Adaptive Equalization of binary encoded signals using LMS Algorithm

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ABSTRACT:

The recent digital transmission systems impose the application of channel equalizers with short training time. Equalization techniques compensate for the time dispersion introduced by communication channels. Adaptive equalization is the technique used to reliably transmit data through a communication channel. Ideally, if the channel is ideal, we can demodulate the signal perfectly at the output without causing any error. However, in practice, all the channels are non-ideal and noisy in nature. So, to recover the original signal after demodulation, equalization filter is used, which will minimize the error between original transmitted signal and demodulated signal passed through equalization filter. 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. A replica of transmitted 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 LMS algorithm employed in the equalizer design. In this paper, an overview of the current state of the art in adaptive equalization technique has been presented for the different binary encoded sequences like Unipolar, polar and bipolar with and without return to zero encoding.

Key words: *LMS Algorithm, Adaptive filter, Channel equalization*

1.0 INTRODUCTION

An adaptive equalizer is an equalization filter that automatically adapts to time-varying properties of the communication channel [1]. It can be implemented to perform tap-weight adjustments periodically or continually. Periodic adjustments are accomplished by periodically transmitting a preamble or short training sequence of digital data known by the receiver. Continual adjustment are accomplished by replacing the known training sequence with a sequence of data symbols estimated from the equalizer output and treated as known data. When performed continually and automatically in this way, the adaptive procedure is referred to as decision directed. If the probability of error exceeds one percent, the decision directed equalizer might not converge. A common solution to this problem is to initialize the equalizer with an alternate process, such AR and MA Processes to provide good channel-error performance.

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. 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.

Adaptive equalization is the technique used to reliably transmit data through a communication channel. Ideally, if the channel is ideal, we can demodulate the signal perfectly at the output without causing any error. However, in practice, all the channels are non-ideal and noisy in nature. So, to recover the original signal after demodulation, our aim is to find an equalization filter which will minimize the error between original transmitted signal and demodulated signal passed through equalization filter. Least Mean Square (LMS), has been proposed to perform this operation of equalization. Here our intention is to adjust the tap weights and calculate the error performance for the different binary encoded signals like Unipolar and polar and bipolar encoded sequences with and without return to zero.

The rest of this paper is organized as follows. In section 2,explains the modeling of the communication channel. The 3rd section narrates the basic concept Channel equalization. Section 4 explains the detailed analysis of LMS Algorithm. The 5th section gives the results and discussion. Section 6 concludes the papers along with future research directions are discussed.

2.0 Modeling the communication channel

We assume the impulse response of the channel in the form

$$h(n) = \begin{cases} \frac{1}{2}[1+\cos(\frac{2\pi}{w}(n-2))] & for\ n = 1,2,3 \\ otherwise \end{cases}$$

The filter input signal will be $u(n) = h * a + v = \sum_{0}^{3} h(k)\ a(n-k) + v(n)$

where the noise variance $\sigma_v^2 = 0.001$

Here both the MA Process and AR Processes are used to perform the equalization process
The number of transverse equalization filter coefficients are being considered are 11, the weights (parameter) of the filter are symmetric with respect to the middle tap (n=5) and the channel input is delayed by 7 units to provide the desired response to the equalizer.

3.0 CHANNEL EQUALIZATION

An equalization filter typically allows the user to adjust one or more parameters that determine the overall shape of the filter's transfer function as explained in the earlier section. Equalizers are used to overcome the negative effects of the channel. Different kinds of Equalizer are available in the literature like Adaptive Equalizer, Fractionally Spaced Equalizer**,** Blind Equalization**,** Decision-Feedback Equalization**,** Linear Phase Equalizer, T-Shaped Equalizer [3]**,** Dual Mode Equalizer[4] and Symbol Spaced Equalizer. Our concentration is only the adaptive equalizer consists of a tapped delay line [5] and adaptive algorithm (LMS Algorithm). The equalizer outputs a weighted sum of the values in the delay line and updates the weights to prepare for the next symbol period. The general channel and equalizer pair and the structure of adaptive equalizers are depicted in Figs.1&2 respectively.

