Adaptive Noise Cancellation Using Transform Domain Adaptive Algorithms

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ABSTRACT
This paper presents the MATLAB simulation of different transform domain adaptive algorithms for adaptive noise cancellation system. The algorithms implemented are transform domain normalized least mean square(TDNLMS), discrete cosine transform domain normalized least mean square (DCTNLMS), transform domain least mean square (TDLMS), and discrete cosine transform least mean square(DCTLMS). The advantages of the transform domain algorithms are its low computational complexity, superior convergence performance and efficient implementation in comparison to conventional NLMS and LMS algorithms. The performances of the implemented algorithms are evaluated by the signal to noise ratio (SNR) improvements, minimum mean square error (MSE),convergence and robustness parameters.

Keywords
Adaptive algorithms, TDNLMS, TDLMS, DCTNLMS, DCTLMS, SNR, MSE

1. INTRODUCTION
An adaptive filter is a system with a linear filter that has a transfer function controlled by variable parameters and a means to adjust the parameters according to an optimization algorithm. An adaptive filter is used in many signal processing areas like adaptive noise cancellation, echo cancellation, equalization, sonar application etc [1-3]. In this paper, the adaptive filter is used for the application of adaptive noise cancellation (ANC) system. Adaptive noise cancellation is a method to cancel out the noise incorporated into desired input signal using adaptive filter algorithms [4]. It is done by estimating noise signal and subtracting is from the given input signal. Here, the aim of adaptive filter is to calculate the difference between the desired signal and adaptive filter output such that the noise is to be minimized. Most of the adaptive algorithms used for optimization are categorized in two types - Least mean square (LMS) and Recursive least square algorithm (RLS). All other algorithms are derived from these two algorithms [5]. The transform domain algorithms offer several advantages over conventional LMS algorithms. The advantages include lower computational complexity, better convergence speed and efficient implementation especially for those applications where long filter impulse response (i.e. long memory) is required [6]. The transform domain adaptive filtering combines the advantages of two complementary methods which are widely used in digital signal processing applications- (i) Block implementation of an FIR filter which allows the efficient use of parallel processing. (ii) Fast Fourier Transform (FFT) or other fast transform algorithms for performing fast convolution (filtering). The speed of convergence of time domain LMS algorithm degrades significantly for highly correlated input signals [7-8]. Because of orthogonal property of discrete Fourier Transform, discrete cosine transform and other related transforms, the transform domain algorithms provides faster convergence speed with low computational complexity. This paper presents the implementation of transform domain least mean square (TDLMS), transform domain normalized least mean square (TDNLMS), discrete cosine transform domain least mean square (DCTNLMS), and discrete cosine transform normalized least mean square (DCTNLMS).

2. TRANSFORM DOMAIN ALGORITHMS
The block diagram of transform domain adaptive filter (TDAF) is shown in fig.1. The input reference noise is used as an excitation signal $x(n)$, for noise cancellation setup converted into transform domain by the block T_N, is applied to adaptive filter. The filter output $y(n)$ is subtracted from noisy signal $d(n)$, which is a transformed version of the noisy signal $S(n)+x'(n)$, used to obtain the error signal. This error signal is again used for number of iterations to change the filter coefficients in such a way that the noise is minimized.

The adaptive filter changes its characteristics based on an adaptive algorithm used and the information available at that time. The information might be about computational resources available or the history of data recently received. The summary of the transformed domain adaptive algorithms [9-14] implemented are as follows-

