Performance Comparison of Transform Domain Adaptive Filters

Sangeeta Sharma

M.Tech (VLSI Design) Electronics and Communication Inderprastha Engineering College, Ghaziabad, U.P India

Abstract - In this paper, transform domain adaptive filter and its orthogonality properties such as Discrete Cosine Least Mean Square Transform (DCLMST), Discrete Sine Least Mean Square Transform (DSLMST), Discrete Fourier Least Mean Square Transform (DFLMST), Wavelet Domain Least Mean Square Adaptive Filter (WDLMSAF) and Wavelet Domain Normalized Least Mean Square Adaptive Filter (WDNLMSAF) are studied and compared on the basis of different performance parameters. In this we are using block implementation for FIR filter, to increase the computational speed. Block implementation in frequency domain is performed by fast block LMS algorithm. Their performance is compared on the basis of signal to noise (SNR) ratio, mean square error (MSE) and computational time. The performance comparison is taken for different noise range (5 dB, 0 dB, -5 dB and -10 dB). We have divided the noise level in to different order according to there range: lower order (10-40), moderate order (40-60) and higher order (60-100). WDLMSAF shows best result for MSE and SNR . A graphical and a tabular view is also given to show the comparison.

Index Terms - Fast block least mean square (FBLMS), discrete cosine least mean square transform (DCLMST), discrete sine least mean square transform (DSLMST), discrete fourier least mean square transform (DFLMST), wavelet domain least mean square adaptive filter (WDLMSAF), wavelet domain normalized least mean square adaptive filter (WDNLMSAF)

I. INTRODUCTION

Noise is one of the unwanted signal. To remove this we use different methods in time domain like least mean square (LMS) and is variants, which are mostly used due to their computational simplicity and stability. LMS is also used in different applications like echo cancellation in adaptive filters, But, LMS is not considered good when we talk about long echo cancellation like in teleconferencing [1], to remove this long echo duration they don't have long memory or long impulse response due to this reason they create problem of increase in computational complexity. To remove this problem we can either use infinite impulse response (IIR) [2], [3] in time domain or transform domain adaptive filter (TDAF). But, IIR causes stability problem therefore, we use TDAF as it has better computational speed, fast convolution and it also enhances the convergence performance of the LMS algorithm. TDAF uses the orthogonality properties of fast fourier transform (FFT), discrete cosine transform (DCT), discrete sine transform (DST) and wavelet transform (WT) in LMS and NLMS (normalized LMS) to achieve a much more improved convergence rate [4]. For frequency domain adaptive filtering block implementation of finite impulse response (FIR) filter can be computed that will increase computational speed. In this we have performed block by block processing of input data in frequency domain, this is known as fast block algorithm. Fast block LMS algorithm (FBLMS) is used for noise cancellation.

II. ADAPTIVE NOISE CANCELLATION IN TRANSFORM DOMAIN

Basic structure for adaptive noise cancellation system is shown in Fig. 1. It is shown by this Fig. that the input to the FIR filter is reference noise $N_1(n)$. The output of the filter is y(n) which is convolution of reference noise $N_1(n)$ & filter tap weight w(n). The noisy signal d(n) which consists of an information bearing signal s(n) corrupted by noise N(n). The d(n) & y(n) are compared to give the error signal e(n). The adaptive filter coefficients are changed iteratively according to the error signal e(n). The filter weights are adjusted continuously to minimize the error between d(n) and y(n), so that the output e(n) is a close approximation of the signal s(n). Both noise signals N(n) and $N_1(n)$ are uncorrelated with the signal s(n) while correlated with each other. The error e(n) gives the estimated clean signal at the output[5].

In digital signal processing applications, frequency domain methods are used for implementation of fast convolution and fast correlation. The significant reduction in computations are achieved using frequency domain. When block -by-block processing of input data is used in LMS algorithm then the algorithm is called Block LMS algorithm. If the processing is done in frequency domain then the algorithm is called Fast Block Algorithm. Noise Cancellation System using Fast Block LMS algorithm(FBLMS) is most commonly used method. In this algorithm, The filter parameters are adapted in frequency domain using different tools for transformation such as Fast Fourier Transform, Discrete Cosine Transform, Discrete Sine Transform, Wavelet Transform (WT) etc.

