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ADAPTIV EQUALIZER PERFORMANCE FOR EFFECTIVE IMAGE COMPRESSIN USING DCT

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Abstract

- The recent digital transmission systems impose the application of channel equalizers with short training time and high tracking rate. Equalization techniques compensate for the time dispersion introduced by communication channels and combat the resulting inter-symbol interference (ISI) effect. Given a channel of unknown impulse response, the purpose of an adaptive equalizer is to operate on the channel output such that the cascade connection of the channel and the equalizer provides an approximation to an ideal transmission medium. Typically, adaptive equalizers used in digital communications require an initial training period, during which a known data sequence is transmitted. A replica of this sequence is made available at the receiver in proper synchronism with the transmitter, thereby making it possible for adjustments to be made to the equalizer coefficients in accordance with the adaptive filtering algorithm employed in the equalizer design. In this paper, an overview of the current state of the art in adaptive equalization techniques has been presented.

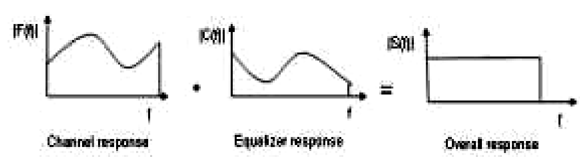
Keywords- Channel Equalizer; Adaptive Equalize; Least Mean Square; Recursive Least Squares.

INTRODUCTION

Uncompressed graphics, audio and video data require considerable storage capacity and transmission bandwidth. Despite rapid progress in mass storage density, processor speeds and digital communication system performance demand for data storage capacity and data transmission bandwidth continues to out strip the capabilities of the available technologies. The recent growths of data intensive digital audio, image, and video based (multimedia) web applications, has sustained the need for more efficient ways. With the growth of technology and the entrance into the Digital Age, the world has found itself amid a vast amount of information. Dealing with such enormous amount of information can often present difficulties. Digital information must be stored and retrieved in an efficient manner in order to put it to practical use. Without some sort of compression, sorting, storing and searching for data would be nearly impossible. Typically television image generates data rates exceeding 10million bytes/sec. There are other image sources that generate even higher data rates. Storage and transmission of such data require large capacity and bandwidth, which could be expensive. Image data compression technique, concerned with the reduction of the number of bits required to store or transmit image withoutany appreciable loss of information.

One of the most important advantages of the digital transmission systems for voice, data and video communications is their higher reliability in noise environment in comparison with that of their analog counterparts. Unfortunately most often the digital transmission of information is accompanied with a phenomenon known as inter symbol interference (ISI) [1]. Briefly this means that the transmitted pulses are smeared out so that pulses that correspond to different symbols are not separable. Depending on the transmission media the main causes for ISI are:

- cable lines – the fact that they are band limited;
- cellular communications – multipath propagation



Obviously for a reliable digital transmission system it is crucial to reduce the effects of ISI and it is where the equalizers come on the scene. The need for equalizers [2] arises from the fact that the channel has amplitude and phase dispersion which results in the interference of the transmitted signals with one another. The design of the transmitters and receivers depends on the assumption of the channel transfer function is known. But, in most of the digital communications applications, the channel transfer function is not known at enough level to incorporate filters to remove the channel effect at the transmitters and receivers For example, in circuit switching communications, the channel transfer function is usually constant, but, it changes for every different path from the transmitter to the receiver. But, there are also non stationary

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channels like wireless communications. These channels' transfer functions vary with time, so that it is not possible to use an optimum filter for these types of channels. So, In order to solve this problem equalizers are designed. Equalizer is meant to work in such a way that BER (Bit Error Rate) should be low and SNR (Signal-to-Noise Ratio) should be high. Equalizer gives the inverse of channel to the Received signal and combination of channel and equalizer gives a flat frequency response and linear phase [1] [4] shown in figure 1.

Figure 1. Concept of equalizer

The static equalizer is cheap in implementation but its noise performance is not very good [3]-[20]. As it is told before, most of the time, the channels and, consequently, the transmission system's transfer functions are not known. Also, the channel's impulse response may vary with time. result of this is that the equalizer cannot be designed. So, mostly preferred scheme is to exploit adaptive equalizers. An

The adaptive equalizer is an equalization filter that automaticaly adapts to time-varying properties of the communication channel. It is a filter that self-adjusts its transfer function according to an optimizing algorithm.