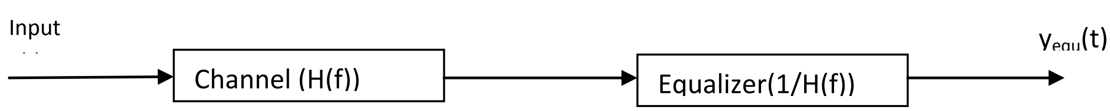


Fig.1: The general channel and equalizer pair

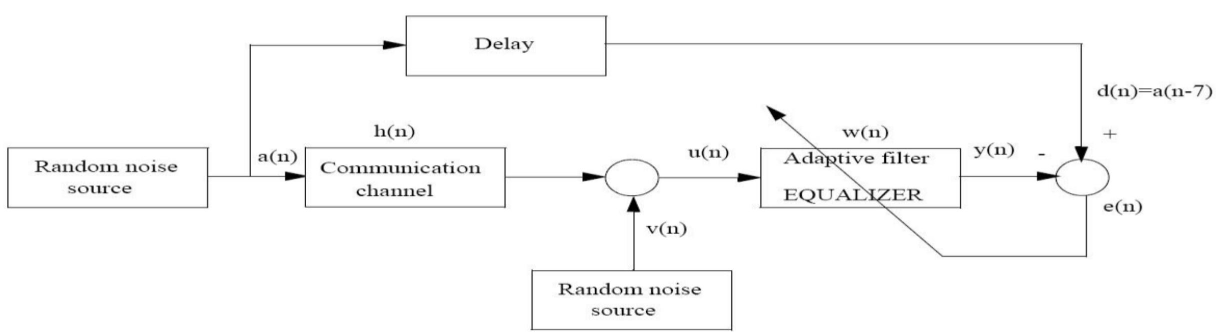


Fig.2: The block diagram of adaptive equalization equipment

To transmit a digital message, which can be a sequence of bits corresponding to voltage levels in modulation technique, through a noisy communication channel with impulse response given by h(n). We can simplify the channel complexity by assuming that the channel noise is AWGN (Additive White Gaussian Noise) in nature and is independent of transmitted signal. So, the received signal u(n) at the demodulator can be given equation 1,

$$u(n) = \sum_{k=0}^{L} d(k)\ h(n-k) + v(n) \qquad 1$$

where d(n) is the transmitted digital message, L is the length of FIR approximation of channel distortion filter[6]. Our aim is now to determine $\hat{d}(n)$ such that Mean square error J, the difference between d(n) and $\hat{d}(n)$ is minimized.

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

$$J = E(e(n)^2) \qquad 2$$

We determine $\hat{d}(n)$ using the adaptive equalizer based on LMS algorithm shown in Fig.2.

4.0 LMS Algorithm

To make exact measurements of the gradient $\nabla J(n)$ vector at each iteration n, and if the step-size parameter is suitably chosen, then the tap-weight vector computed by using the steepest descent algorithm would converge to the optimum wiener solution [7]. The exact measurements of the gradient vector are not possible and since that would require prior knowledge of both the autocorrelation matrix **R** of the tap inputs and the cross correlation vector between the tap inputs w(n) and the desired response d(n), the optimum wiener solution could not be reached [8].

Consequently, the gradient vector must be estimated from the available data when system is operated in an unknown environment.The least mean squares (LMS) algorithms adjust the filter coefficients to minimize the cost function. Assuming that all the signals involved are real-valued signals the LMS the elements for LMS algorithm are (Haykin, 1996; Hayes, 1996)

