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Fast Recursive DCT-LMS Speech enhancement For Performance Enhancement Of Digital Hearing Aid

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ABSTRACT
Hearing impairment is the number one chronic disability-affecting people in the world. Background noise is particularly damaging to speech intelligibility for people with hearing loss especially for sensorineural loss patients. Several investigations on speech intelligibility have demonstrated that sensorineural loss patients need 5-15 dB higher Signal to Noise Ratio (SNR) than the normal hearing subjects. This paper describes Fast Recursive Discrete Cosine Transform Power Normalized Least Mean Square (simply DCT-LMS) algorithm to improve the SNR and to reduce the convergence rate of the Least Means Square (LMS) for sensorineural loss patients.

The Discrete Cosine Transform (DCT) has good ortho-normal, separable, and energy compaction property. Although the DCT does not separate frequencies, it is a powerful signal decorrelator. It is a real valued function and thus can be effectively used in real-time operation. The advantages of DCT-LMS as compared to standard LMS algorithm are shown via SNR and eigenvalue ratio computations. The computer simulations results show superior convergence characteristics of the proposed algorithm and faster convergence speed and better time and frequency characteristics. In this work we have used fast recursive DCT to reduce the number of multiplications and additions.

Keywords
Hearing Impairment, Fast DCT Adaptive filter, Sensorineural loss patients, Convergence rate, SNR improvement.

1. Introduction
Hearing impairment is the preamble chronic disability, affecting people in the world. Many people have great difficulty in understanding speech with background noise. This is especially true for a large number of elderly peoples and sensorineural impaired persons. Hearing loss or deafness can be broadly classified into 2 types. *Conductive loss*: This is associated with a defect of the middle ear or eardrum. This type of hearing disability can be measured by audiograms and is considered as a mild disability. Because, it attenuates the incoming acoustic signal without introducing any significant distortion. So the intelligibility of the signal can be easily resorted by amplification. *Sensorineural loss:* This is a broad class of hearing impairments its origin is in the cochlea or auditory nervous system. Sensorineural loss disorders are difficulty to remedy. This type of defects may be due to congenital or hereditary factors, disease, tumors, old age, long-term exposure to industrial noise, acoustic trauma or the action of toxic agents etc.

The sensorineural loss patient's experiences difficulty in making fine distinction between speech sounds, particularly those having a predominance of high frequency Energy [5], [16]. He may hear the speaker's voice easily, but be unable to distinguish. For example between the words 'fat' and 'sat' [7], [9]. Two features of sensorineural impairment particularly detrimental to the perception of speech are high tone loss and compression of the dynamic range of the ear. A high tone loss is analogous to low pass filtering. Amplification of the high tones may improve intelligibility, but in these circumstances dynamic range of the ear is a handicap [13], [14]. Because the dynamic range of the impaired ear may not be sufficient to accommodate the range of intensities in speech signals. So, the stronger components of speech are perceived at a level, which is uncomfortably loud, while the weaker components are not heard at all [10], [11], [16].

Several investigations on speech intelligibility have demonstrated that subjects with sensorineural loss patients need 5 to 15db higher SNR than the normal hearing subjects. While most of the defects in transmission chain up to cochlea can now-a-days be successfully rehabilitated by means of surgery. The great majority of the remaining inoperable cases are sensorineural hearing impaired patients [5], [16]. Digital signal processing methods offer great potential for designing a hearing aid but, today's Digital Hearing Aid are not up to the expectation for sensorineural loss patients. Hearing-impaired patients applying for hearing aid reveal that more than 50% are due to sensorineural loss. So for only Adaptive filtering methods are suggested in the literature for the minimization of noise from the speech signal for sensorineural loss patients [8].

