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Nonlinear Channel Equaliser using Discrete Gabor Transform

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ABSTRACT

The adaptive equaliser makes use of adaptive digital filters whose filter coefficients are modified depending on the channel characteristics at the front end of the receiver. The noise introduced in the channel gets nullified and hence the signal-to-noise ratio of the receiver improves. Discrete Gabor Transform (DGT) helps decorrelate input data because of which the convergence speed of the Mean Square Error (MSE) improves considerably. It is found that the time domain LMS equaliser is slow in convergence. To improve the convergence rate and MSE floor level transform domain-using DFT, DGT and DWT (2, 5, 6 and 7) has been studied. It is found that all the orthogonal transforms perform similar in convergence rate and MSE level. This paper aims at the evaluation of channel performance using Gabor transform, which is both frequency and time domain transform. The nonlinear channel equaliser using Discrete Gabor Transform is reported in this paper. Though Gabor Transform is a nonlinear transform as well as non orthogonal transform it is expected to be better fitted for nonlinear channel. Gabor transform based adaptive equaliser, though has a longer training time, has been found to have better noise recovery property and Lower MSE level, especially when the additive noise in the channel is large.

Keywords: Adaptive Channel Equaliser, MSE: Mean Square Error, DFT, DGT, EVR: eigenvalue ratio.

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1. ADAPTIVE FILTER IN CHANNEL EQUALISER

Adaptive filter is a programmable filter, whose frequency response is adapted in such a way that in the output we extract the desired signal without degradation and reduce the distortion to the best possible extent. The adaptive filter updates its filter coefficients from the knowledge of past inputs, and the present error generated from the reference and estimated output. The update procedure is based on any one of the adaptive algorithms. In case of the N-tap FIR adaptive filter, the desired signals d(k) is estimated using a linear combination of delayed samples of the input signal x(k) and found to be

$$y(k) = X(k)^T W(k) \qquad (1)$$

where, W(k) is the column vector of filter weights at the k-th instant and X(k) is a column vector of last N input signal samples, which are represented by

$W(k) = [w_0(k), w_1(k) \ldots\ldots, w_{N-1}(k)]^T$

and $X(k) = [x(k)\ x(k-1) \ldots\ldots x(k-N+1)]^T$

The task of the adaptive algorithm is to interactively define the value of W(k) at any time k, so as to make the mean square error between the desired and the estimated signals to the optimum value. The output estimation error at k-th instant is given by

$$e(k) = d(k) - y(k) \qquad (2)$$

The mean square error ξ is given by

$$\xi = E[e^2(k)] = E[(d(k) - y(k))^2]$$
$$= E[d^2(k)]-2E[d(k)W^TX] + E[W^TXX^{TW}] \quad (3)$$

The LMS algorithm (4) uses the instantaneous value e(k)X(k) to estimate the gradient. The adaptive procedure used by the LMS algorithm is described by the following weight vector update formula.

$$W(k+1) = W(k) + 2\mu e(k) X(k) \qquad (4)$$

where, μ = the convergence gain of the algorithm. This formula is a modified version of the steepest - descent method. In the steepest - decent technique, the weight vector is modified in the direction of decreasing gradient of the mean-square error surface of the process.

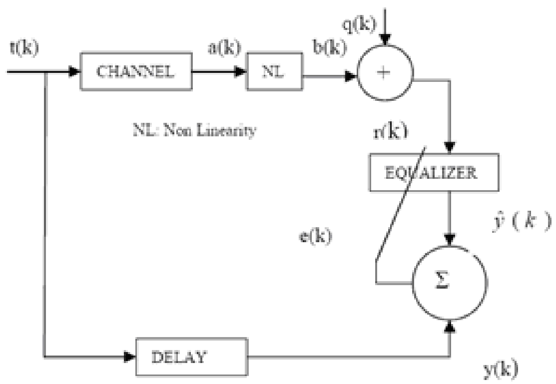

Fig. 1: ADAPTIVE CHANNEL EQUALISER

For reasons of stability, the range of μ is

$$0 < \mu < \frac{1}{\lambda_{max}}$$

$$W^{*} = R^{-1} P \qquad (5)$$

where λ_{max} is the maximum eigenvalue of the autocorrelation matrix R. It has been shown by Widrow et. el (4)that for sufficiently small values of μ, the LMS algorithm converges to the optimum Weiner Solution(1).

3. NONLINEARITY IN CHANNEL EQUALISER

The different types of nonlinearity are given as below.