Input Reference Noise Samples:

$$x(n), x(n-1), ..., x(n-N+1)$$

Orthogonal Transform: T

$$X_T(n) = Tx(n)$$

Transform Output:

$$X_{T,0}(n), X_{T,1}(n), ..., X_{T,N-1}(n)$$

Tap-Weights:

$$W_{T,0,} W_{T,1,.......,} W_{T,N-1}$$

The orthogonal transform matrix T is selected such that $T^T T = TT^T = 1$

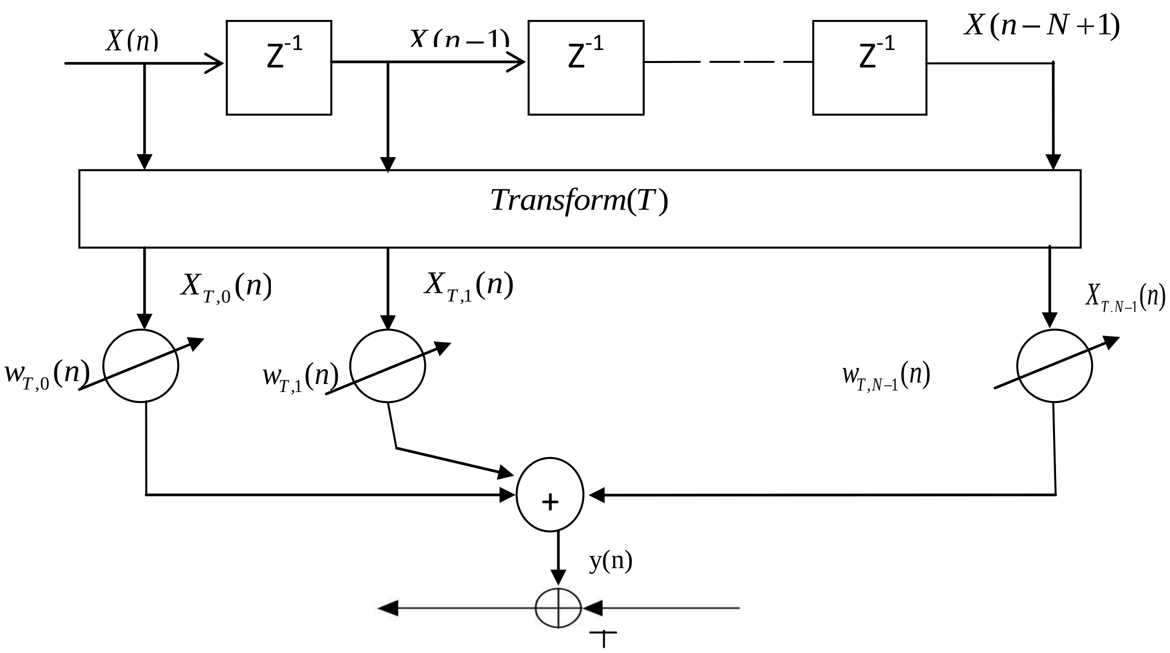

Fig 1: Block diagram of transform domain adaptive filter.

It is assumed that the input signals of the adaptive filter are real-valued and the elements of T are also real-valued.

Summary of TDLMS algorithm:

(1) Transformation:

$$\overline{X}_T = T\overline{x}(n)$$

(2) Filtering :

$$y(n) = \overline{W}^T{}_T \overline{X}_T(n)$$

(3) Error estimation:

$$e(n) = d(n) - y(n)$$

(4) Tap input power estimate for i=0 to N-1:

$$\sigma^2_{T,i}(n) = \beta\sigma^2_{T,i}(n-1) + (1-\beta)X^2_{T,i}(n)$$

(5) Tap weight vector update:

$$\overline{W}_T(n+1) = \overline{W}_T(n) + 2\mu D^{-1} e(n)\overline{X}_T(n)$$

Where, $D = diag\left[\sigma^2_{X_{T,0}}\sigma^2_{X_{T,1}}....\sigma^2_{X_{T,N-1}}\right]$

DCTLMS: Discrete cosine transform (DCT) is one of the most popular orthogonal transform. For speech signals, the DCT is a good approximation for the “Karhunen-Loéve transform (KLT)”.