2.CHANNEL EQUALIZATION

As mentioned in the introduction the inter symbol interference imposes the main obstacles to achieving increased digital transmission rates with the required accuracy. ISI problem is resolved by channel equalization [5] in which the aim is to construct an equalizer such that the impulse responsof the channel/equalizer combination is as close to $z^{-\Delta}$ as possible, where Δ is a delay. Frequently the channel parameters are not known in advance and moreover they may vary with time, in some applications significantly. Hence, it is necessary to use the adaptive equalizers, which provide the means of tracking the channel characteristics. The following
figure shows a diagram of a channel equalization system

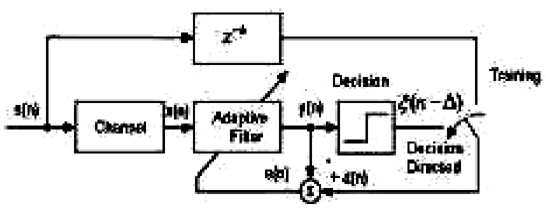

Figure2.1 Digital transmission system using channel equalization

In the previous figure, s(n) is the signal that you transmit through the communication channel, and x(n) is the distorted output signal. To compensate for the signal distortion, the adaptive channel equalization system completes the following two modes:

- Training mode - This mode helps you determine the appropriate coefficients of the adaptive filter. When you transmit the signal $s(n)$ to the communication channel, you also apply a delayed version of the same signal to the adaptive filter. In the previous figure, $z^{-\Delta}$ is a delay function and $d(n)$ is the delayed signal, $y(n)$ is the output signal from the adaptive filter and e(n) is the error signal between $d(n)$ and $y(n)$. The adaptive filter iteratively adjusts the coefficients to minimize $e(n)$ .After the power of e(n) converges, $y(n)$ is almost identical to $d(n)$,which means that you can use the resulting adaptive filter coefficients to compensate for the signal distortion.

- Decision-directed mode - After you determine the appropriate coefficients of the adaptive filter, you can switch the adaptive channel equalization system to decision-directed mode. In this mode, the adaptive channel equalization system decodes the signal and $y(n)$ produces a new signal, which

is an estimation of the signal $s(n)$ except for a delay of Δ taps [6].

Here, Adaptive filter plays an important role. The structure of the adaptive filter [7] is showed in Fig.3

To start the discussion of the block diagram we take the following assumptions:

The input signal is the sum of a desired signal $d(n)$ and interfering noise v (n)

$$x(n) = d(n) + v(n) \tag{1}$$

The variable filter has a Finite Impulse Response (FIR) structure. For such structures the impulse response is equal to the filter coefficients. The coefficients for a filter of order p are defined as

$$w_n = [w_n(0), \quad w_n(1), \quad \ldots, \quad w_n(p)]^T \tag{2}$$

the error signal or cost function is the difference between the desired and the estimated signal

$$e(n) = d(n) - \hat{d}(n) \tag{3}$$

The variable filter estimates the desired signal by convolving the input signal with the impulse response. In vector notation this is expressed

$$\hat{d}(n) = w_n * x(n) \tag{4}$$

Where

$$x(n) = [x(n), \quad x(n-1), \quad \ldots, \quad x(n-p)]^T \tag{5}$$

is

an input signal vector. Moreover, the variable filter updates the filter coefficients at every time instant

$w_{n+1} = w_n + \Delta w_n$ (6) Where Δw_n is a correction factor for the filter coefficients .The adaptive algorithm generates this correction factor based on the input and error signals.

3. ADAPTATION ALGORITHMS

There are two main adaptation algorithms one is least mean square (LMS) and other is Recursive least square filter (RLS).

A. Least Mean Squares Algorithm (LMS)

Least mean squares (LMS) algorithms are a class of adaptive filter used to mimic a desired filter by finding the filter coefficients that relate to producing the least mean squares of the error signal (difference between the desired and the actual signal). It is a stochastic gradient descent method in that the filter is only adapted based on the error at the current time. LMS filter is built around a transversal (i.e. tapped delay line) structure. Two practical features, simple to design, yet highly

effective in performance have made it highly popular in various application. LMS filter employ, small step size statistical theory, which provides a fairly accurate description of the transient behavior. It also includes H∞ theory which provides the mathematical basis for the deterministic robustness of the LMS filters [1]. As mentioned before LMS algorithm is built around a transversal filter, which is responsible for performing the filtering process. A weight control mechanism responsible for performing the adaptive control process on the tape weight of the transversal filter [9] as illustrated in Figure 4.