NL = 0: $b(k) = a(k)$,
NL = 1: $b(k) = \tanh(a(k))$,
NL = 2: $b(k) = a(k) + 0.2a^{2}(k) - 0.1a^{3}(k)$,
NL = 3: $b(k) = a(k) + 0.2a^{2}(k) - 0.1a^{3}(k) + 0.5\cos(\pi a(k))$. (6)

NL = 0 corresponds to a linear channel model. NL = 1 corresponds to a nonlinear channel which may occur in the channel due to saturation of amplifiers used in the transmitting system. NL = 2 and NL = 3 are two arbitrary nonlinear channels. The nonlinear channel model NL=2 was introduced (ref to Fig. 1)

4. TIME DOMAIN ADAPTIVE EQUALISER

A common approach to data transmission is to code the amplitudes of successive pulses in a periodic pulse train with a discrete set of amplitude levels. The coded pulse train is then linearly modulated transmitted through the channel, demodulated, equalized and synchronously sampled and quantized. As a result of distortion of the pulse shape by the channel, the number of detectable amplitude levels has very often been limited by inter symbol interference rather than additive noise. In principle, if the channel characteristics are known precisely, it is always possible to design an equaliser that will make the inter symbol interference (at the sampling instants) arbitrarily small. However, in practice a channel is random in the sense of obeying one of the ensembles of possible channels. Consequently, fixed equalisers designed on average channel characteristics may not adequately reduce inter symbol interference. An adaptive equaliser is then needed which can be trained with the guidance of a training signal transmitted through the channels to adjust its parameters to optimum values.

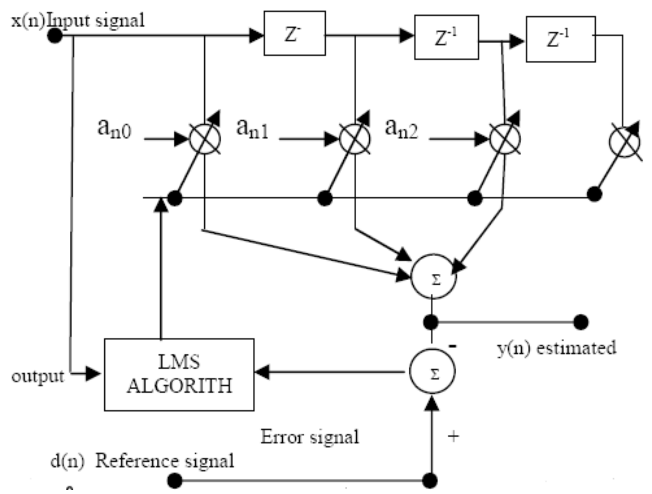

Fig. 2: LMS BASED (TIME DOMAIN) ADAPTIVE FILTER

If the channel is also time varying, an adaptive equaliser operating in a tracking mode is needed which can up-to-date its parameter values by tracking the changing channel characteristics during the course of normal data transmission. In both cases adaptation may be achieved by observing or estimating the error between actual and desired equaliser responses and using this error to estimate the direction in which the parameters should be changed to approach the optimal values.

5. TRANSFORM DOMAIN ADAPTIVE EQUALISER

It is a well-known fact that when the input sequence is transformed via an orthogonal transform, the eigenvalue spread of the input sequence is squeezed. To exploit this fact input signal of the time domain adaptive equaliser is passed through an orthogonal transform. The transform sequence is fed to the adaptive algorithm of the equaliser. The behavior of this transformed domain equaliser is studied in this paper and some important conclusions are found out. The LMS algorithm has been used and the convergence rate and MSE floor level has been chosen as the performance criteria.

5.1. THE TRANSFORM DOMAIN ADAPTIVE LMS EQUALISER ALGORITHM (3)

The input vector X_n is first transformed into another vector Z_n.

$$Z_n = [Z_{no}, Z_{n1}, \ldots\ldots, Z_{n(N-1)}]^T \qquad (7)$$

Using an orthogonal transformation

$$Z_n = WX_n \qquad (8)$$

where W is a unitary matrix of rank n.
Now, the vector Z_n is multiplied by the transform domain weight vector

$$B_n = [b_{n0}, b_{n1} \ldots\ldots b_{n(N-1)}]^T \qquad (9)$$

to form the adaptive output. The output and the corresponding error signal are

$$Y_n = Z_n^{\,T} B_n \qquad (10)$$

$$\text{and} \quad \varepsilon_n = d_n - Y_n \qquad (11)$$

The weight update equation is

$$b_{(n+1)i} = b_{ni} + 2\mu_1 \varepsilon_n Z_{ni},\ i = 0, 1, \ldots, N-1 \qquad (12)$$

where, $\mu_1 = \mu / E(Z_{ni}^2)$, $i = 0, 1, \ldots\ldots, N-1$ is the adaptive step size for the i th transform component and μ is a positive constant that governs the rate of convergence. Let Λ^2 be a N x N diagonal matrix whose (i,j)th element is equal to the power estimate(computed by averaging with a moving window) of the $Z_{ni.}$ The weight vector equation in matrix form is

$$B_{(n+1)i} = B_n + 2\mu\, \Lambda^{-2} \varepsilon_n Z_n \qquad (13)$$

The inverse of matrix Λ^2 exists as long as the data autocorrelation matrix R_{xx} is positive definite. It can be shown that if μ properly chosen, the weight vector converges to the transform domain optimum Weiner solution.