The fast block LMS algorithm using FFT method is developed by clark *et al.*(1981, 1983) and ferrara (1980) [5]. Here, Overlap-save method and overlap-add method is used to provide fast convolution. Most commonly used method for FBLMS is overlap-save method [5]. In this paper Overlap-save method with 50 percent overlap is implemented and explained. Since, the 50 percent overlap is used, M filter weights are padded with M number of zeros and N-point FFT is computed such that N = 2M.

923

924

The process of implementation of FBLMS are shown in Fig. 2. Instead of FFT, other transformations methods may be used in FBLMS named DCT, DST etc.



Figure 1: Adaptive Noise Cancellation System

the corresponding FBLMS algorithms are called DCLMST, DFLMST, DSLMST, WDLMSAF and WDNLMSAF respectively. Wavelet transform domain adaptive filters are also used in adaptive noise cancellation systems [5]. Wavelet Transform Domain Least Mean Square (WDLMSAF) adaptive filter and Wavelet Transform Domain Normalized Least Mean Square (WDNLMSAF) adaptive filter with Daubechies wavelets are used to minimize the undesired noise from speech signals.



Figure 2: Wavelet domain adaptive filter

The block diagram of Wavelet Transform Domain Adaptive Filter [5] setup is shown in Fig. 3. Here input signal is first divided into corresponding sub-bands. These sub-bands represent the signal at different resolution levels. The sub-band signals are then used as inputs to an adaptive filter. Each sub-band signal is then multiplied by corresponding weights and added to give output y(n). y(n) is then compared with desired signal d(n) and error e(n) is produced.



Figure 3: Overlap-save FDAF (Frequency domain adaptive filter)

III. SIMULATION AND RESULT

For evaluating the performance of the algorithms, the first requirement is the availability of proper noisy signal. In this paper, Noisy database was prepared by artificially adding babble noise [6] to clean database at 5 dB, 0 dB, -5 dB and -10 dB SNR levels. Clean signal 'DHOWBIN JAB SO KAR UTHTHI TO DEKHTI KI CHAWKA SAAF PADAA HAI AUR BARTAN MANJEY HUEYN HAIN' is used in these algorithms. The noisy database of this sentence was prepared by adding noises at different SNR levels.

The noisy signal was fed into the mathematical simulation of FBLMS algorithm using DFT, DCT, DWT and DST for transformation (named as DFLMST, DCLMST and DSLMST respectively), also in WDLMSAF and WDNLMSAF algorithms with Daubechies wavelets with the help of MATLAB. The noise cancellation system is analyzed for filter order 10, 50 and 100 at -10 dB, -5dB, 0dB and 5dB SNR level. The resulting outputs were then analyzed in order to study the behavior of these algorithms. The performance of algorithms was compared based on the improvement in SNR at various SNR levels, Mean Square Error and computational time.

By comparing DCLMST, DSLMST, DFLMST, WDLMSAF and WDNLMSAF transform algorithms, we get appropriate result. The readings are calculated in decibel. These appropriate readings are then converted in to graphical form and a comparison chart is made.



Figure 4: comparative analysis of various parameter of transform domain adaptive filter at filter order 10 & 5dB input SNR level







Figure 6: comparative analysis of various parameter of transform domain adaptive filter at filter order 10 & -5dB input SNR level



Figure 7: comparative analysis of various parameter of transform domain adaptive filter at filter order 10 & -10dB input SNR level



200 180 160 140 120 100 80 Value in dB 60 40 20 0 DCLMST WDLMSAF WDNLMSAF DCLMST WDLMSAF WDNLMSAF -20 DSLMST DFLMST DSLMST DSLMST DFLMST DCLMST DFLMST WDNLMSAF -40 -60 -80 -100 -120 SNR Comp Tm MSF -140

Figure 8: comparative analysis of various parameter of transform domain adaptive filter at filter order 50 & 5dB input SNR level

Figure 9: comparative analysis of various parameter of transform domain adaptive filter at filter order 50 & 0dB input SNR level



Figure 10: comparative analysis of various parameter of transform domain adaptive filter at filter order 50 & -5dB input SNR level



Figure 11: comparative analysis of various parameter of transform domain adaptive filter at filter order 50 & -10dB input SNR



Figure 12: comparative analysis of various parameter of transform domain adaptive filter at filter order 100 & 5dB input SNR level