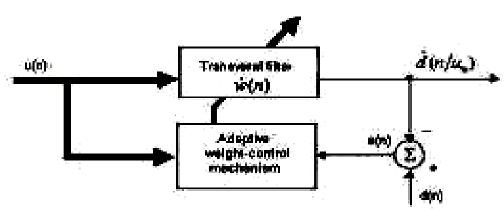

Figure3.1 Block diagram of adaptive transversal filter employing LMSalgorithm.

The LMS algorithm in general, consists of two basics procedure:

Filtering process, which involve, computing the output $(d(n-d))$ of a linear filter in response to the input signal and generating an estimation error by comparing this output with a desired response as follows:

$$e(n) = d(n) - y(n) \quad (7)$$

$y(n)$ is filter output and is the desired response at time n

Adaptive process, which involves the automatics adjustment of the parameter of the filter in accordance with the estimation error.

$$w(n+1) = w(n) + \mu(u)e^{*}(n) \quad (8)$$

Where μ is the step size, $(n+1)$ = estimate of tape weight vector at time $(n+1)$ and If prior knowledge of the tape weight vector (n) is not available, set $(n) = 0$

The combination of these two processes working together constitutes a feedback loop, as illustrated in the block diagram of Figure 4. First, we have a transversal filter, around which the LMS algorithm is built; this component is responsible for performing the filtering process. Second, we have a mechanism for performing the adaptive control process on the tap weight of the transversal filter- hence the

i.LMS is the most well-known adaptive algorithms by a value that is proportional to the product of input to the equalizer and output error.

ii.LMS algorithms execute quickly but converge slowly, and its complexity grows linearly with the no of weights.

iii. Computational simplicity

iv. In which channel parameter don't vary very rapidly.

B. Recursive Least Square Algorithm (RLS)

The Recursive least squares (RLS)[11] adaptive filter is an algorithm which recursively finds the filter coefficients that minimize a weighted linear least squares cost function relating to the input signals. This in contrast to other algorithms such as the least mean squares (LMS) that aim to reduce the mean square error. In the derivation of the RLS, the input signals are considered deterministic, while for the LMS and similar algorithm they are considered stochastic. Compared to most of its competitors, the RLS [11] exhibits extremely fast convergence. However, this benefit comes at the cost of high computational complexity, and potentially poor tracking performance when the filter to be estimated changes.

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As illustrated in Figure 5, the RLS algorithm has the same to procedures as LMS algorithm, except that it provides a tracking rate sufficient for fast fading channel, moreover RLS algorithm is known to have the stability issues due to the covariance update formula p(n) [13], which is used for automatics adjustment in accordance with the estimation error as follows: [14].

$$p(0) = \delta^{-1} I \qquad (9)$$

Where p is inverse correlation matrix and δ is regularization parameter, positive constant for high SNR and
negative constant for low SNR.

n=1,2,3………..

for each instant of time

$$\pi(n)=p(n-1)u(n) \qquad (10)$$

$$k(n)= \frac{\pi(n)}{\lambda + (n)\ \pi(n)\ u^{H}} \qquad (11)$$

time verying gain vector

$$\xi(n) = d(n) \text{ -) } w^{\wedge} H(n-1)u(n) \qquad (12)$$

$$w^{\wedge}= (n-1) +) \ w^{\wedge} k(n)\xi(n) \qquad (13)$$

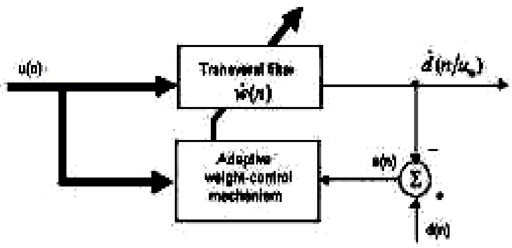

Figure3.2 Block diagram of adaptive transversal filter employing RLS
Algorithm

4.THE DISCRETE COSINE TRANSFORM

The discrete cosine transform is a fast transform that takes a input and transforms it into linear combination of weighted basis function, these basis functions are commonly the frequency, like sine waves. It is widely used and robust method for image compression, it has excellent energy compaction for highly correlated data, which is superior to DFT and WHT. Though KL T minimizes the MSE for any input image, KLT is seldom used in various applications as it is data independent obtaining the basis images for each sub image is a non-trivial computational task, in contrast DCT has fixed basis images. Hence most practical transforms coding systems are based on DCT which provides a good compromise between the information packing ability and computational complexity. Compared to other independent transforms it has following advantages, can be implemented in single integrated circuit has ability to pack most information in fewer number of coefficients and it minimizes the block like appearance, called blocking artifact that results when the boundary between sub images become visible.