1.1 Adaptive Filtering

The least mean square algorithm was first introduced by Widrow and Hoff in 1959 is simple, robust and is one of the most widely used algorithm for adaptive filtering. LMS algorithm is very popular because of its simplicity and easy of computations. LMS algorithm is generally the best choice for many different applications [18], [19]. This method can be effectively applied to reduce the noise i.e. to improve the SNR for sensorineural loss patients [6], [12], [15]. Unfortunately, its convergence rate is highly dependent on the feedback coefficient μ and the input power to the adaptive filter [18], [19]. The mean square error of an adaptive filter trained with LMS decreases over time as a sum of exponentials whose time constants are inversely proportional to the eigenvalues of the autocorrelation matrix of the filter inputs. Therefore, small eigenvalues create slow convergence modes in the means square error function. Large on the other hand, put a limit on the maximum learning rate that can be chosen without encountering stability problems [1]-[3].

The DCT has a strong energy compaction property. Most of the signal information tends to be concentrated in a few low frequency components of the DCT. It is a close relative of Discrete Fourier Transform (DFT) – a technique for converting a signal into elementary frequency components, and thus DCT can be computed with a Fast Fourier Transform (FFT). Unlike DFT, DCT is a real valued and provides a better approximation of a signal with fewer coefficients. The DCT is central to many kinds of signal processing [18]. For non-stationary signals like speech signals, the DCT provides good approximation of a signal with fewer coefficients [3], [4].

1.2 A Fast Recursive DCT Algorithm

A block transform based on the DCT or DFT is equivalent to a filter bank consisting of multiple band pass filters. Such a filter bank is called as a Time Domain Aliasing Cancellation Filter bank (TDAC)

The DCT of a data sequence $x(m), m = 0,1,.........(M-1)$ is defined as:

$$G_x(0) = \frac{\sqrt{2}}{M}\sum_{m=0}^{M-1} x(m)$$

$$G_x(k) = \frac{2}{M}\sum_{m=0}^{M-1} x(m)\cos\frac{(2m+1)k\pi}{2M} \qquad (1)$$

Where $G_x(k)$ is the kth DCT coefficient. It can be seen that the set of basis vectors $\{\frac{1}{\sqrt{2}}, \cos\frac{(2m+1)k\pi}{2M}\}$ is actually a class of discrete Chebyshev polynomials.

Similarly the Inverse DCT is defined as:

$$x(m) = \frac{1}{\sqrt{2}}G_x(0) + \sum_{k=1}^{M-1} G_x(k)\cos\frac{(2m+1)k\pi}{2M} \qquad (2)$$

for $m = 0,1,.........(M-1)$

The basis set actually used in TDAC systems is slightly modified and takes on the form:

$$X(k) = 2\sum_{n=0}^{N-1} z(n)\cos(\frac{2\pi}{N}(n+n_o)(k+\frac{1}{2})), 0 \le k \le N/2 \qquad (3)$$

Where $z(n)$ is the windowed input sequence.

Such TDAC with the DCT as the transform is called as the Modified Discrete Cosine Transform or MDCT.

$$x(n) = \frac{2}{N}\sum_{k=0}^{\frac{N}{2}-1} X(k)\cos(\frac{2\pi}{N}(n+n_o)(k+\frac{1}{2})), 0 \le n \le N \qquad (4)$$

Where, $X(k)$ are the spectral co-efficient. In both expressions $n_o = (N/2+1)/2$. The entire transform requires $\sqrt{\frac{N^2}{2}}$ real multiplications and $\frac{N}{2}(N-1)$ real additions. Thus the complexity of computations is of the order $O(N^2)$. Similarly for the IMDCT, we require $\frac{N^2}{2}$ real multiplications and $N(\frac{N}{2}-1)$ real additions, again a complexity of $O(N^2)$. Ideally we would like computation times logarithmic or at least linear in the size of the input block length to make the use of these transforms feasible in real time signals. This in turn motivates us to look for algorithm, which computes the MDCT and the IMDCT expressions as fast as efficiently as possible.