Discrete cosine transform(DCT)

The DCT of a input sequence $x(n), x(n-1),......, x(n-N+1)$ is defined as

$$X_{DCT_K}(n) = \sum_{l=0}^{N-1} C_{kl}x(n-l),\ for..k = 0,1,2,....N-1$$

Where,

$$C_{kl} = \begin{cases} \dfrac{1}{\sqrt{N}} & ,k=0, and, l = 0,1,2,....N-1 \\ \sqrt{\dfrac{2}{N}}\cos\dfrac{\pi(2l+1)k}{2N} & ,k = 1,2...N-1, and, l = 0,1,2,..N-1 \end{cases}$$

TDNLMS & DCTNLMS: The convergence speed is limited in LMS algorithm because of constant step size parameter. It is significantly improved in NLMS. The difference between LMS and NLMS is that in NLMS the step size parameter is normalized by the following equations-

$\mu = \alpha / (\beta + X(n)^T X(n))$, where α and β are taken as positive constant.

3. SIMULATION SETUP AND RESULTS

In this paper, simulations of different transform domain algorithms are done in reference to adaptive noise cancellation system, which is a system identification approach of adaptive filters. For MATLAB simulation, the clean speech sample “YAHA SAI LAGHBAG PANCH MEAL DAKSHIN PASCHIM MAI KATGHAR GAON HAI” is taken from standard Hindi database [15]. The noisy signal is prepared by adding babble16 noise, car noise and factory noise signals which are taken from NOISE 92X database [16] at input SNR levels of -5, -10, -15, -20, -25. The performance parameter used to evaluate these implemented algorithms is SNR improvement. The SNR improvement parameter is used as a measure to compare the level of a desired signal to the level of the noise added and is expressed in decibel as-

$$SNR(dB) = 10\log_{10}\left((SP - NP) / NP \right)$$

Where, ‘*SP*’ is the signal power calculated using output error signal and ‘*NP*’ is the noise power calculated using estimated noise signal. The next performance parameter measured is the mean square error (MSE). For MSE calculation, first, the error signal is calculated for each iteration by subtracting the desired signal from filter output signal. Then the mean square value of error gives the MSE value. The third parameter measured is the robustness of the system which is verified by observing the output for different types of noises added with the same standard clean speech signal at various input SNR levels.

Table 1: MSE & SNR improvement analysis (noise - babble16)

Algorithm Name	Input SNR (dB)	MSE	SNR Improvement (dB)
TDLMS	-5	0.0057	11.8163
TDNLMS	-5	0.2796	6.7372
DCT-LMS	-5	0.2447	7.2865
DCT-NLMS	-5	0.0063	6.6563
TDLMS	0	0.0057	2.3988
TDNLMS	0	0.0056	2.4373
DCT-LMS	0	0.0056	0.5289
DCT-NLMS	0	0.0058	2.3628
TDLMS	-10	0.0111	10.5498
TDNLMS	-10	0.0105	9.767
DCT-LMS	-10	0.0159	10.1672
DCT-NLMS	-10	0.0239	9.6511
TDLMS	-15	0.015	14.7756
TDNLMS	-15	0.014	14.3723
DCT-LMS	-15	0.021	14.4508
DCT-NLMS	-15	0.0239	14.0101
TDLMS	-20	0.0201	19.3397
TDNLMS	-20	0.019	19.1522
DCT-LMS	-20	0.0253	19.0435
DCT-NLMS	-20	0.0272	18.6408
TDLMS	-25	0.0246	24.0963
TDNLMS	-25	0.0238	24.0292
DCT-LMS	-25	0.0281	23.8149
DCT-NLMS	-25	0.0292	23.2343

Table-1 shows the analysis of all said algorithms for the speech signal corrupted with babble16 noise for filter order 10. Here the corrupted signal is prepared at -5dB, 0dB, -15dB, -20dB & -25dB input SNR levels. Also, the same analysis is done for filter orders 15, 20, 25 & 30.

Table-2 and Table-3 shows the same analysis for the speech signal corrupted with factory noise and car noise respectively for filter order 10.

The graphical analysis of these algorithms showing the performance comparison for SNR improvement and MSE value is depicted in figures 2 to 7. From figure-2, figure-3 and figure-4, it is clear that TDNLMS shows superior performance than TDLMS, DCTLMS and DCT-NLMS in terms of SNR improvements. The maximum SNR improvement of 24.0292db is achieved at input SNR value of -25dB for babble16 noise. For car noise and factory noise, the maximum SNR improvement values obtained are 23.8778db and 23.8939db respectively.