One dimensional DCT is defined as:

$$c(i) = a(n)\sum_{x=0}^{N-1} f(n)\cos\left[\frac{(2x+1)i\pi}{2N}\right] \qquad (2.1)$$

where i=0,1,2,…….,N-1

Inverse DCT is defined as:

$$f(n) = a(i)\sum_{x=0}^{N-1} c(i)\cos\left[\frac{(2x+1)i\pi}{2N}\right] \qquad (2.2)$$

Where n=0,1,2,…….,N-1

$$a(n) = \sqrt{\frac{1}{N}} \quad \text{for } n= 0$$

$$a(n) = \sqrt{\frac{2}{N}} \quad \text{for } n = 1,2,3\ldots N-1$$

The correlation between different coefficients of DCT is quite small for most of the image sources and since DCT processing is Asymptotically Gaussian. Those transformed coefficients are treated as they are mutually independent .In general, DCT correlatesthe data being transformed so that most of its energy is pa cked in a few of its transformed coefficient's. The goal of the transformation process is to de-correlate the pixels of each sub images or to pack as much information as possible into the smaller number of transform coefficients. The Quantization stage then selectively eliminates or more coarsely quantizes the coefficients that carry the least information. These coefficients have the smallest impact on the reconstructed sub image quality. The encoding process terminates by coding the quantized coefficients.

5. COMPRESSION PROCEDURE

For a given image , you can compute the DCT of, say each row, and discard all values in the DCT that are less than a certain threshold. We then save only those DCT coefficients that are above the threshold for each row, and when we need to reconstruct the original image, we simply pad each row

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with as many zeroes as the number of discarded coefficients, and use the inverse DCT to reconstruct each row of the original image. We can also analyze image at the different frequency bands, and reconstruct the original image by using only the coefficients that are of a particular band. The steps for compression are as follows:

Step 1: Digitize the source image into a signal s, which is the string of numbers.

Step 2: Decompose the signal into a sequence of transform coefficients w.

Step 3: Use threshold to modify the transform coefficients fro w to another

Sequence w'.

Step 4: Use quantization to convert w' to a sequence q.

Step 5: Apply entropy coding to compress q into a sequence e.The detail Compression steps a

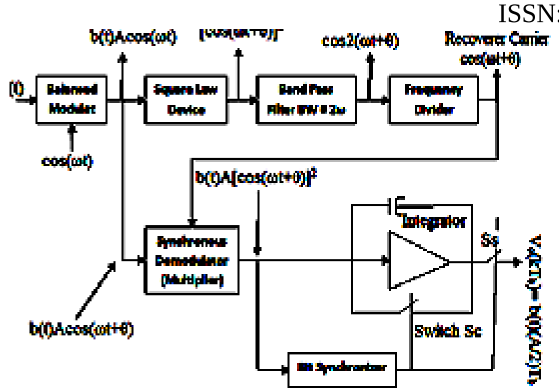
A. SIGNAL MODULATION USING BINARY PHASE SHIFTKEYING (BPSK)

In binary phase shift keying (BPSK) the transmitted signal is a sinusoid of fixed amplitude. It has one fixed phase when the data is at one level & when the data is at the other level the phase is different by 180 degree. If the sinusoid is of amplitude A, then transmitted signal is either A.cos(ωt) or – A.cos(ωt). In BPSK, the data b(t) is a stream of binary digits with voltage levels whichas a matter of convenience, we take to be at +1V or -1V. When b(t)=1V we say it is at logic level 1 & when b(t) = -1V we say it is at logic level 0. Hence V(bpsk) can be written, with no loss of generality, as:

V(bpsk)=b(t). A.cos(ωt) (5.1)

B. RECEPTION OF BPSK SIGNAL

The received signal has the form V(bpsk)=b(t).A.cos(ωt+θ). Here θ is the phase shift corresponding to the time delay which depends on the length of the path from transmitter to receiver & the phase shift produced by the amplifiers in the front end of the receiver preceding the demodulator. The original data b(t) is recovered in the demodulator. The demodulation technique usually employed is called synchronous demodulation & requires that there be available at the demodulator the wave form cos(ωt + θ). A scheme for generating the carrier at the demodulator & for recovering the baseband signal is shown in Figure 5.1.



ure 6.1 Scheme to recover the baseband signal in BPSK

The received signal is squared to generate the signal (cos(ωt+θ))2 = ½(1 + cos(ωt+θ))

