DHT-LMS Algorithm for Sensorineural Loss Patients

Sunitha S. L., and V. Udayashankara

***Abstract*—**Hearing impairment is the number one chronic disability affecting many 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 sensorineural loss patients need 5-15 dB higher SNR than the normal hearing subjects. This paper describes Discrete Hartley Transform Power Normalized Least Mean Square algorithm (DHT-LMS) to improve the SNR and to reduce the convergence rate of the Least Means Square (LMS) for sensorineural loss patients. The DHT transforms n real numbers to n real numbers, and has the convenient property of being its own inverse. It can be effectively used for noise cancellation with less convergence time. The simulated result shows the superior characteristics by improving the SNR at least 9 dB for input SNR with zero dB and faster convergence rate (eigenvalue ratio 12) compare to time domain method and DFT-LMS.

***Keywords*—**Hearing Impairment, DHT-LMS, Convergence rate, SNR improvement.

I. 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 people 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. This type of hearing disability can be measured by audiograms and is considered as a mild disability.

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 speakers voice easily, but 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 [5]. 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]. Today's Digital Hearing Aids 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].

A. Adaptive Filtering Method and DHT

The LMS was first introduced by Widrow and Hoff in 1959 is simple, robust and is one of the most widely used algorithms. 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. 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 [18], [19]. 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].

In this work we use DHT-LMS to improve the SNR and to reduce the convergence rate of the LMS for sensorineural loss patients. DHT-LMS algorithm is suited for non-stationary inputs like speech signals and the convergence time is also less compare to direct LMS techniques. A DHT is similar to the DFT, with analogous applications in signal processing. Its main distinction from the DFT is that it transforms real inputs to real outputs, with no intrinsic involvement of complex numbers. Just as the DFT is the discrete analogue of the continuous FT, the DHT is the discrete analogue of the continuous Hartley Transform [18]. The usual tool for performing this transformation is the FFT. But for most applications, there is an even faster method called the Hartley transform [19]. The Hartley transform was first proposed in 1942 by Ralph Hartley. Just as in the FT, the Hartley transform starts with a sequence of samples in the time domain. Let X (t) is such a sequence. The Hartley transform of this sequence is another sequence, H (f) for f = 0…N-1., given by:

$$H(f) = \frac{1}{N}\sum_{t=0}^{N-1} X(t)\left[\cos\left(\frac{2\pi ft}{N}\right) + \sin\left(\frac{2\pi ft}{N}\right)\right]$$

It is possible to define a whole class of reversible transforms based on other phase-shifted sine functions. But the specific sine function used in the Hartley transform exhibits certain symmetry between the transform and its inverse. The DHT-LMS has faster convergence rate than the time domain LMS algorithm and is even faster compare to DFT-LMS [17], [18].In this work the flow of input samples is continuously transformed by a fixed data-independent transform. That is meant to de-correlate the input signals; this pre processing 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. Therefore, in this case, we derive the eigenvalue distribution of the auto correlation matrix after DHT and power normalization. This provides the good tracking capabilities in non-stationary environments. In the introduction, we briefly discussed about the sensorineural loss patients and brief review about the convergence rate of the LMS and Hartley Transform. Section 2, considers DHT-LMS. Simulated results are discussed in section 3 and section 4 concludes the paper.

II. DHT-LMS

The discrete Hartley transform is a linear, invertible function *H*: $\mathbf{R}^n$ -> $\mathbf{R}^n$ (where **R** denotes the set of real numbers). The *n* real numbers x_0, ..., x_{n-1} are transformed into the *n* real numbers h_0, ..., h_{n-1} according to the formula. The transform can be interpreted as the multiplication of the vector (x_0, ..., x_{n-1}) by an *n*-by-*n* matrix; therefore, the DHT is a linear operator. The matrix is invertible; the inverse transformation, which allows one to recover the x_k from the h_j, is simply the DHT of h_j multiplied by 1/*n*. DHT-LMS is composed of three stages as shown in Fig 1.

1) Transformation by DHT

The input to the filter is

$$x_k = [x_k, x_{k-1}, ..., x_{k-n+1}]^T \tag{1}$$

This vector is processed by DHT. The orthogonal transform matrix T is selected to be a unitary matrix, i.e.

$$T_n T_n^T = T_n^T T_n = I \tag{2}$$

Transforming an input signal (1) by a matrix T_n transforms its Toeplitz autocorrelation matrix

$$R_{xx} = E[x_k^T x_k] \tag{3}$$

into a non-Toeplitz matrix

$$B_n = E[T_n^T T_n x_k^T x_k] = T_n^T R_{xx} T_n . \tag{4}$$

The transformation operation is

$$u_k(n) = T_n[x_k] \tag{5}$$

The transformed output then form a vector $u_k(n) = [u_k(0), u_k(1), ...u_k(n-1)]^T$

2) Power Normalization

$u_k(i)$ is then normalized by the square root of their power $p_k(i)$. In this work, power normalization is as follows.

