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Development of Novel Digital Equalizers for Noisy Nonlinear Channel using Artificial Immune System

Satyasai Jagannath Nanda, Ganapati Panda, Babita Majhi
Dept. of Electronics and Communication Engineering
National Institute of Technology, Rourkela
Rourkela, Orissa, India
E mail: nanda.satyasai@gmail.com, ganapati.panda@gmail.com, babita.majhi@gmail.com

***Abstract*—Transmission and storing of high density digital information plays an important role in the present age of communication and information technology. These data are distorted while reading out of the recording medium or arriving at the receiver end due to inter symbol interference in the channel. The adaptive channel equalizer alleviates this distortion and reconstructs the transmitted data faithfully. In recent years the area of Artificial Immune System (AIS) has drawn attention of many researchers due to its broad applicability to different fields. In this paper, we propose a novel digital channel equalizer using AIS algorithm. Simulation study has been carried out to show superior performance of the proposed equalizer particularly for nonlinear noisy channels compared to that offered by LMS and GA based training.**

Keywords- Artificial Immune System, Nonlinear Equalizer, ISI, LMS, Genetic Algorithm, Clonal Selection, BER plot

I. INTRODUCTION

The biological immune system (BIS) is a multilayer protection system in which each layer provides different types of defense mechanisms for detection, recognition and responses. It also resists infectious diseases and reacts to foreign substances. Following the BIS principle a new branch of computational intelligence known as artificial immune system (AIS) [1] has evolved which finds applications in optimization, computer security, data clustering, pattern recognition, fault tolerance etc. Like other evolutionary computing algorithms it also helps to develop efficient computational models. The clonal selection principle of AIS is proposed in [2] is chosen to develop the proposed equalizer and as it is simple and is expected to provide better performance.

Digital Communication channels are often modeled as low pass FIR filter. When a sequence of symbols is transmitted, the low pass filtering effect of the channel distorts the transmitted symbols over successive time intervals causing symbols to spread and overlap with adjacent symbols. This resulting linear distortion is known as inter symbol interference (ISI). In addition nonlinear distortion is also caused by cross talk in the channel and use of amplifiers. Thus adaptive channel equalizers play an important role in recovering digital information from digital communication channels/storage media. An ANN based equalization technique has been proposed [5] to alleviate the ISI present during read back from the magnetic storage channel. Recently Sun et al have reported [6] an improved Viterbi detector to compensate the nonlinearities and media noise. Preparta had suggested [7] a simple and attractive scheme for dispersal recovery of digital information based on the Discrete Fourier Transform. Subsequently Gibson et al have reported [8] an efficient nonlinear ANN structure for reconstructing digital signals from the corrupted ones. In a recent publication [9] the authors have proposed optimal preprocessing strategies for perfect reconstruction of binary signals from dispersive communication channels. Touri et al have developed [10] deterministic worst case frame work for perfect reconstruction of discrete data transmission through a dispersive communication channel. Thus in recent past new adaptive equalizers have been suggested using soft computing tools such as Artificial Neural Network (ANN), FLANN [3]. It has been reported that these methods are best suited for nonlinear and complex channels. Recently, Chebyshev Artificial Neural Network has also been proposed for nonlinear channel equalization [4]. The drawback of these equalizers are that during training, the estimated weights do not reach to their optimum values due to the mean square error (MSE) being trapped to local minimum. In other words true Weiner solution is not achieved because of gradient based training. When the channel is highly noisy and nonlinear in nature the gradient based techniques do not perform satisfactorily. To alleviate this problem in this paper a new AIS based derivative free method is proposed to develop an efficient channel equalizer.

The paper is organized as follow. In Section II we begin with a review of adaptive channel equalizer. The basic principle of cloning is dealt in section III. The proposed equalizer using AIS is discussed in section IV. The comparison of performance obtained from simulation of LMS, GA and the proposed equalizer for few benchmark complex nonlinear channels at high noise condition is presented in section V.