The dc component is removed by the band pass filter whose pass band is centered around 2fo and we then have the signal whose waveform is that of cos2(ωt+θ). A frequency divider (composed of a flip-flop & a narrow band filter tuned at fo) is used to regenerate the wave form cos(ωt+θ).Only the waveforms of the signals at the outputs of the squarer, filter and divider are relevant to our discussion & not their amplitudes. Accordingly in Figure 6.1, we have arbitrarily taken amplitude to be unity. In practice the amplitude will be determined by features of these devices which are of no present concern. In any event, the carrier having been recovered, it is multiplied with the received signal to generateb(t). A.[cos(ωt)]2 = b(t) $\frac{A}{2}$[1+cos(ωt)]

This is then applied to an integrator as shown in Figure 6.1. We have included in the system a bit synchronizer. This device precisely recognizes the moment which corresponds to the end of the time interval allocated to one bit and the beginning of the next. At that moment it closes the switch Sc very briefly to discharge(dump) the integrator capacitor & leaves the switch Sc open during the entire course of the ensuing bit interval, closing switch again very briefly at the end of the next bit time. This circuit is called an integrate and dump circuit.

The output signal of interest to us is the integrator output at the end of a bit interval but immediately before the closing of switch Sc. The output signal is made available by switch Ss which samples the output voltage just prior to dumping the capacitor.For simplicity the bit interval Tb is equal to the duration of an integral number n of cycles of the carrier frequency fo, that is 2πn=ωTb.

In this case the output voltage Vo(kTb) at the end of a bit interval extending from time (k-1)Tb to kTb is :

$$\mathrm{Vo(kTb)} = \mathrm{Ab}(\mathrm{kt_b})\int \frac{1}{2}\,\mathrm{dt} + \mathrm{Ab}(\mathrm{kt_b})\int \frac{1}{2}\cos 2(\omega t + \theta)\,\mathrm{dt}$$

$$= \mathrm{Ab}(\mathrm{kt_b})\left(\frac{A}{2}\right)\mathrm{T_b}$$

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Since the integral of a sinusoid over a whole number of cycles has the value zero. Thus we see that our system reproduces at the demodulator output the transmitted bit stream b(t)

C.DIGITAL MODULATION AND CHANNEL EQUALIZATION

The basic idea of linear equalization is then to remove the effect of the ISI using the equalization filter C(z). Roughly this means designing an inverse filter to remove the effect of H(z). More specifically, the optimization of the equalizer C(z) depends on
The optimization criterion, e.g., Zero-Forcing (ZF) or Mean-Squared-Error (MSE) and
The available computational resources.
The idea of ZF is to minimize ISI (without thinking the additive noise at all) whereas the idea of MSE is to minimize the square error between the output of the equalizer Qkand transmitted symbol Ak. Obviously, the MSE criterion takes the ISI and noise into account, yet the both methods (ZF and MSE) being equal in the high SNR case. In other words, when SNR increases and if computational resources (equalizer length) are sufficient, C(z) approaches “1/H(z)”.
The equalizer output Qk,as shown in figure 6.2, is given by Qk= C’Rk

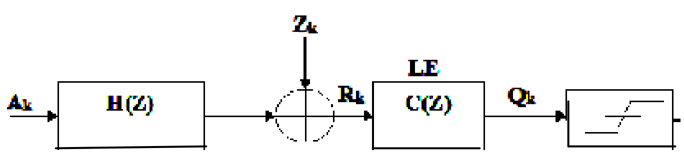

Figure 5.2 Calculating the Equalizer Coefficients Iteratively – LMS Approach

D.CHANNEL EQUALIZATION USING LEAST MEAN SQURE ERROR TECHNIQUE

Equalizer coefficients can also be calculated iteratively using the LMS (least -mean-square) approach as
c(k+1)=c(k)+β*E(k)Rk*
Where E(k) is the error signal given by E(k) = A(k)-Q(k) = A(k)-C’R(k)&β is the step size.

