

In eq. (15), to reduce the complexity of the implementation, the powers of input signals, $\delta^2_{x_{ij}}(k)$ are replaced by

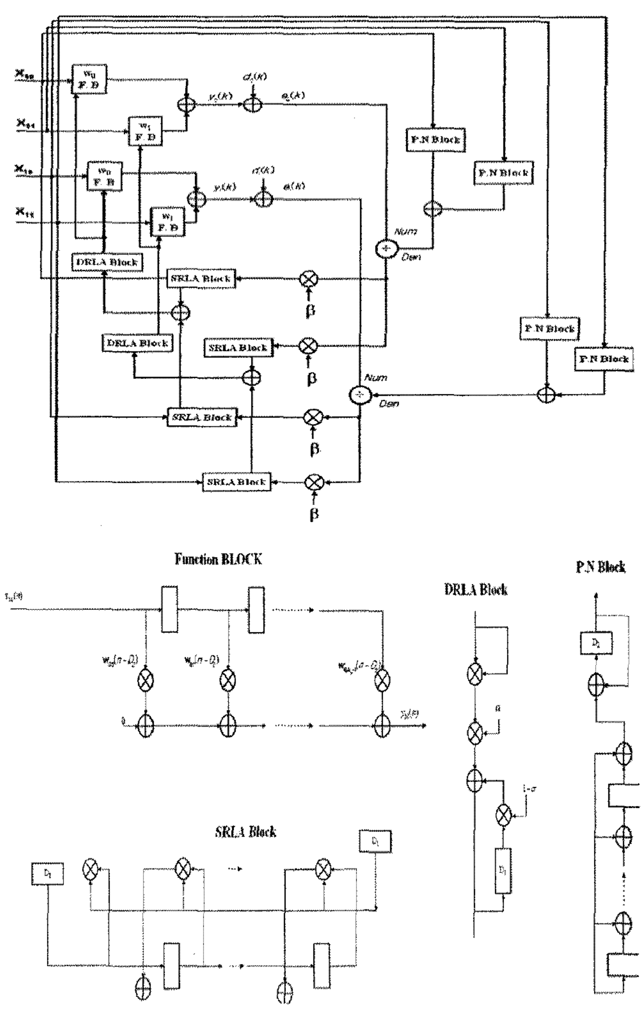


Fig.2. The D_2-step pipelined structure for updating w_0 of the proposed PIPMPDSAP in the two subband adaptive system identification model ($P_s = 1, M = 2$, PNBlock : Power Normalization Block, SRLABlock : Sum Relaxed Look Ahead Block, DRLABlock : Delay Relaxed Look Ahead Block)

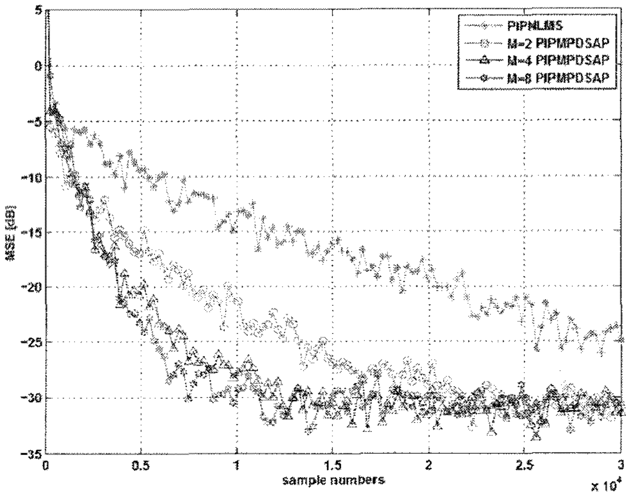
$$w_i(k+1) = w_i(k-D_2+1) + \beta \sum_{t=0}^{LA-1} \sum_{j=0}^{LA-1} \left[\frac{u_{ji}(k-D_1+t+1) e_i(k-D_1+t+1)}{\delta^2_{\xi j} + \delta^2_{\xi j}} \right] \quad (15)$$

$$\delta^2_{x_{ij}}(k) = (1-\alpha)\delta^2_{x_{ij}}(k-1) + \alpha X_{ij}(k) \quad (16)$$