Power normalizing $T_n x_k$ transforms its elements

$$(T_n x_k)(i) \text{ into } \frac{(T_n x_k)(i)}{\sqrt{Powerof\,(T_n x_k)(i)}} . \tag{6}$$

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

$$v_k(i) = \frac{u_k(i)}{\sqrt{p_k(i) + \varepsilon}} \tag{7}$$

Where $p_k(i) = \beta p_{k-1}(i) + (1-\beta)u_k^2(i)$ (8)

for $i = 0,1,........n-1$. The signals $v_k(i)$ are equal to the discrete hartley transformed outputs $u_k(i)$, but the learning constant μ in LMS filtering is replaced by a diagonal matrix whose elements are proportional to the inverse of the powers $p_k(i)$. This type of LMS is referred to as power-normalized LMS. DHT 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

$$S_n \triangleq E(diagB_n)^{-1/2} B_n (diagB_n)^{-1/2} . \tag{9}$$

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. The output vector after power normalization is

$$v_k(n) = [v_k(0), v_k(1), ...v_k(n-1)]^T \tag{10}$$

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

$$w_k(n) = [w_k(0), w_k(1), ...w_k(n-1)]^T \tag{11}$$

Then the filter output is given by

$$y_k(n) = w_k^T(n) v_k(n) \tag{12}$$

and the instantaneous output error is

$$e_k = d_k - \sum_{i=0}^{n-1} y_n(i). \tag{13}$$

Where d_k is the desired signal.

$$w_{k+1}(i) = w_k(i) + \mu e_k v_k(i) \tag{14}$$

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

The parameters used in algorithm are:

The sentence is "This is ", Number of samples=20000, β=0.45 and filter order=10.

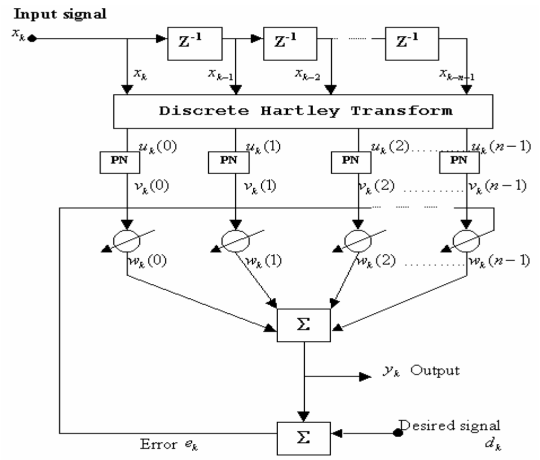

Fig. 1 Block Diagram For DHT-LMS

III. 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. 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. Fig.2 shows the input signal, desired signal and the filtered signal for SNR zero dB. The table 1 shows the SNR of the DHT-LMS outputs for input SNR zero dB.

TABLE I
Output SNR for Zero dB Input SNR

Type of transformation	Input SNR in dB	Output SNR in dB	Eigenvalue Ratio
DFT	0	7	120
Hartley	0	9	12

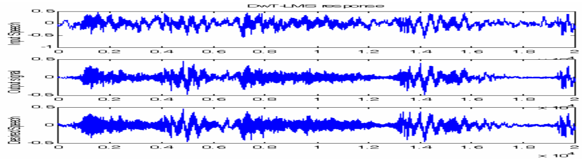

Fig. 2 DHT response for input SNR=0 dB

IV. Conclusion

The SNR improvement of at least 8 dB is obtained for all the input SNR, which is higher than the other transformation techniques like DFT-LMS and DWT-LMS [17] [20]. Even in both the methods the eigenvalue distribution is calculated after the transformation and power normalization. But, are unable to give good SNR improvement and the convergence ratio is also very high.

References

[1] Shaul Florian and Neil J Bershad. " A Weighted Normalized Frequency Domain LMS Adaptive Algorithm". IEEE Transactions on Acoustics speech and signal processing., Vol. 36, 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. Pp. 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. pp. 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), pp. 399-409.

[8] Chung.K., "Challenges and recent developments in Hearing Aids"., Trends Amplif.2004:8(3). Pp. 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), pp. 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)., pp. 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). pp. 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). Pp. 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). Pp 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). Pp. 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. 1993:30(1). Pp.. 49-72.

[16] Dr. Harry Levitt, " Noise reduction in Hearing aids: An overview ". Journal of Rehabilitation Research and Development, Vol.38. No.1, Jan-2001.
[17] Sunitha S.L and Dr.V Udayashankara, " DFT-LMS Speech Enhancement Technique for Sensorinueural loss Patients". Journal of Bioinformatics India, Vol 3. 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)

V.Udayashankara received the B.E. degree in Electronics and Communication Engineering from Sri Jayachamarajendra College of Engineering, university of Mysore, India, in 1983, M.E. degree in Electrical Communication Engineering from the Indian Institute of Science, India, in 1988 and Ph.D. from Indian Institute of Science, India, in 1996.
Currently he is a Professor with the department of Instrumentation Technology, at Sri Jayachamarajendra College of Engineering, Visveswaraiah Technological University, India. His research interests include Rehabilitation Engineering, Digital Signal Processing, Speech recognition, Speech enhancement and EEG analysis. He has authored more than 50 publications in Journals, National and International Conferences in these areas.

Sunitha S.L received the B.E. degree in Instrumentation Technology from Malnad College of Engineering, Hassan University of Mysore, India. MTech. degree in Biomedical Engineering from Sri Jayachamarajendra College of Engineering, Mysore from Visveswaraiah Technological University, Karnataka. India.
Currently she is a research scholar with Sri Jayachamarajendra College of Engineering, India and is teaching at SJMIT, Chitradurga. Her research interests include Digital Signal Processing, Speech processing, Neural Networks and Wavelet transforms.