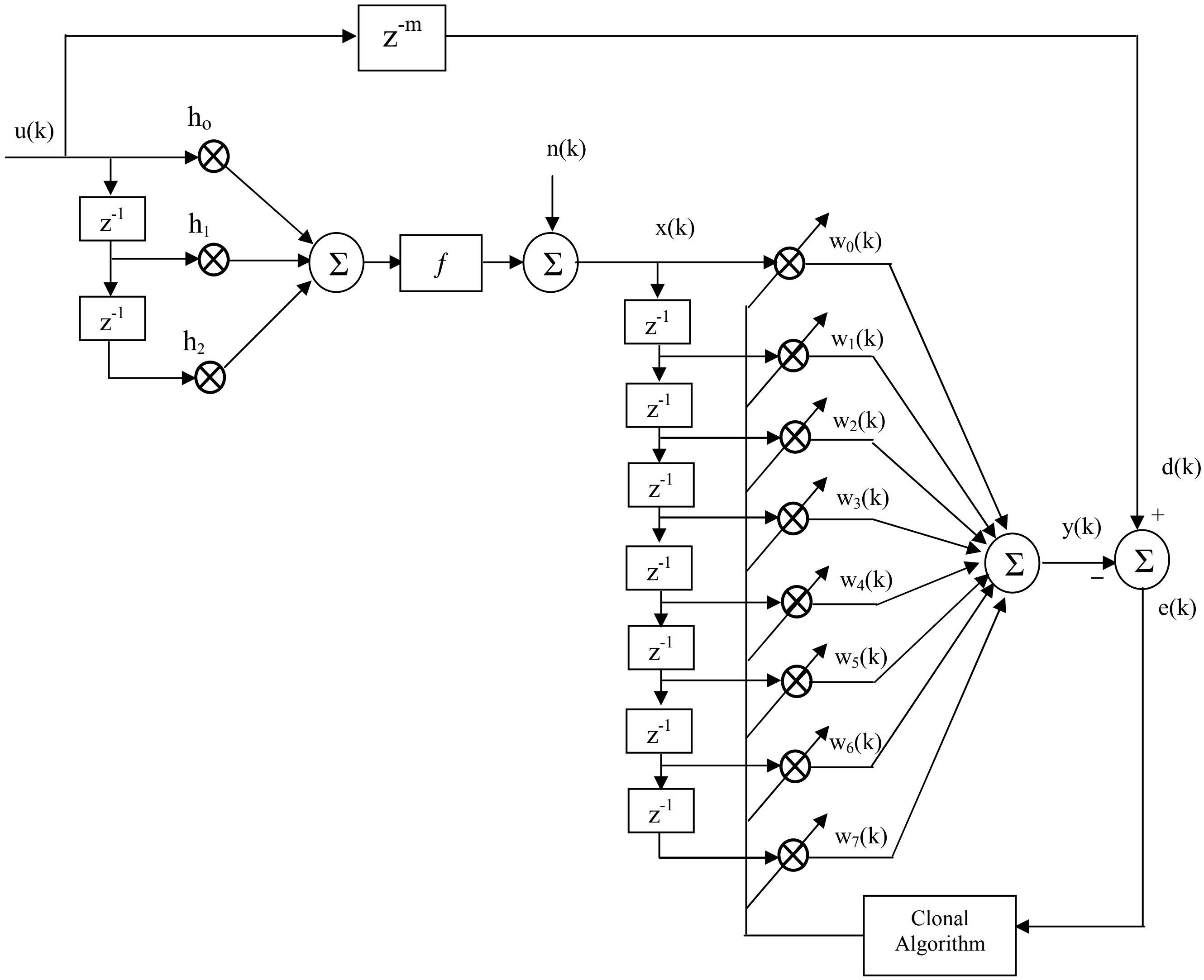

Fig 1. An AIS based adaptive digital channel equalizer

Finally section VI presents the concluding remarks of the investigation made in the paper.

II. Principle of Adaptive Channel Equalization

The basic block diagram of a digital channel equalizer with AIS based training is shown in Fig.1 in which the channel is considered as nonlinear in nature and is associated with additive white gaussian noise (AWGN). Since the equalizer is connected in series with the channel and its transfer function is inverse to the transfer function of the channel (1/H(z)) where H(z) = channel transfer function. The symbols u(k), d(k), y(k) and e(k) represent the input from the data source, desired, estimated output of the equalizer and the error signal respectively. The output of the communication channel is represented by

$$x(k) = \sum_{K=1}^{N} f(h * U(k)) + n(k) \tag{1}$$

where h= $\{h_0, h_1, h2\}$ represents coefficient vector of the channel filter and $U(k) = \{u(k), u(k-1), u(k-2)\}$ is the binary input vector applied. Symbols f and n (k) signifies the nonlinearity and AWGN associated with the channel. The symbol * denotes linear convolution operation and N is the number of taps of the channel filter. At the same k^{th} instant the output of the equalizer is given by

$$y(k) = \sum_{n=0}^{Q-1} x(k-n) * \bar{w}(k) \tag{2}$$

where Q is order of equalizer, $\bar{w}(k)$ is the adaptive weight vector associated with it.The desired signal d(k) is formed by delaying the input sequence u(k) by m samples. In practice m is usually taken as (Q/2) or ((Q+1)/2) depends on Q even or odd. The error signal e(k) is represented by

$$e(k) = d(k) - y(k) \tag{3}$$

The objective of designing an adaptive equalizer is to minimize the error e(k) recursively such that y(k) approaches d(k). When error is minimized by the use of a recursive algorithm the effect of the channel is nullified and transmitted or stored data is received more accurately. In this paper the mean square error (MSE) minimization is performed using clonal principle of AIS.