Generally fast MDCT algorithms can be broadly classified into two categories: indirect computation and direct computation. The proposed algorithm belongs to the second type. Indirect computation makes use of existing fast algorithms such as the FFT, FHT etc., to compute the MDCT. Direct computation reduces the computational complexity by matrix factorizations and recursive decomposition. This algorithm is similar to decimation in frequency Cooley-Tuckey FFT. An N point MDCT is computed by first mapping it to an N/2 point type-II DCT. The DCT is further computed efficiently from two lower order DCT. We have considered the special case of block length, which is a power of two. Transform expression for the forward MDCT is

$$X(k) = 2\sum_{n=0}^{N-1} x(n)\cos(\frac{\pi}{2N}(2n+1+N/2)(2k+1)),$$
$$0 \le k \le N/2-1 \qquad (5)$$

Ignoring the scaling factor and nothing that $X(k)$ has the symmetric property,

$$X(0) = X(-1) \qquad (6)$$

We consider $X(k)+X(k-1)$

$$X(k)+X(k-1) =$$
$$\sum_{n=0}^{N-1} x(n)\{2\cos(\frac{\pi}{2N}(2n+1+\frac{N}{2})2K)$$
$$\cos(\frac{\pi}{2N}(2n+1+\frac{N}{2}))\}$$
$$= \sum_{n=0}^{N-1}\{2x(n)\cos(\frac{\pi}{2N}(2n+1+\frac{N}{2}))\}$$
$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})k) \qquad (7)$$

Therefore,

$$X(k)+X(k-1)$$
$$= \sum_{n=0}^{N-1} r(n)\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})K)$$
$$= \sum_{n=0}^{\frac{N}{2}-1} r(n)\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})k)$$
$$+ \sum_{n=0}^{\frac{N}{2}-1} r(n+N/2)\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2}+N)K)$$
$$= \sum_{n=0}^{\frac{N}{2}-1} (r(n)+(-1)^k r(n+\frac{N}{2}))$$
$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})K)$$
$$= X_r(k) \qquad (8)$$

Where, $r(n) = 2x(n)\cos(\frac{\pi}{2N}(2n+1+\frac{N}{2}))$ (9)

This is a $\frac{N}{2}$ point type - 2 DCT. Using the initialization condition in (6) and the type-2 DCT we can compute an N point MDCT. The type - 2 DCT can be computed using any of the available fast algorithms. But we are using a simple and modular recursive algorithm to compute the DCT. We can decompose the DCT in (8) into two balanced sub problems; the even indexed output and the odd indexed output, that is,

$$E(k) = X_r(2k), k \in [0, \frac{N}{2}-1] \qquad (10)$$

$$O(k) = X_r(2k+1), k \in [0, \frac{N}{2}-1] \qquad (11)$$

Consider $E(k)$, the even indexed output of the DCT,

$$E(k) = \sum_{n=0}^{\frac{N}{2}-1} (r(n)+(-1)^{2k} r(n+\frac{N}{2}))$$
$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})2k)$$
$$= \sum_{n=0}^{\frac{N}{2}-1} [r(n)+r(n+N/2)]$$
$$\cos(\frac{\pi}{2N/4}(2n+1+\frac{N}{2})k)$$

$$= \sum_{n=0}^{\frac{N}{4}-1} \{(r(n)+r(n+N/2)]+$$
$$(-1)^k (r(n)+N/4)+r(n+N/2+N/4))\}$$
$$\cos(\frac{\pi}{2N/4}(2n+1+\frac{N}{2})k) \qquad (12)$$

This is a DCT of length N/4. The odd indexed output $O(k)$ is given by,

$$O(k) = \sum_{n=0}^{\frac{N}{2}-1} (r(n)+(-1)^{2k+1} r(n+N/2))$$
$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})(2k+1) \qquad (13)$$

Since $O(0) = O(-1)$;

Let $(O)^I(k) = O(k)+O(k-1)$ (14)