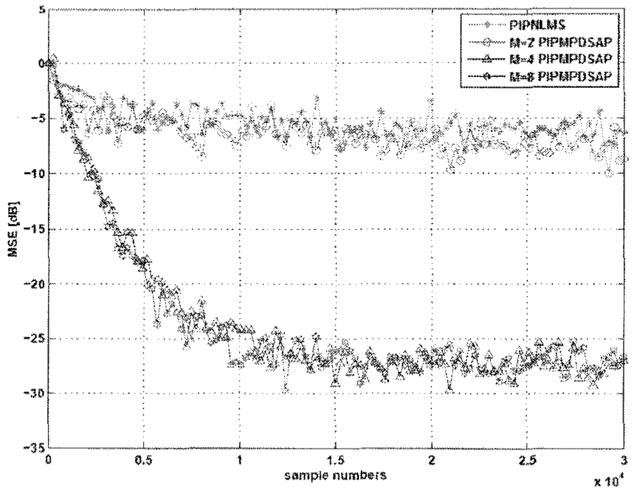
where i and $j = 1, 2, \ldots M-1$, α is a forgetting factor, and $0 < \alpha < 1$. From Fig. 2, we know that the proposed PIPMPDSAP adaptive filter has a simple weight-updating formula such as normalized LMS (NLMS).

Ⅳ Simulation Results

To evaluate the performances of the proposed PIPMPDSAP, we carry out computer simulations in

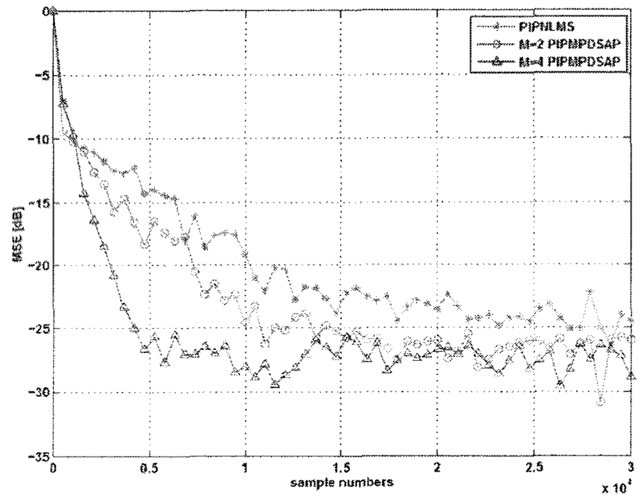


(a) AR(1)

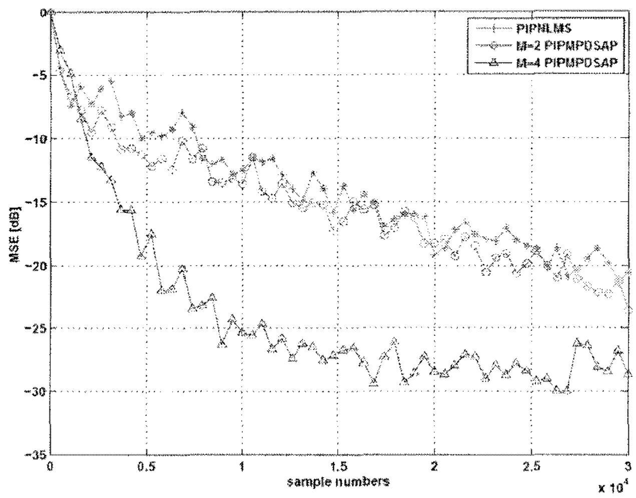


(b) AR(4)

Fig.3. MSE curves of the proposed PIPMPDSAP and PIPNLMS for real echo path (Input : AR(1) and AR(4) with SNR = 30dB, N = 64, D_1 = 8, D_2 = 4, LA =2)



(a) $N = 16$



(b) $N = 32$

Fig.4. MSE curves of the D_2-step PIPMPDSAP for different lengths of adaptive filter (Input : AR(4), N = 16 and 32, D_1 = 8, D_2 = 4, LA =2)