Tap-weight vector $w = [w_1, w_2, w_3 ----w_{N-1}]^T$ 3

The signal input $x(n) = [x(n), x(n-1), \ldots\ldots\ x(n-N+1)]^T$ 4

Filter output $y(n) = w^T x(n)$ 5

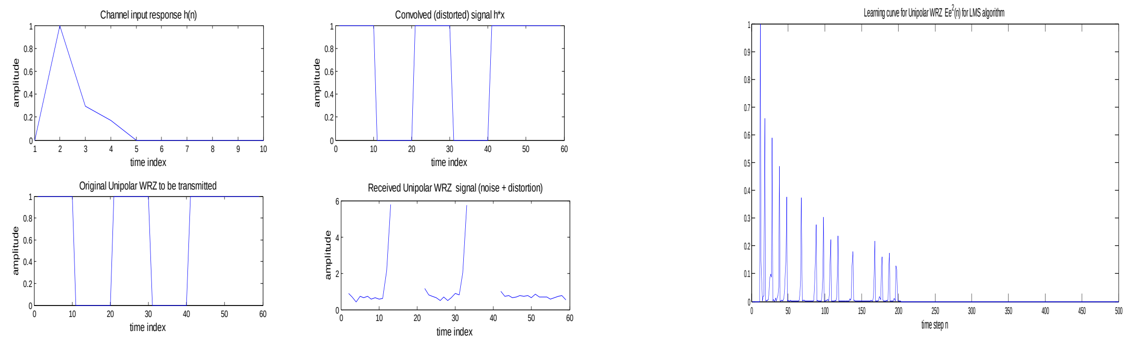
Estimation error or error signal $e(n) = d(n) - y(n)$ 6

The tap weight adaption: $w(n) = w(n) + \eta\ e(n)\ x(n)$ 7

Equations (5) and (6) define the estimation error $e(n)$, the computation of which is based on the current estimate of the tap weight vector $w(n)$. Note that the second term, on the right hand side of equation (6) represents the adjustments that are applied to the current estimate of the tap weight vector $w(n)$. The iterative procedure is started with an initial guess $w(0)$ .The algorithm described by equations (5) and (6) is the complex form of the adaptive least mean square (LMS) algorithm. At each iteration or time update, this algorithm requires knowledge of the most recent values $u(n)$, $d(n)$ $w(n)$. The LMS algorithm is a member of the family of stochastic gradient algorithms. In particular, when the LMS algorithm operates on stochastic inputs, the allowed set of directions along which we "step" from one iteration to the next is quite random and therefore cannot be thought of as consisting of true gradient directions.

5.0 Results and Discussion

The LMS algorithm is one of the powerful adaptive algorithm for equalization of the communication channel. This has been done by considering the binary encoded signals namely Unipolar with and without return to zero, Polar with and without return to zero and bipolar with and without return to zero encoding schemes. For all these schemes the AR and MA processes are employed to equalize the communication channel and also analyzed the learning curves for the various values of learning rates. The simulation of adaptive equalization and corresponding learning curve also depicted in the Figs. Fig. 4 -15. From the Fig. 4,6,8,10,12 and 14 is observed that the noise has been reduced much but some part of the signal is missing when Autoregressive Process(AR) is used in the adaptive equalization using LMS Algorithm. Even though the nose reduction with Moving Average process (MA) is less compared to the AR Process, It is inferred from the Figs.5,7,9,11, 13 and 15 that the equalized channel output appears almost same as the transmitted one.. The learning curves corresponding to all binary encoding schemes are also depicted though the Figs. 4-15. From the learning curves, it is observed that the algorithm converges fast as the step size μ increases. However, we can't increase the step size to any value as condition for convergence requires that step size should be less than the inverse of energy of the correlation matrix of received signal. One of the most important observations from these learning curves is that the algorithm converges faster for channel corresponding Channel parameters



(a) (b)

Fig.4. (a) Adaptive equalization of LMS Algorithm using AR Process of Unipolar WRZ
(b) Corresponding performance Curve