Therefore,

$$(O)^I(k) = \sum_{n=0}^{\frac{N}{2}-1} (r(n)-r(n+N/2))$$
$$\{2\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2}))$$
$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})2k)\}$$

$$= \sum_{n=0}^{\frac{N}{4}-1} \{2(r(n) - r(n+N/2))$$

$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2}))\}$$

$$\cos(\frac{\pi}{2N/4}(2n+1+\frac{N}{2})k)$$

$$- \sum_{n=0}^{\frac{N}{4}-1} \{2(r(n+N/4) - r(n+N/2+N/4))$$

$$\sin(\frac{\pi}{2N/2}(2n+1+\frac{N}{2}))\}$$

$$(-1)^k \cos(\frac{\pi}{2N/4}(2n+1+\frac{N}{2})k) \quad (15)$$

$$(O)^I(k) = 2\sum_{n=0}^{\frac{N}{4}-1} \{(r(n) - r(n+N/2))$$

$$\cos(\frac{\pi}{2N/2}(2n+1+\frac{N}{2}))$$

$$-(-1)^k (r(n) + N/4) - r(n+N/2+N/4))$$

$$\sin(\frac{\pi}{2N/2}(2n+1+\frac{N}{2})k))\}$$

$$\cos(\frac{\pi}{2N/4}(2n+1+\frac{N}{2})k) \quad (16)$$

This is again a DCT of length N/4.

Since $O(0) = O(-1);$

We get $O(0) = \frac{(O)^I(0)}{2}$. Hence using (14) we can compute the odd indexed points of the DCT. The whole process can be repeated, $(\log_2 N - 1)$ times, to compute the $N/2$ point type - DCT. Thus an MDCT of length N can be calculated using the property;

$$X(k) = X_r(k) - X(k-1), k \in [0, N-1] \quad (17)$$

Arithmetic Complexity and Comparison with other algorithms:

Using the recursive formula in (17), we compute a length N MDCT with a type-2 DCT of length N/2. This requires additional N-1 real additions.
RA (N point MDCT)= RA (N/2 point DCT)+N-1
RM (N point MDCT)= RM (N/2 point DCT)
Where, RA=number of real additions and RM= number of real multiplications.

The length N/2 type-II DCT is decomposed into two DCT's each of length N/4. This requires an additional N real multiplications and N/2 real additions. The decomposition is performed recursively ($\log_2$N-1) times, giving a total complexity of N ($\log_2$N-1) real multiplications and (N/2) ($\log_2$N-1) real additions.
In section 1, we briefly discussed about the Sensorineural loss patients and brief review about the convergence rate of the adaptive algorithm and about Fast DCT algorithm. Section 2, considers LMS filtering in DCT domain. Simulated results are discussed in section 3 and section 4 concludes the paper.

2. DCT-LMS:

DCT-LMS is composed of three stages as shown in Figure 1.

Stage 1: Transformation

The input to the filter is $x_k = [x_k, x_{k-1}, ..., x_{k-n+1}]^T$. (1)

The transformation as explained in the previous section

$$u_k(n) = T_n[x_k] \quad (2)$$

The transform outputs then form a vector

$$u_k(n) = [u_k(0), u_k(1), ...u_k(n-1)]^T \quad (3)$$

Stage 2: Power Normalization

The transformed signal $u_k(i)$ is then normalized by the square root of their power $p_k(i)$.

Where $i = 0,1,........n-1$.

The powers $p_k(i)$ can be estimated by the following methods

1. The powers $p_k(i)$ can be estimated by filtering the $u_k^2(i)$ with an exponentially decaying window of parameter $\beta \in (0,1)$.
2. The powers $p_k(i)$ can also be estimated based on a sliding rectangular window or with the help of an arbitrary weighting filter.

In this work, power normalization is as follows.
Power normalizing $T_n x_k$ transforms its elements

$$(T_n x_k)(i) \text{ into } \frac{(T_n x_k)(i)}{\sqrt{Powerof(T_n x_k)(i)}}. \quad (4)$$

Where the power of $(T_n x_k)(i)$ can be found on the main diagonal of B_n.