$$B^* = R_{zz}^{-1} R_{zd} \qquad (14)$$

where, $R_{zz} = E(Z_n Z_n^T) = WR_{xx} W^T$

$$\text{and} \quad R_{zzd} = E(Z_n d_n) = WR_{xd} \qquad (15)$$

Then (3.23) can be written as .

$$B^* = (W R_{xx} W^T)^{-1} W R_{xd} = W R_{xx}^{-1} R_{xd} \qquad (16)$$

Using (12) , B^* can be expressed as

$$B^* = WA^* \qquad (17)$$

The speed of convergence of the weight vector B_n now depends on the eigenvalue spread of the matrix

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$(\Lambda^{-1}R_{zz})$ .Without loss of generality, assume that the input signal power is unity i.e.,

$$E(x_n^2) = 1 \qquad (18)$$

Let Tr(A) denote the trace and Det(A) denote the determinant of square matrix A. Then from matrix theory $\lambda_{max.} \leq$ Tr(A). For N larger than 2, it can be generally shown that $\lambda_{max.} \geq$ Det(A). Therefore, the ratio

$$\gamma(A) = Tr(A) / Det(A) \qquad (19)$$

can be used as an upper bound for $\lambda_{max.} / \lambda_{min.}$.

Now, $Det(\Lambda^{-2} R_{zz}) = Det(\Lambda^{-2}) Det(R_{zz})$

$$= Det(\Lambda^{-2}) Det(R_{xx}) \qquad (20)$$

And $Tr(\Lambda^{-2}R_{zz}) = Tr(R_{xx}) = N$ (21)

Therefore, $\gamma(\Lambda^{-2} R_{zz}) = Det(\Lambda^{2})\gamma(R_{xx})$ (22)

Since $Tr(\Lambda^2) = N$, the $Det(\Lambda^2)$ is always assumed to be less than or equal to unity. Hence,

$$\gamma(\Lambda^{-2}R_{zz}) < \gamma(R_{xx}) \qquad (23)$$

That is, for a properly chosen orthogonal transform W, some reduction in the eigenvalue spread can be expected. As a consequence of this, the transform domain adaptive algorithm can be expected to have a better convergence property than the corresponding time domain algorithm. A block diagram of the transform domain adaptive equaliser is shown in Fig. 3

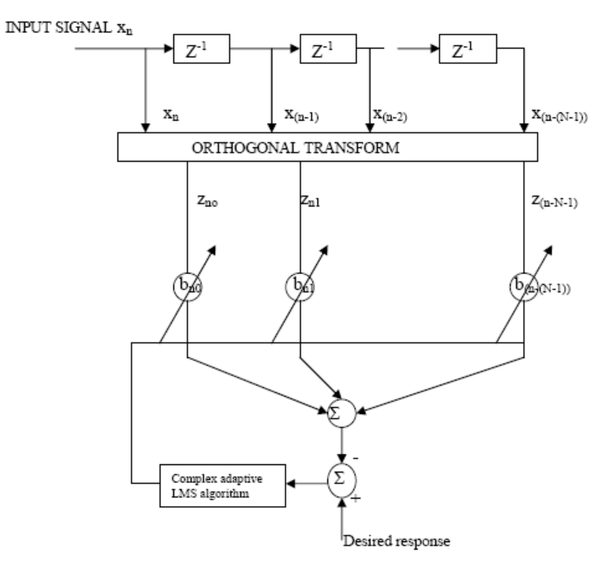

Fig. 3: TRANSFORM DOMAIN ADAPTIVE LMS EQUALISER

6. DFT DOMAIN LMS ALGORITHM (10)

Here, the input signal is filtered by a bank of large N complex band pass filter, implemented digitally by the DFT. That is, z_{nk} is given by the equation

$$z_{nk} = \sum_{p=0}^{N-1} x_{n-p}\, e^{-j(2\pi/N)pk}, k = 0, 1, ..., N-1 \qquad (24)$$