Figure 13: comparative analysis of various parameter of transform domain adaptive filter at filter order 100 & 0dB input SNR level



Figure 14: comparative analysis of various parameter of transform domain adaptive filter at filter order 100 & -5dB input SNR level



Figure 15: comparative analysis of various parameter of transform domain adaptive at filter order 100 & -10dB input SNR level

We have divided the noise order in to lower order (10-40), moderate order (40-60), higher order (60-100). Table 1. Shows that DCLMST shows best performance in terms of SNR and computational time but for mean square error WDLMSAF shows result. Table 2. for moderate order WDLMSAF is best in terms of MSE and DCLMST Shows the least computational time. For SNR, DFLMST is best for noise level (5 dB and 0 dB) and for noise level (-5 dB and -10 dB) WDLMSAF shows good result. Table 3. for noise range (5 dB, 0 dB and -10 dB) DFLMST shows best performance but for noise level -10 dB WDLMSAF shows best result. WDLMSAF is best for MSE but at the cost of increased computational time and DCLMST requires lest computational time.

Table 1: Comparative chart for lower order	(M=10-40),	for different	noise rang	je
--	------------	---------------	------------	----

M=10-40			
Noise	SNR	MSE	Computational Time
5 dB	DCLMST	WDLMSAF	DCLMST
0 dB	DCLMST	WDLMSAF	DCLMST
-5 dB	DCLMST	WDLMSAF	DCLMST
-10 dB	WDLMSAF	WDLMSAF	DCLMST

Table 2: Comparative chart for moderate order (M=40-60), for different noise range

M=40-60			
Noise	SNR	MSE	Computational Time
5 dB	DFLMST	WDLMSAF	DCLMST
0 dB	DFLMST	WDLMSAF	DCLMST
-5 dB	WDLMSAF	WDLMSAF	DCLMST
-10 dB	WDL MSAF	WDLMSAF	DCLMST

Table 3: Comparative chart for higher order (M=60-100), for different noise range.

	M=	M=60-100		
Noise	SNR	MSE	Computational Time	
5 dB	DFLMST	WDLMSAF	DCLMST	
0 dB	DFLMST	WDLMSAF	DCLMST	
-5 dB	DFLMST	WDLMSAF	DCLMST	
-10 dB	WDLMS	WDLMSAF	DCLMST	

As above we have compared different parameters on the basis of different order now, we will do the comparison on the basis of noise range. Table 4 defines that DCLMST shows best performance in term of computational time and WDLMSAF is best in terms of MSE. Table 5 shows that DCLMST shows best result for computational time and MSE and SNR, WDLMSAF shows best performance.

Table 4: Comparison of parameters on the basis of noise range (5 dB - 0 dB)

5 dB-0 dB		
SNR	MSE	Computational Time
DFLMST	WDLMSAF	DCLMST

Table 5: Comparison of parameters on the basis of noise rate
--

- 5 dB10 dB			
SNR	MSE	Computational Time	
WDLMSAF	WDLMSAF	DCLMST	

930

IV. CONCLUSION

By comparing the above tabular graphs we can conclude that WDLMSAF shows best performance in terms of SNR (signal to noise ratio) and MSE (mean square error) but at the cost of increased computational time.

References

- [1] Kazuo Murano, Shigeyuki Unagami and Fumio Amano, "Echo cancellation and applications," IEEE Communications Magazine, pp. 49-55, January 1990.
- [2] Athanasios P. Liavas and Phillip A. Regalia, "Acoustic echo cancellation: Do IIR models offer Better modeling Capabilities than their FIR counterparts," IEEE Transactions on Signal Processing, vol. 46, no. 9, pp. 2499-2504, September 1998.
- [3] John J. Shynk, "Adaptive IIR filtering," IEEE Acoustic, Speech and Signal Processing, Magazine, pp. 4-21, April 1989.
- [4] Narayan S, Malibu CA, Peterson A.M, and Narasimha M.J, "Transform domain LMS algorithm," IEEE Transaction on Acoustics, Speech and Signal Processing, vol. 31, pp. 609-615, January 1983.
- [5] Symon Haykin, Adaptive filter theory, 3rd edition, Prentice-Hall, 1996.
- [6] http://www.xilinx.com/univ/teaching_materials/dsp_primer/sample/workbook/Xilinx_DSP_workbook_adaptive.pdf.