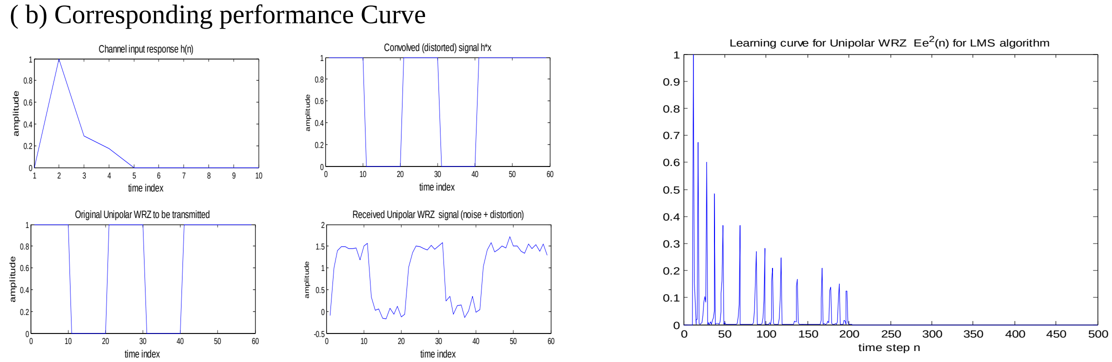


Fig.5. (a) Adaptive equalization of LMS Algorithm using MA Process of Unipolar WRZ
(b) Corresponding performance Curve

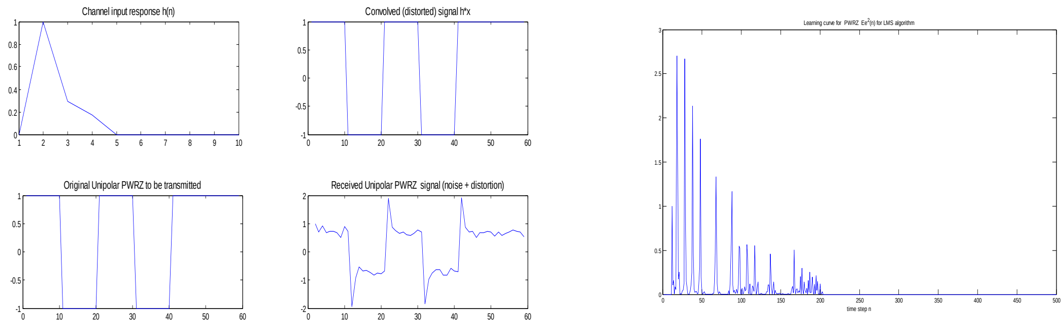


Fig.6. (a) Adaptive equalization of LMS Algorithm using AR Process of Polar WRZ
(b) Corresponding performance Curve

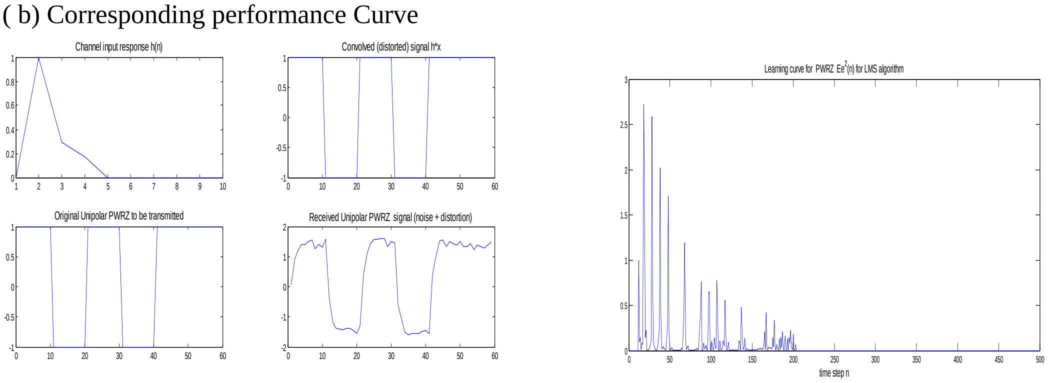


Fig.7. (a) Adaptive equalization of LMS Algorithm using MA Process of Polar WRZ
(b) Corresponding performance Curve