It can be easily shown that the corresponding recursive equation for z_{nk}

$$z_{nk} = \sum_{p=0}^{N-1} z_{(n-1)k}\, e^{-j(2\pi/N)^{k}} + x_n - x_{n-N}, k = 0, 1 ...., N-1 \qquad (25)$$

A block diagram of frequency domain adaptive filter is shown in Fig.3. The filtered signals are weighted and summed to produce the time domain output signal. The complex LMS algorithm (27, 29) is used to recursively update the weight vector B_n. The weight vector update equation is

$$B_{(n+1)} = B_n + 2\mu \Lambda^{-2} \varepsilon_n Z_n, \qquad (26)$$

Where μ is the adaptive step size and Λ^2 is an N x N diagonal matrix whose (i, i) element is equal to the power estimate (computed by averaging with a moving window) of the i th DFT output Z_{ni}. When both the input and the desired signals are real, b_{n0} is also real and the other components of the weight vector B_n satisfy the relation

$$b_{ni} = \bar{b}_{n(N-i)}, i = 1, 2, ..., \frac{N}{2}. \qquad (27)$$

This fact can be used to reduce the computational requirements for weight vector updating. The inverse of the matrix Λ^2 exists as long as the data autocorrelation matrix R_{xx} is positive definite. The use of $\mu\ \Lambda^{-2}$ in controlling the adaptive step size is functionally equivalent to normalizing the power in each of the DFT bins to unity before weighting.

7. DGT DOMAIN EQUILISER AND LMS ALGORITHM (13, 14, 15, 16 and 17)

The Gabor transform is non-orthogonal transform and difficult to find out the Gabor coefficients. Using some approximation a novel technique is used to find out the Gabor coefficients and utilize it for channel equalisation. The Gabor transform for continuous signal is given by the following formula.

$$x(t)=\sum_{-\infty}^{\infty} M \sum_{-\infty}^{\infty} K C_{MK} \exp \frac{-\pi(t-MT)^2}{2T^2} e^{j2\pi 2\pi K t_1} \quad (28)$$

As the elementary signal is not orthogonal the coefficients are best obtained by successive approximation. In the approximation it is considered that each horizontal strip with suffix M itself and expand the function x(t) as if the other strips do not exist, in the interval (t_n – ½ T) to (t_n + ½ T). In the exponential function, which is independent of K has been brought over to the left. Then the new equation is given by

$$x(t)\exp \frac{\pi(t-MT)^2}{2T^2} = \sum_{K=0}^{\infty} C_{MK} e^{j2\pi kt/T_1} \quad (29)$$

Using the above equation and approximation the coefficients C_{MK} can be found out easily because now the elementary signal is orthogonal.

A. Critical Sampling

In critical sampling the T is equal to T_1 as given in the equation 26. The shifting period of the Gaussian window is taken to be T = ST_2, where T_2 is the time period between two signal sequences or sampling period. T_2 is taken to be unity, so T = S. The critical sampling the new equation is given by

$$x(t)\exp \frac{\pi(t-MS)^2}{2S^2} = \sum_{K=0}^{\infty} C_{MK} e^{j2\pi 2\pi K t} \quad (30)$$

Considering the continuous case the coefficients C_{MK} can be found out by Fourier series taking one strip at a time (for different values of M). Using the principle of DFT evaluation for finite length sequence and discretising the continuous signal the coefficients can be found out as follows:

$$C_{n_0 k} = \sum_{P=0}^{S-1} x_{n-P} \exp \frac{\pi(P)^2}{2S^2} W_S^{KP}, 0 \le K \le S-1 \quad (31)$$

Where, $W_S^{KP} = e^{-j(2\pi/S)KP}$

$$C_{n_1 k} = \sum_{P=S}^{2S-1} x_{n-P} \exp \frac{\pi(P-S)^2}{2S^2} W_S^{KP}, 0 \le K \le S-1 \quad (32)$$

In this way the coefficients for the strips can be found out. Here n stands for nth iteration and 0, 1,… stands for different strips. A block diagram of the transform domain adaptive filter is shown in Fig.5. 2. The input signal is filtered by a band pass filters, implemented physically by Discrete Gabor Transform (DGT). The filtered are weighted and summed to produce the time domain output signal.