III. Principle of Clonal Selection Algorithm

Immunity refers to a condition in which an organism can resist disease. The cells and molecules responsible for immunity constitute biological immune system (BIS).AIS is developed by following the principles of BIS. Bersini first used immune algorithms to solve problems. The books [12], [13] provide the details about the various principles and algorithms of AIS. The clonal selection principle of AIS describes how the immune cells react to pathogens (foreign cells also known as antigens) and is simple but efficient evolutionary computing tool for achieving optimum solution.

L.N.de Castro and F. J. Von Zuben have dealt the clonal selection in [2] .When a pathogen invades the organism; a number of immune cells that recognize these pathogens survives. Among these cells some become effecter cells, while others are maintained as memory cells. The effecter cells secrete antibodies and memory cells having longer span of life

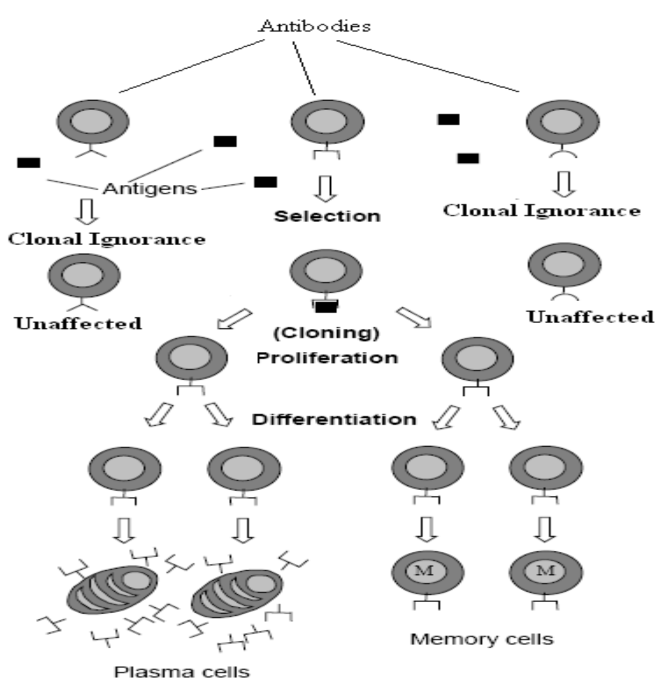

Fig 2. The Clonal Selection Principle

so as to act faster or more effectively in future when the organism is exposed to same or similar pathogen. During the cellular reproduction, the somatic cells reproduce in an asexual form, i.e. there is no crossover of genetic material during cell mitosis. The new cells are copies of their parents as shown in Fig.2 .During this process they under go an mutation mechanism which is known as somatic hypermutation as described in [2] and [11].

The affinity of every cell with each other is a measure of similarity between them. It is calculated by the distance between the two cells. The antibodies present in a memory response have on average a higher affinity than those of early primary response. This phenomenon is referred to as maturation of immune response. During the mutation process the fitness as well as the affinity of the antibodies gets changed. So in each iteration after cloning and mutation those antibodies which have higher fitness and higher affinity are allowed to enter the pool of memory cell .Those cells with low affinity or self-reactive receptors must be eliminated.

The clonal selection algorithm has several interesting features such as population size is dynamically adjustable, exploration of the search space, location of multiple optima, capability of maintaining local optima solutions and defined stopping criteria.

IV. Weight Update of Adaptive Equalizer using Clonal Selection Algorithm

1. Determination of output of channel:
The input is a random binary signal drawn from a uniform distribution .Let ‘k’ be the numbers of input samples taken. The input sample is then passed through the channel to produce output x(k) as given in (1).

2. Equalizer input:
The out put of the channel x(k) is passed through the tap delay portion of the equalizer to produce the input vector.

3. Initialization of a group of cells:
As it is an evolutionary algorithm we begin with a group of solutions .Here a group of weight vector of equalizer is taken. A weight vector consists of Q no of elements. Each element of weight vector is represented by a cell which is basically a binary string of definite length. So a set of binary strings is initialized to represent a weight vector and n number of such weight vectors is taken each of which represent probable solution.

4. Calculation of desired output of the equalizer:
The desired signal d(k) is formed by delaying the input sequence u(k) by m samples.