acoustic echo cancellation scenario. The unknown system is an actual impulse response of the echo path in a room, sampled at 8 kHz and truncated to 32 (N=32) samples. For signal-partitioning in all experiments, we use the cosine modulated filter banks (CMFB) [13]. For efficient subband decomposition of input signals, the lengths of analysis filters are increased with M so that the ratio of the transition band to the passband is maintained nearly the same for all values of M. The prototype filters' lengths are 32 and 64 for M = 2 and 4, respectively. The input signals are zero mean wide sense stationary AR(P) and a real speech sampled at 8 kHz. The coefficients of AR(P) are $a=[1\ 0.9]^T$ for AR(1) and $a=[1\ 0.999\ 0.99\ 0.995\ 0.9]^T$ for AR(4). The modeling noise signal, f(k), is zero mean and unit variance white Gaussian random process. The measurement noise, r(k), is added to desire signal d(k) such that SNR = 30dB. In acoustic echo cancellation systems as shown in Fig. 1, we compare the mean square error (MSE) and the echo return loss enhancement (ERLE) performances of the PIPNLMS and the proposed PIPMPDSAP algorithm.

The step sizes are set to $\mu=0.1$, $\mu=0.05$, and $\mu=0.025$ for PIPNLMS, M=2 PIPMPDSAP, and M=4 PIPMPDSAP, respectively. In all experiments, we assume that the double talk condition is not active.

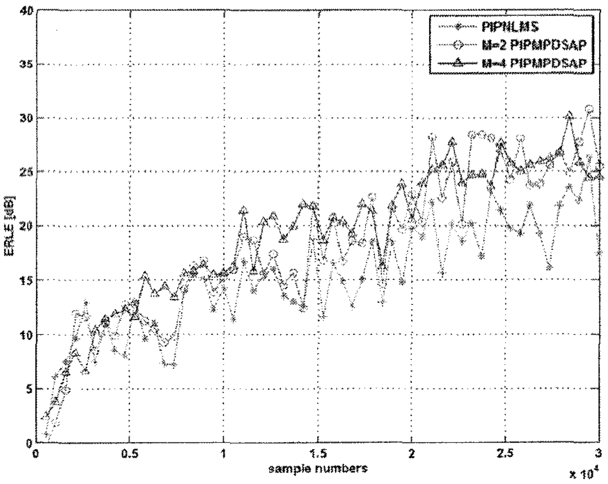


Fig.5. ERLE curves of the proposed PIPMPDSAP and PIPNLMS (N = 64, D_1 = 8, D_2 = 4, LA =2)

A. Convergence Performance of The MPDSAP Adaptive Filter

Fig. 3 shows the MSE curves of the PIPMPDSAP and PIPNLMS with AR(1) and AR(4) inputs respectively. The parameters for the pipelining delay are set to $D_1=8$, $D_2=4$, and LA=2. The convergence rate of the proposed PIPMPDSAP goes up with M. In the proposed PIPMPDSAP, the increment of M allows the adaptive sub-filter to use a higher projection order with small computational complexity.

We evaluated the convergence performances of the PIPMPDSAP for different length of the adaptive filter. Fig. 4 shows the MSE performances of PIPMPDSAP. In Fig. 4, the unknown system to be identified are length N = 16 and 32 FIR filters with coefficients chosen randomly. The input signals are AR(4) with SNR=30dB. In Fig. 4, the convergence rate of PIPMPDSAP decreases with the increment of N, however, PIPMPDSAP with large M is not much affected by the performance degradation, because the input signal is sufficiently whitened by the subband partitioning.

B. ERLE Performance of The MPDSAP Adaptive Filter

Fig. 5 shows the ERLE performances of the PIPNLMS and the proposed method for different numbers of subbands (M=2, 4, and 8). The input signals are AR(4) processors with SNR=30dB. From these results, we can doubtless know that the convergence rate of adaptive filter is improved by the subband filtering and speeds up with the increment of M.

V. Conclusions

In this paper, we present a new pipelined structure for a practical implementation of subband affine projection algorithm. The SAP algorithm can be simplified by partitioning over the number of subbands as the projection order and the weight-updating formula of the MPDSAP is suitable for pipelining. The pipelined MPDSAP (PIPMPDSAP) achieves better performances than the pipelined NLMS (PIPNLMS). In PIPMPDSAP, shorten adaptive sub-filters are not much affected by the performance degradation due to pipelining delays because they require a smaller number of delays for weight-updating. Several simulation results support the theoretical predictions and show the improved performances.

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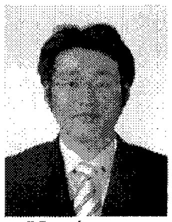

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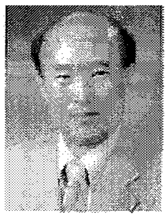

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