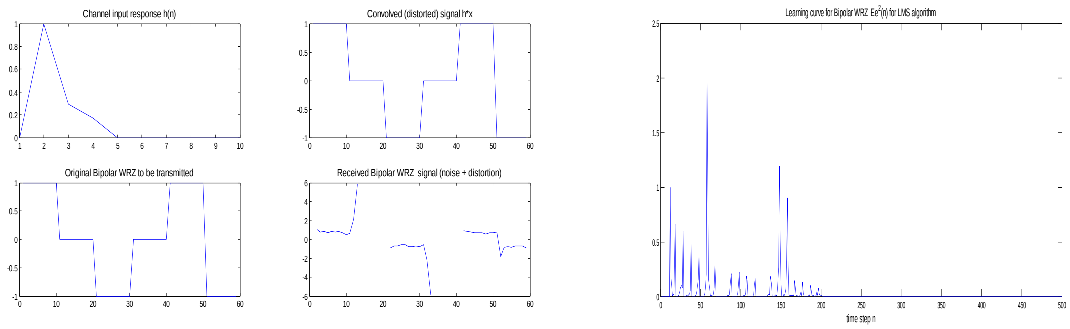


Fig.8. (a) Adaptive equalization of LMS Algorithm using AR Process of Bipolar WRZ
(b) Corresponding performance Curve

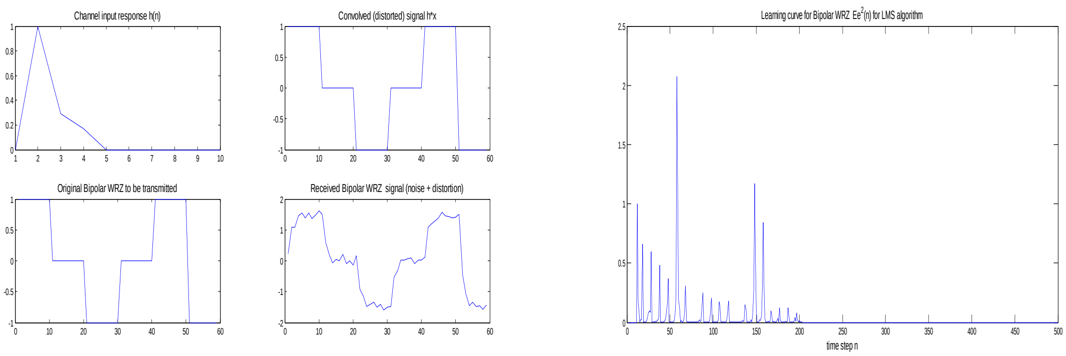


Fig.9. (a) Adaptive equalization of LMS Algorithm using MA Process of Bipolar WRZ
(b) Corresponding performance Curve

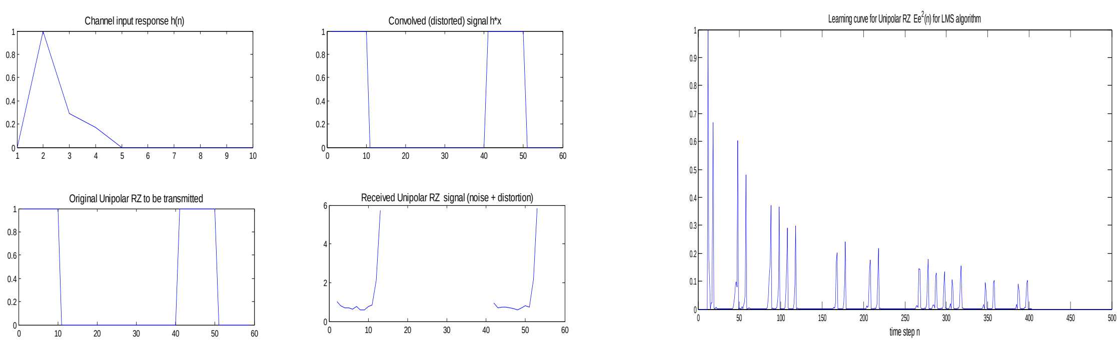


Fig.10. (a) Adaptive equalization of LMS Algorithm using AR Process of Unipolar RZ
(b) Corresponding performance Curve