$$Z_{n_0} = \left[Z_{n00} Z_{n01} \ldots\ldots\ldots Z_{n0(S-1)}\right]^T.$$

The vector Z_{n0} is coefficient of the first strip, where $Z_{n00} = C_{n00,}$

$Z_{n01} = C_{n01}$, is related to the input vector X_{n0} ($x_{n-p,}$ p = 0, 1, ……………., S – 1) by the orthogonal transform $Z_{n0} = WX_{no,}$ where W is a S x S DFT matrix whose (p, q) th element is $e^{-j(2\pi\pi pq/)}$. The output of the first strip is given by :

$$Y_{n0S} = Z_{n0}^T B_{n0} \quad (33)$$

The output for the second strip is given by :

$$Y_{n1S} = Z_{n1}^T B_{n1} \quad (34)$$

In this way output for other strips can be found out. The total output and error signal are found to be:

$$Y_n = Y_{n0} + Y_{n1} + Y_{n2} \ldots$$

and $\varepsilon_n = d_n - y_n$ respectively, where $B_n = [B_{n0}\ B_{n1}\ B_{n2}\ \ldots\ldots\ldots\ldots]^T$ is the frequency domain vector B_n. The weight vector update equation is given by:

$$B_{n+1} = B_n + 2\mu\mu_n \begin{bmatrix} \Lambda_0^{-2} Z_{n0} \\ \Lambda_1^{-2} Z_{n1} \\ \Lambda_2^{-2} Z_{n2} \\ \Lambda_3^{-2} Z_{n3} \\ \cdot \\ \cdot \\ \cdot \\ \cdot\Lambda_{N-1}^{-2} Z_{n(N-1)2} \end{bmatrix} \text{Nx1 matrix} \qquad (35)$$

Where μ is the adaptive step size and Λ_0^2, Λ_1^2.............. are S x S diagonal matrix whose (i, i) th element is equal to the power estimate of the i th DFT output of the different strips. The DGT LMS algorithm is used to update the weight vector B_n. When both the input and desired signals are real, the components of the weight vector B_n satisfy the relation.

$$b_{n0i} = \bar{b}_{0n(S-i)}, i = 1, 2 \ldots\ldots\ldots\ldots S/2$$

B. Over Sampled Case

In over sampled case T_1 is greater than T in the equation 26. In this case the numbers of coefficients are greater than number of signal sequences. Here the elements in the weight vector are greater than the number of input sequences. Mathematical equation in the over sampling is same as the critical sampling case.

$* \left[X(k) = \sum_{n=0}^{N-1} x(n) W_N^{nk}, 0 \le k \le N-1 \right]$ is a formula for finding DFT. If sequence x(n) is shorter than N, for finding the coefficients X(k) zero is placed in the vacant place of x(n) sequence. This principle is adopted in over sampling case.

8. ALGORITHM ISSUES

Here the input vector X_n and Z_n is the Gabor transformed vector. The vector Z_n is related to the input vector X_n by the Gabor transformation $Z_n = WX_n$ where, W is an N x N Gabor matrix. Thus Z_{nk} is given by the equation

$$Z_{nk} = \sum_{p=mN}^{(m+1)N-1} x(n-p) W_N^{kp}$$

k = 0, 1, …, N – 1. m = 0, 1, 2…

The output and corresponding error signal are $Y_n = Z_n^T B_n$ and $\varepsilon_n = d_n - y_n$ respectively. The DGT LMS algorithm is used to recursively update the weight vector B_n. The weight vector equation is $B_{(n+1)i} = Bn + 2\mu\ \Lambda^{-2}\ \varepsilon_n\ Z_n$, where μ is the adaptive step size and Λ^2 is an N x N diagonal matrix whose (i,i) element is equal to the power estimate (computed by averaging with a moving window) of the i th DGT output Z_{ni}.

9. SIMULATION, EXPERIMENTAL RESULTS & ANALYSIS

In this paper we have studied the performance of digital adaptive channel equaliser using three different techniques. In these study three channels of British telecommunications with eigenvalue 1.0, 11.8, and 68.6 have been used. The impulse response for 3 channels of British Tele-communication is given in the table.

Table 3

CHANNEL No.	IMPULSE RESPONSE	EIGENVALUE
1	$1.0 + 0.0z^{-1} + 0.0z^{-2}$	1.0
2	$0.2602 + 0.9298z^{-1}$	11.8
3	$0.3482 + 0.8704z^{-1} + 0.3482z^{-2}$	68.6

The effect additive noise on the performance of the channel equaliser has been seen by introducing -40 dB and -20dB noise to the channel. In the first techniques the equaliser is of time domain and uses most popular LMS algorithm for adaptation. The second

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technique the delayed data samples are passed through an orthogonal discrete transform block and the transformed samples are used in the equaliser. In the third technique, DGT is used for equalization. As observed from the experiment, it is concluded that the time domain LMS equaliser is quite slow in convergence. The transform domain equaliser is much faster in convergence as compared to both time domain and DGT based equaliser. The DGT based equaliser is quite slow in convergence, but in this equaliser the noise recovery is better specially when the additive noise is large and the channel EVR is large.