6.DIGITAL COMMUNICATION SYSTEM INPLEMENTATION

BLOCK DAIGRAM OF SYSTEM

As to transmit an image through a channel a complete system is required which includes the blocks as shown in figure below, as we have already gone through some details for each block, this block diagram suffices the need of understanding of the system

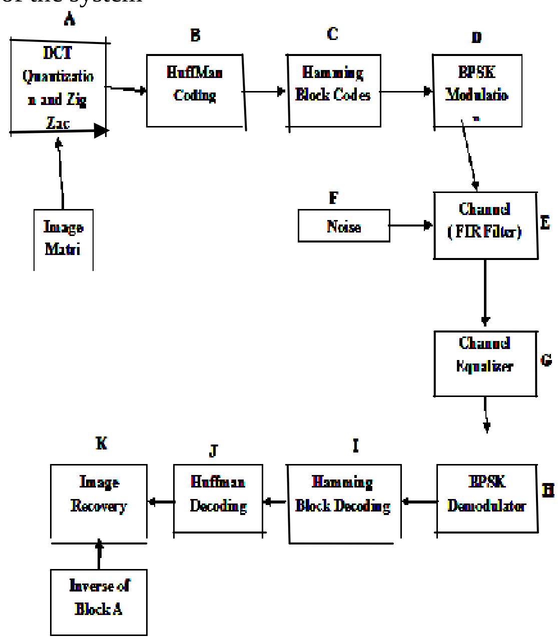

Figure 6.1Block diagram of image compression and Communication System

7.RESULTS (OBSERVATIONS)

A. CHANNEL EQUALIZER PERFORMANCE

The SNR value of the signal obtained after being passed through the channel equalizer for the input signal with a fixed value of SNR (due to noise present in the channel).
Variation in parameters like step size for updating weights coefficient & number of iterations done using LMS algorithm for weights update results in different value of SNR of the output signal.

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Step Size	Number of Iterations using LMS Algorithm	SNR of the Input Signal(dB)	SNR of the Output Signal(dB)
0.005	50	8	9.21
0.005	80	8	9.90
0.005	100	8	10.29
0.005	200	8	12.11
0.005	300	8	12.16
0.01	50	6	10.89
0.01	80	6	12.01
0.01	100	6	13.35
0.01	200	6	14.21
0.01	300	6	14.17
0.03	50	9	11.31
0.03	80	9	13.49
0.03	100	9	13.44
0.03	200	9	13.47
0.03	300	9	13.41

C. LIMITING VALUES FOR NOISE

Limiting value of the minimum SNR value of the input signal (or correspondingly the maximum value of noise in the channel) that can be handled by the channel equalizer for the proper functioning of the Channel Encoder-Decoder system for variation in different parameters is shown below:
The weight coefficients of the filter used for channel equalization are updated using least mean Square (LMS) Algorithm
Limiting value of the minimum SNR value of the input signal (or correspondingly the maximum value of noise in the channel) that can be handled by the channel equalizer for the proper functioning of the Channel Encoder-Decoder system for variation in different parameters is shown below:
The weight coefficients of the filter used for channel equalization are updated using least mean Square (LMS) Algorithm

Step Size	Number of Iterations using LMS Algorithm	SNR of the Input Signal(dB)	SNR of the Output Signal(dB)
0.005	80	3.10	3.81
0.005	100	2.76	4.10
0.005	200	2.91	3.96
0.005	300	2.82	3.96
0.01	50	2.66	3.91
0.01	80	2.47	4.01
0.01	100	2.19	4.13
0.01	200	2.07	3.91
0.01	300	1.98	3.99
0.03	50	3.03	4.31
0.03	80	2.88	4.49
0.03	100	2.61	4.44
0.03	200	2.61	4.47

8. CONCLUSION

The continuing evolution of communication standards and competitive pressure in the market-place dictate that communication system architects must start the engineering design and development cycle while standards are still in a fluid state. Third and future generation communication infrastructure must support multiple modulation formats and air interface standards. FPGAs provide the flexibility to achieve this goal, while simultaneously providing high levels of performance. The SDR implementation of traditionally analog and digital hardware functions opens-up new levels of service quality, channel access flexibility and cost efficiency. In this paper, the several aspects of adaptive equalizer for communication systems are reviewed. Bandwidth-efficient data transmission over telephone and radio channels is made possible by the use of adaptive equalization to compensate for the time dispersion introduced by the channel. Spurred by practical applications, a steady research effort over theIMAGR COMPRESSION USING DCT Variation in parameters like step size for updating weights coefficient & number of iterations done using LMS algorithm for weights update results in different value of SNR of the output signal.

last two decades has produced a rich body of literature in adaptive equalization and the related more general fields of reception of digital signals, adaptive filtering, and system identification. There is still more work to be done in adaptive equalization of nonlinearities with memory and in equalizer algorithms for coded modulation systems. However, the emphasis has already shifted from adaptive equalization theory toward the more general theory and applications of adaptive filters, and toward structures and implementation technologies which are uniquely suited to particular applications.

9.ACKNOWLEDGMENTS

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