Table 2: MSE & SNR improvement analysis (factory noise)

Algorithm Name	Input SNR (dB)	MSE	SNR Improvement (dB)
TDLMS	-5	0.0061	5.9361
TDNLMS	-5	0.0066	5.9434
DCT-LMS	-5	0.0176	4.6668
DCT-NLMS	-5	0.0097	5.7181
TDLMS	0	0.0057	1.6314
TDNLMS	0	0.0059	1.6086
DCT-LMS	0	0.0127	0.4085
DCT-NLMS	0	0.0076	1.3496
TDLMS	-10	0.0202	9.3239
TDNLMS	-10	0.0196	9.337
DCT-LMS	-10	0.0228	9.2494
DCT-NLMS	-10	0.0232	9.2283
TDLMS	-15	0.0251	14.0878
TDNLMS	-15	0.0246	14.1003
DCT-LMS	-15	0.0267	14.0163
DCT-NLMS	-15	0.027	13.996
TDLMS	-20	0.0285	18.9558
TDNLMS	-20	0.0282	18.968
DCT-LMS	-20	0.0293	18.8859
DCT-NLMS	-20	0.027	13.996
TDLMS	-25	0.0305	23.8819
TDNLMS	-25	0.0305	23.8939
DCT-LMS	-25	0.0308	23.8129
DCT-NLMS	-25	0.0308	23.7932

Table 3: MSE & SNR improvement analysis (car noise)

Algorithm Name	Input SNR (dB)	MSE	SNR Improvement (dB)
TDLMS	-5	0.0052	1.6796
TDNLMS	-5	0.0051	0.7455
DCT-LMS	-5	0.0053	0.5447
DCT-NLMS	-5	0.0056	0.3081
TDLMS	0	0.0052	-9.2137
TDNLMS	0	0.0051	-10.1519
DCT-LMS	0	0.0053	-10.2814
DCT-NLMS	0	0.0055	-10.379
TDLMS	-10	0.0084	11.7218
TDNLMS	-10	0.0085	11.4283
DCT-LMS	-10	0.0285	11.2237
DCT-NLMS	-10	0.0103	9.8163

TDLMS	-15	0.0088	17.0882
TDNLMS	-15	0.0091	17.0688
DCT-LMS	-15	0.0099	16.9687
DCT-NLMS	-15	0.0136	15.4793
TDLMS	-20	0.0101	20.8961
TDNLMS	-20	0.0109	20.9102
DCT-LMS	-20	0.0129	20.7932
DCT-NLMS	-20	0.0183	15.4793
TDLMS	-25	0.0129	25.0225
TDNLMS	-25	0.0144	25.0205
DCT-LMS	-25	0.0176	24.881
DCT-NLMS	-25	0.0227	23.8778

It is also clear that these algorithms performs well and shows superior result for higher negative values of input SNR levels i.e. for the signals corrupted with higher noise values. The mean square error comparison of all the said algorithms is shown in Figure 5, Figure 6 & figure 7 and it is observed that TDNLMS has a minimum MSE value of 0.0056, 0.0049, 0.0059 for babble16, car and Factory noise respectively. This means TDNLMS shows better performance than other said algorithms. The robustness of all the above said algorithms is verified by simulating the algorithms for different noises at different SNR inputs.

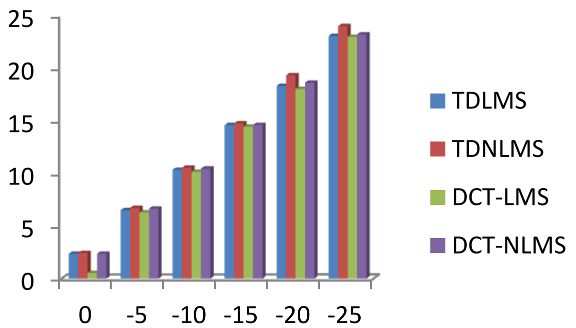

Fig 2: SNR comparison for speech signal corrupted with Babble16 noise, Filter order 10