10. PERFORMANCE COMPARISON

In Fig 4, 6, and 8 the performance characteristics of the three types of equalisers

(i) LMS time domain
(ii) transform domain (DFT) and
(iii)Gabor based adaptive equalisers are shown with additive noise level of –40dB.

In Fig 5, 7 and 9 the performance characteristics of the three types of equalisers are shown with additive noise level of –20dB. The performance characteristics of channel 1, 2, 3 for the three adaptive have been compared in Fig 10, 11, 12. From this it can be seen that the time domain equaliser settles to –40dB MSE levels at about 300 iterations where as transform domain equaliser settles to –40dB at about 100 iterations. But the DGT domain equaliser settles to about –38.7 dB at 2000 iterations. Fig 13, 14, 15 show the performance of channel 1, 2and 3 with additive noise -20 dB. The time domain equaliser settles at –35 dB in 2000 iteration and transform domain equaliser settles at -35 dB in 400 iterations where as DGT equaliser settles to –36.5 dB at 2000 iteration. Fig 10 shows the performance characteristics of channel 1. The MSE level settles at –12, -22 and –23 dB for time domain, transform domain and DGT equaliser respectively. Fig 13, 14 and 15 depicts the performance characteristics of 3 channels in case of –20dB additive noise. Fig 13 indicates the performance of channel 1. From this it can be seen that the time domain equaliser settles at –20 dB at 300 iterations and transform domain equaliser settles at –18dB at 100 iterations where as the DGT domain equaliser settles at –20dB at 200 iterations. Fig 14 shows the performance of channel 2. The MSE settles at about –18 dB and –16 dB for the time domain and transform domain equaliser respectively but the rate of convergence is faster in latter case. The Digit domain equaliser settles at –18 dB in 1000 iterations. Fig 15 indicates the channel 3 performance both Time domain and Transform domain equaliser settles at about –12 dB where as the DGT domain equaliser settles at –12 dB in 2000 iterations.

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Table 4

PERFORMANCE COMPARISON OF DIFFERENT CHANNRL EQUALISERS

Additive Noise in dB	**Channel Number**	**Time Domain 1**		**Transform Domain 2**		**DGT Domain 3**	
		MSE Floor level in dB	**No. of Iterations For Setting**	**MSE Floor Level in dB**	**No. of Iterations For Setting**	**MSE Floor level in dB**	**No. of Iterations For Setting**
-40dB	1	-40	300	-40	100	-38.7	2000
	2	-35	2000	-35	500	-36.5	2000
	3	-12	2000	-22	1000	-23	2000
-20dB	1	-20	300	-18	100	-20	200
	2	-18.3	1300	-16	400	-18	1000
	3	-12	2000	-14	1900	-12	2000

11. RESULT ANALYSIS

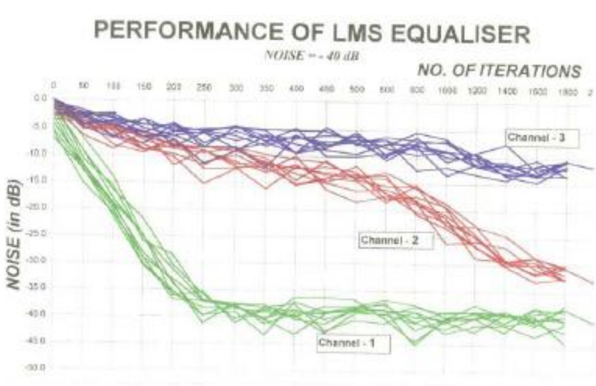

Fig. 4: Performance characteristics of LMS Time Domain channel Equaliser: -40dB case

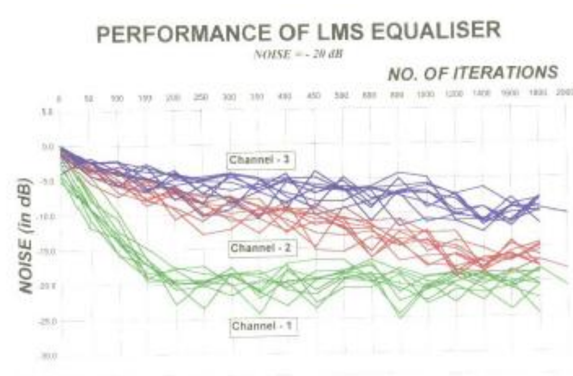

Fig. 5: Performance characteristics of LMS Time Domain channel Equaliser: -20dB case