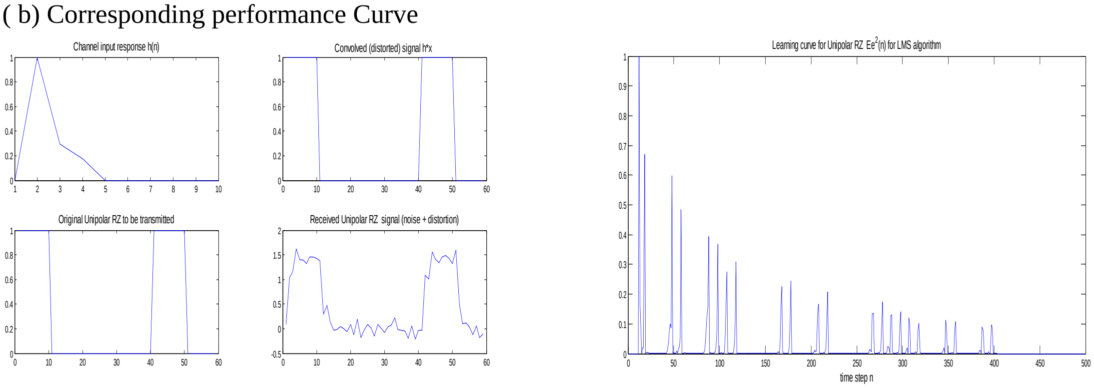


Fig.11. (a) Adaptive equalization of LMS Algorithm using MA Process of Unipolar RZ