Then the power-normalized signal is

$$v_k(i) = \frac{u_k(i)}{\sqrt{p_k(i) + \varepsilon}} \quad (5)$$

Where

$$p_k(i) = \beta\, p_{k-1}(i) + (1-\beta) u_k^2(i) \quad (6)$$

for $i = 0,1,........n-1$. The small constant ε is introduced to avoid numerical instabilities when $p_k(i)$ is close to zero. This type of LMS is referred to as **power-normalized LMS.** Discrete cosine transformation followed by a power normalization stage, causes the eigenvalues of the LMS filter inputs to cluster around one and speeds up the convergence of the adaptive weights.

The autocorrelation matrix after transformation and power normalization is thus

$$S_n \triangleq E(diagB_n)^{-1/2} B_n (diagB_n)^{-1/2} . \qquad (7)$$

If T_n decorrelated x_k exactly, B_n would be diagonal, S_n would be an identity matrix I_n, and all the eigenvalues of S_n would be equal to one, but since practically the DCT is not a perfect decorrelator, this does not work out exactly [2]. But the power normalization makes the eigenvalues of the LMS filter inputs to cluster **around one** and speeds up the convergence of adaptive weights.

The output vector after power normalization is

$$v_k(n) = [v_k(0), v_k(1),........v_k(n-1)]^T \qquad (8)$$

Stage 3: LMS filtering

The resulting equal power signals $v_k(i)$ are applied as an input to an adaptive linear combiner whose weights $w_k(i)$ are adjusted using LMS algorithm described below. The weight vector is defined as

$$w_k(n) = [w_k(0), w_k(1),........w_k(n-1)]^T \qquad (9)$$

Then the filter output is given by

$$y_k(n) = w_k^T(n) v_k(n) \qquad (10)$$

and the instantaneous output error is

$$e_k = d_k - \sum_{i=0}^{n-1} y_n(i) . \qquad (11)$$

Where d_k is the desired signal.

This error is used to update the adaptive filter taps using a modified for of the LMS algorithm

$$w_{k+1}(i) = w_k(i) + \mu e_k v_k(i) \qquad (12)$$

for $i = 0,1,........n-1$.

The parameters used in algorithm are:

Number of samples=20000, β=0.45 & filter order=32.

3. Simulated results:

The algorithm works on the corrupted speech signals with different types of noise signals like cafeteria noise, low frequency noise, babble noise etc. in several SNR. The various parameters like β, μ, and filter order were changed and their influence has been checked. For different input SNR the output SNR and convergence ratios are calculated. Although the SNR improvement has a limited meaning in the speech processing, we used this figure to indicate an over-all score. A more meaningful quantity is the eigenvalue spread is calculated to find out how well the algorithm convergence to the optimum Wiener solution. We have found that both the parameters, SNR and convergence ratio are strongly depending on the number of samples in the input signal, β, μ and filter order. As the number of samples in the input signal increases SNR decreases and convergence ratio increases. Figure 2, 3, 4 and 5 shows the input signal that is corrupted signal, desired signal and the filtered signal for different input SNR.

The Table 1 shows the SNR of the DCT adaptive filtered outputs for different input signal SNR and Table 2 shows the computational complexity of DCT and Recursive DCT.

4. Conclusion

The SNR improvement of at least 10 dB is obtained for the input SNR less than and equal to 0dB, which is higher than the other techniques like adaptive DFT (DFT-LMS) and adaptive Wavelet transform method (DWT-LMS) [17], [20]. We have already stated that the filtering technique depends on the number of samples in the input signal, β, μ and filter order. In this work, we have tested for only few values and their influence has been checked. By testing with few more different values, it may be possible to get further improvements. The algorithm convergence time and stability depends upon the ratio of the largest to the smallest eigenvalues associated with the correlation matrix of the input sequence. As the eigenvalue spread of the input autocorrelation matrix increases, the convergence speed of LMS deteriotes. So in this case, we derived the eigenvalue distribution for the input auto correlation matrix after DCT and power normalization. This provides the good tracking capabilities in different noisy environments. Even in the case of DFT-LMS and DWT-LMS, the eigenvalue distribution of the input autocorrelation matrix is calculated after the Transformation and power normalization. But, it is unable to give good SNR improvement and the convergence ratio is also very high [17], [20]. Proposed algorithm is not comparable with direct least mean square algorithm in terms of convergence ratio, where the eigenvalue ratio is in terms of thousands [6], [18].