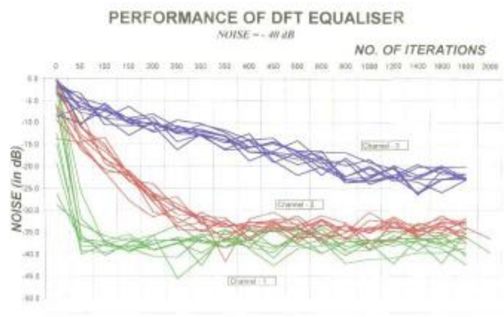

Fig. 6: Performance characteristics of DFT Transform Domain Adaptive Equaliser: -40dB

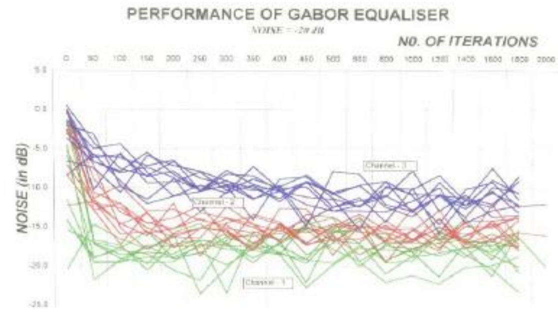

Fig. 9: Performance characteristics of Gabor based Equaliser: -20dB case

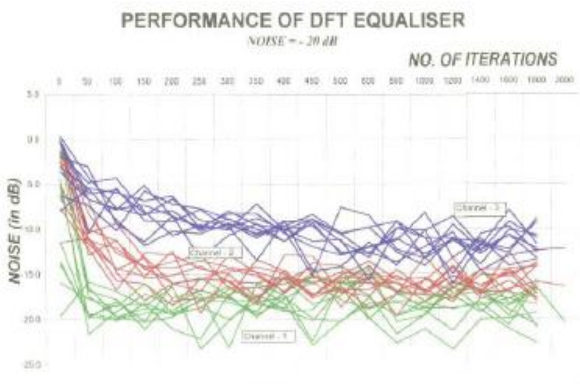

Fig. 7: Performance characteristics of DFT Transform Domain Adaptive Equaliser: -20dB case