(b) Corresponding performance Curve

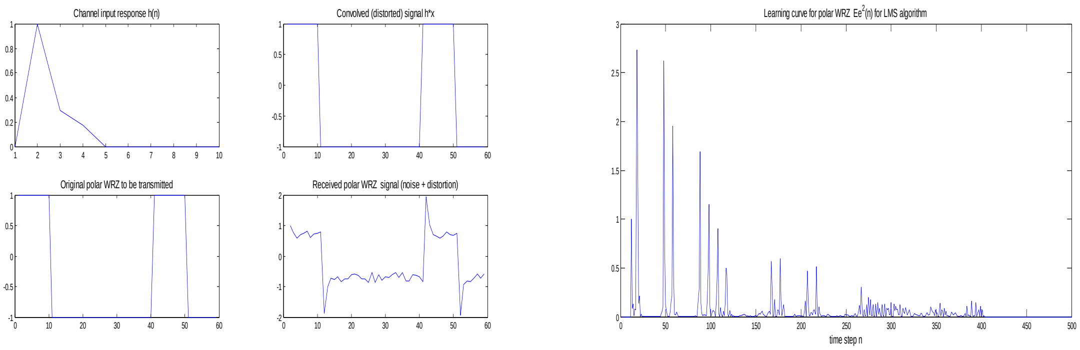


Fig.12. (a) Adaptive equalization of LMS Algorithm using AR Process of polar RZ

(b) Corresponding performance Curve

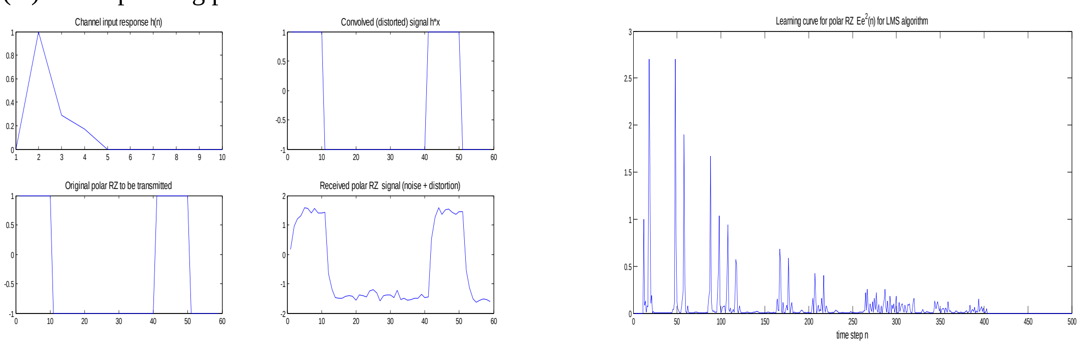


Fig.13. (a) Adaptive equalization of LMS Algorithm using MA Process of polar RZ

(b) Corresponding performance Curve

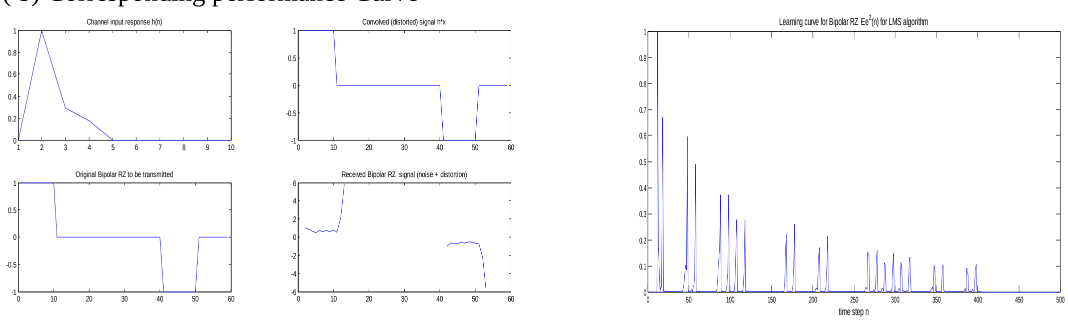


Fig.14. (a) Adaptive equalization of LMS Algorithm using AR Process of Bipolar RZ

(b) Corresponding performance Curve

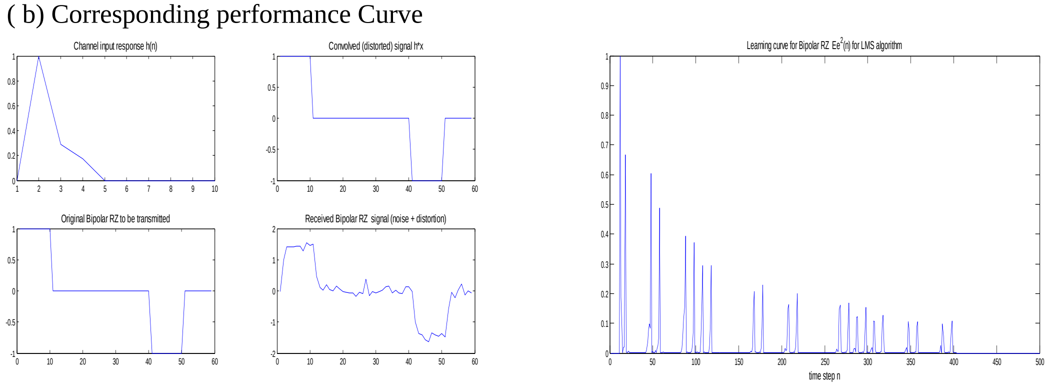


Fig.15. (a) Adaptive equalization of LMS Algorithm using MA Process of Bipolar RZ

(b) Corresponding performance Curve

6.0 CONCLUSION

In this paper, the LMS algorithm is giving a very good convergence results for chosen value of step size However, the no. of iterations required for convergence of algorithm is in the order of thousands. By comparing the schemes of AR and MA Processes of adaptive equalization it is concluded that even though the amount of noise reduction using MA Process equalization is less compared to AR process ,MA Process give better equalization and good convergence of the algorithm.

7.0 REFERENCES

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