5. REFERENCES

[1]Shaul Florian and Neil J Bershad. “ A Weighted Normalized Frequency Domain LMS Adaptive Algorithm”. IEEE Transactions on Acoustics speech and signal processing Vol36, no 7 July 1998

[2] Francosie Beaufays. “ Trasnform domain adaptive filters: An analytical approach”. IEEE Transactions on Signal processing vol 43 no 2. Feb 1995

[3] Mohammed A Shamma. “ Improving the speed and performance of adaptive equalizers via transform based adaptive filtering ”. 2591 Ashurst Rd. University Heights, Ohio, 44118, USA.

[4] Adaptive filter theory. By Simon Haykin.

[5] V.Udayashankara, A.P.Shivaprasad., " Digital Hearing Aid: A Review". World congress on Medical physics & Biomedical Engineering. Brejil, Aug. 1994. Page No 21-26.

[6] V.Udayashankara , A.P.Shivaprasad. " The application of voltera LMS Adaptive filtering to speech enhancement for the Hearing Impairment ". 4th Euro-speech conference on speech communication and Technology, Mandrid, Spain. Sept.1995. Page No 18-21.

[7] Moore. B.C., Stainsby . T.H., Alcantara. J.I., Kuhnel. V., "The effect of speech intelligibility of varying compression time constants in a digital hearing aid". International Journal on Audio logy. 2004 Jul-Aug: 43(7), Page No. 399-409.

[8] Chung.K., "Challenges and recent developments in Hearing Aids"., Trends Amplif.2004:8(3). Page No 83-124.

[9] Shanks. J.E., Wilson. R.H.Larson, Williams. D., " Speech recognition performance of patients with sensorineural hearing loss under unaided and aided conditions using linear and compression hearing aids". Ear hear. 2002 Aug:23(4), page No. 280-90.

[10] Baer.T., Moore.B.C., Kulk.K., " Effects of low pass filtering on the intelligibility of speech in noise for people with and without dead regions at high frequencies". Journal on Acoustic soc Am. 2002 Sept:112(3 pt 1)., page No 1133-44.

[11] Hornsby.B.W., Ricketts.T.A., "The effects of compression ratio, signal-to-noise ratio and level on speech recognition in normal-hearing listners". Journal on Acoustics soc Am. 2001 June: 109(6). Page No 2964-73.

[12] Shields.P.W., Campbell.B.R., " Improvements in intelligibility of noisy reverberant speech using a binaural sub band adaptive noise-cancellation processing scheme". Journal on Acoustics Soc Am. 2001Dec: 110(6). Page No 3232-42.

[13] Wouters.J., Litiere.L., Van Wieringen.A., " Speech intelligibility in noisy environment with one and two microphone hearing aids". Audiology. 1999 Mar-Apr:38(2). Page No 91-8.

[14] Rankovic.C.M., " Factors governing speech reception benefits of adaptive linear filtering for listeners with sensorineural loss". Jpurnal on Acoustics Soc Am. 1998 Feb:103(2). Page No 1043-57.

[15] Baer. T., Moore.B.C., Gatechouse. S., "Spectral contrast enhancement of speech in noise for listeners with sensorineural hearing impairment: effects on intelligibility, quality, and response times". Journal on Rehabilitation Res Dev. !993:30(1). Page No 49-72.

[16] Dr. Harry Levitt, " Noise reduction in Hearing aids: An overview ". Journal of Rehabilitation Research and Development . Vol.38. No.1, Jan-Feb 2001.

[17] Sunitha S.L and Dr.V Udayashankara, " DFT-LMS Speech Enhancement Technique for Sensorinueural loss Patients". Journal of Bioinformatics India, Vol 30. Jan-March 2005.

[18] Simon Haykin, Adaptive Filter Theory", Pearson Education Asia, 4th Edition, 2002.