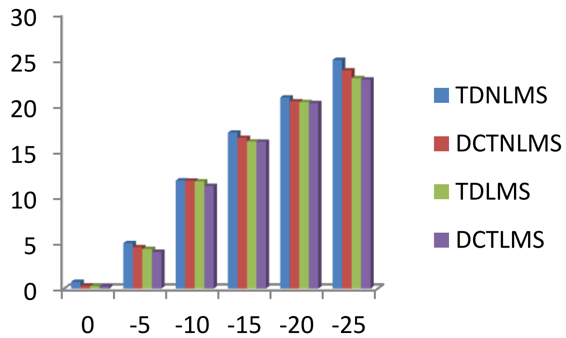

Fig 3: SNR comparison for speech signal corrupted with Car noise, Filter order 10

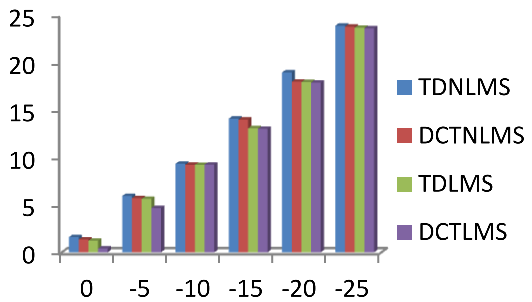

Fig 4: SNR comparison for speech signal corrupted with Factory noise, Filter order 10

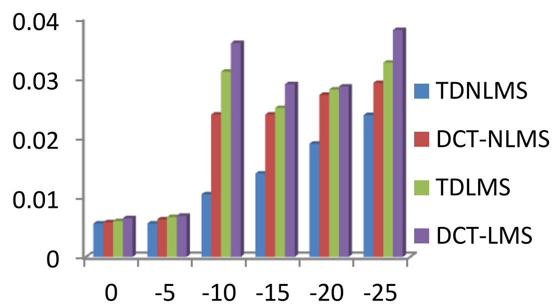

Fig 5: MSE comparison for speech sample corrupted with Babble16 noise

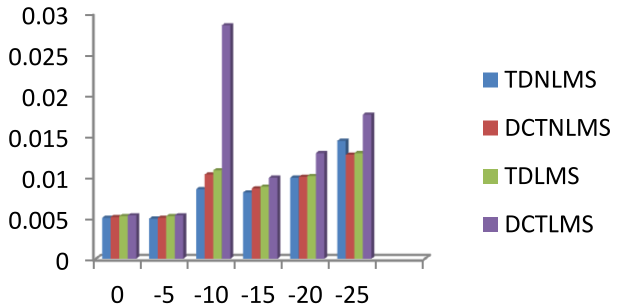

Fig 6: MSE comparison for speech signal corrupted with Car noise, Filter order 10

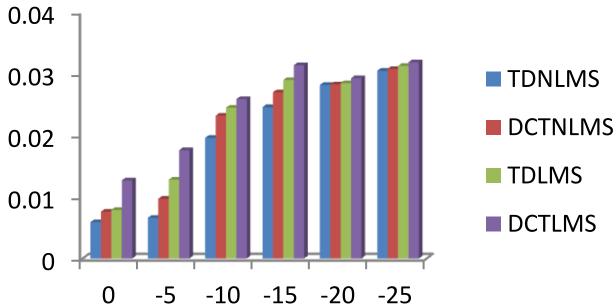

Fig 7: MSE comparison for speech signal corrupted with Factory noise, Filter order 10

4. CONCLUSION

In this paper, the Transform Domain Normalized Least Mean Square (TDNLMS), Discrete Cosine Transform Domain Normalized Least Mean Square (DCTNLMS), Transform Domain Least Mean Square (TDLMS), and Discrete Cosine

Transform Least Mean Square (DCTLMS) algorithms are implemented for adaptive noise cancellation system. The performance of all the said algorithms is measured for the SNR improvements, minimum mean square error and robustness. Result shows that the TDNLMS works best compared to others in all aspects.

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