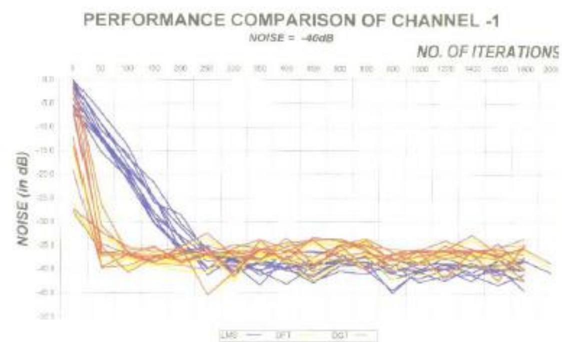

Fig. 10: Performance characteristics of LMS, DFT and DGT Equaliser: -40dB case

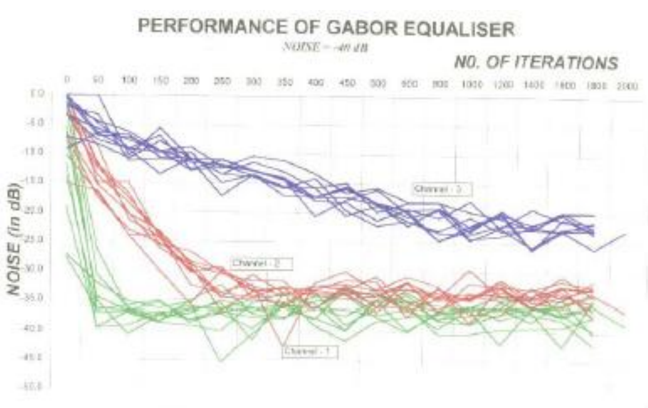

Fig. 8: Performance characteristics of Gabor based Equaliser: -40dB case

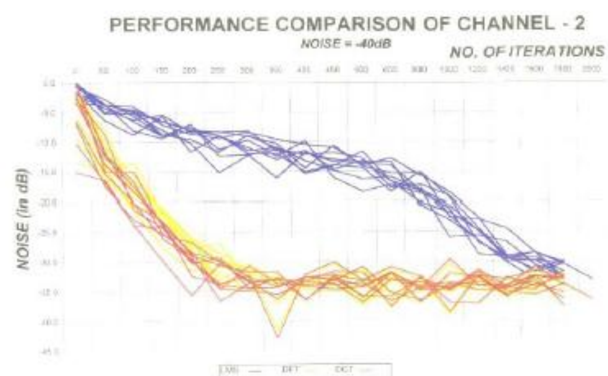

Fig. 11: Performance characteristics of LMS, DFT and DGT Equaliser: -40dB case

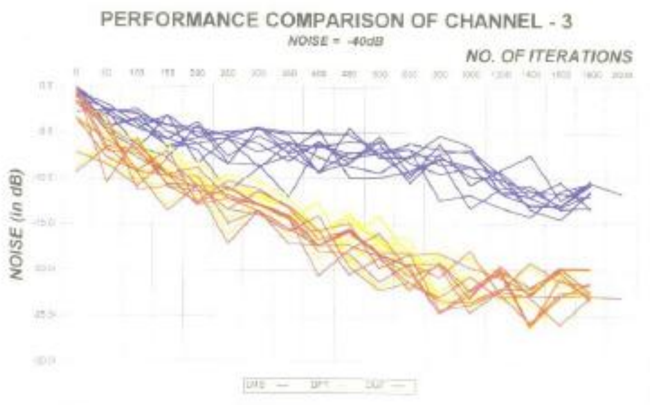

Fig. 12: Performance characteristics of LMS, DFT and DGT Equaliser: -40dB case

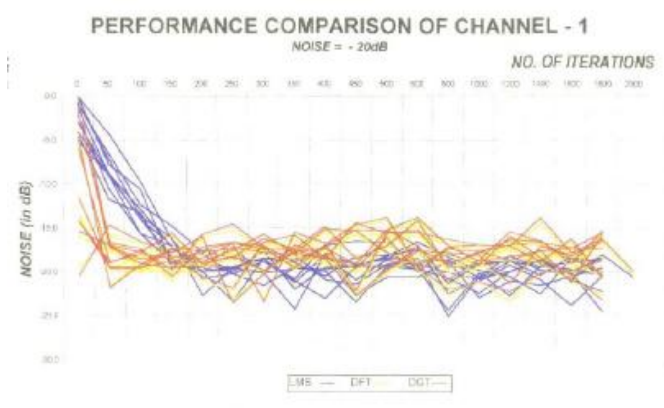

Fig. 13: Performance characteristics of LMS, DFT and DGT Equaliser: -20dB case

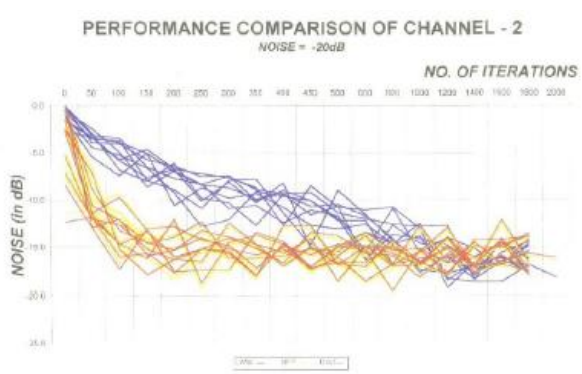

Fig. 14: Performance characteristics of LMS, DFT and DGT Equaliser: -20Db case

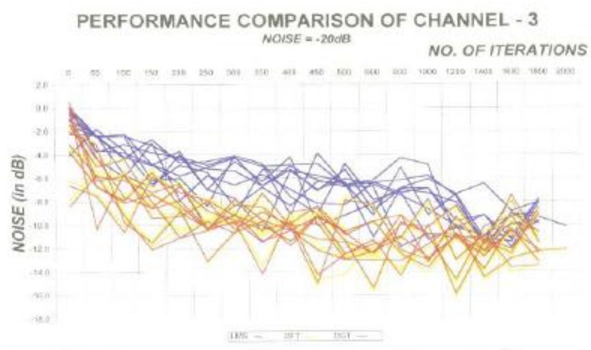

Fig. 15: Performance characteristics of LMS, DFT and DGT Equaliser: -20Db case

CONCLUSION

The present work deals with design and performance evaluation of different adaptive equalisers based on (i) time domain, (ii) transform domain and (iii) DGT domain. It is observed that the DGT domain adaptive equaliser performs better in comparison to the time domain and DFT domain equaliser. Gabor transform based equaliser, though has longer training time has been found to have better noise recovery property and lower MSE level especially when the additive noise in the channel is large. For example in channel 1 for –20 dB additive noise DGT domain adaptive equaliser settles at –20 dB at 200 iterations where as transform domain equaliser settles at about –18 dB at 100 iterations. Further studies may be carried out for reducing the convergence time of DGT domain equalisers and to develop other algorithms for better performance of DGT domain equalisers under high noise and channel EVR.

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