[19] Bernard Widrow and Samuel D.Stearns. " Adaptive Signal Processing", Pearson Education Asia, 2002.

[20]Sunitha S.L and Dr.V. Udayashankara. " DWT-LMS Speech Enhancement Technique for Performance Enhancement of Digital Hearing Aid", ICSCI, Jan 2005. (Best paper of the session has been taken for this paper)

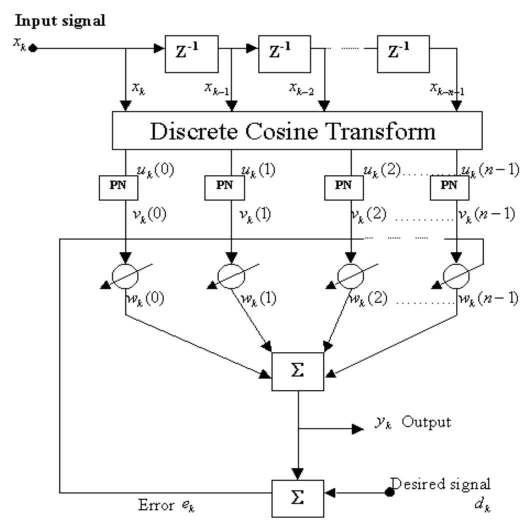

Figure 1. Block Diagram of DCT-LMS algorithm

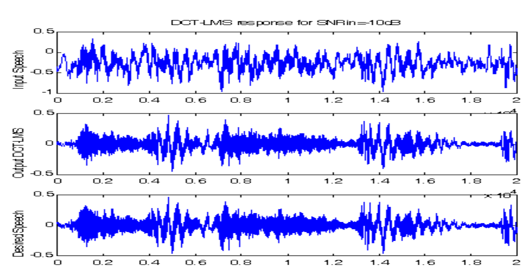

Figure 2. DCT response for input SNR= -10dB

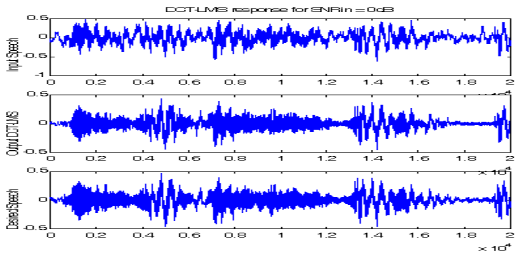

Figure 3. DCT response for input SNR= 0dB

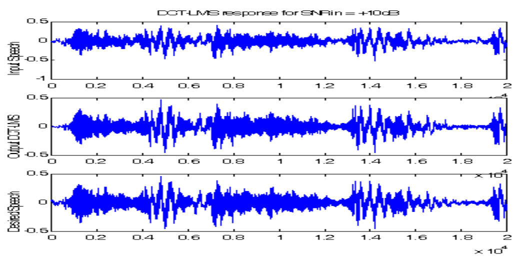

Figure 4. DCT response for input SNR= +10dB

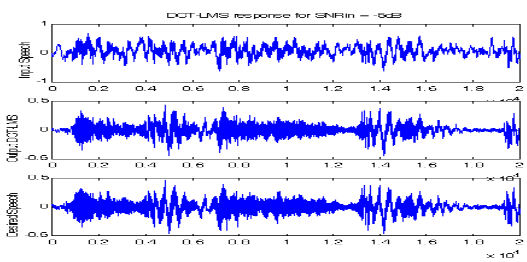

Figure 5. DCT response for input SNR= -5dB

SNR of the input signal In dB	SNR of the output signal in dB	Eigen value ratio
-10	10.2	5.5
0	10.0	6.09
+5	11.24	5.44
+10	13.20	5.6

Table 1. Output SNR for different input SNR

Type of transform	Number of real multiplications	Number of real additions
MDCT	32	28
IMDCT	32	24
Fast DCT using FFT	7	15
Fast Recursive DCT	16	8

Table2.Shows the Computational complexity for N=8.