5. Fitness Evaluation:
The output of the equalizer y(k, n) due to k^{th} sample and n^{th} vector, is compared with the desired output d(k, n) to produce error signal given by

$$e(k,n) = d(k,n) - y(k,n) \tag{4}$$

For each n^{th} weight vector the mean square error (MSE) is determined and is used as fitness function given by

$$MSE(n) = \frac{\sum_{k=1}^{K} e^2(k,n)}{K} \tag{5}$$

The objective is to minimize the fitness function of (5) by clonal selection principle.

6. Selection:
To select the weight vector (corresponding cells) for which MSE is minimum.

7. Clone:
The weight vector (corresponding cells) which yields best fitness value (minimum MSE) is duplicated.

8. Mutation:
Mutation operation introduces variations into the immune cells. Probability of mutation P_m is chosen to be a smaller value which indicates that the operation occurs occasionally. The total number of bits to mutate is the product of total number of cells, number of bits in each cell and probability of mutation of each cell. Among the cloned cells the cell to be mutated is chosen randomly. A random position of the cell is chosen first and then its bit value is altered.

9. Stopping Criteria:
The weight vector which provides the desired solution (minimum MSE) and corresponding cells are known as memory cells. Until a predefined minimum MSE is obtained steps 4 -8 are repeated.

V. SIMULATION STUDY OF CHANNEL EQUALIZERS

In designing of the new equalizer represented in Fig.1 is simulated for nonlinear channels whose linear part is given by either of

CH1: $0.2600 + 0.9300\ Z^{-1} + 0.2600\ Z^{-2}$
CH2: $0.3040 + 0.9030\ Z^{-1} + 0.3040\ Z^{-2}$ (6)

Each of the above channels is assumed to be associated with three different types of nonlinearities represented by

$$f_1(k) = \tanh(p(k))$$
$$f_2(k) = p(k) + 0.2 * p^2(k) - 0.1 * p^3(k) \tag{7}$$
$$f_3(k) = p(k) + 0.2 * p^2(k) - 0.1 * p^3(k) + 0.5 * \cos(\pi p(k))$$

where p(k) is the output of each of linear part of the channels(6). The additive noise is white Gaussian with -5dB and -10dB strengths. In this study a 8-tap adaptive FIR filter is used as an equalizer. The desired signal is generated by delaying the input binary sequence by half of the order (four samples in this case) of the equalizer. For simulation of AIS the no of input sample taken is 80. Weights are trained for 190 iterations. Initial population of cells is taken as 20. For simulating GA based equalizer the no of input sample taken is 80. Weights are trained for 190 iterations. Initial population of chromosome is taken as 20.

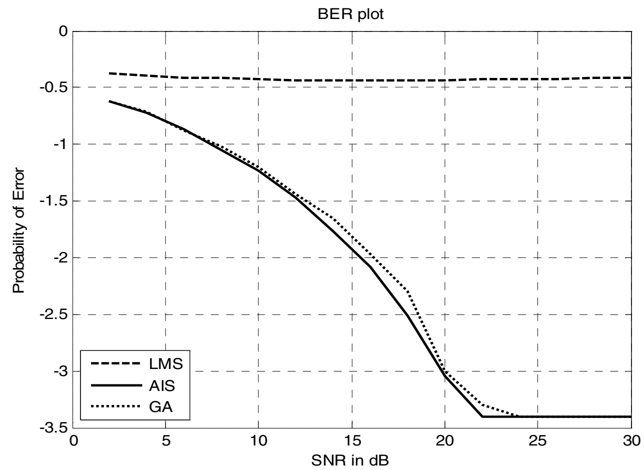

Fig.3 (a)

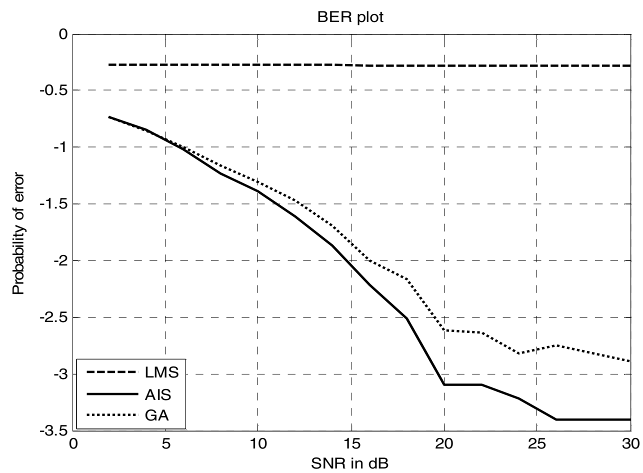

Fig.3 (b)

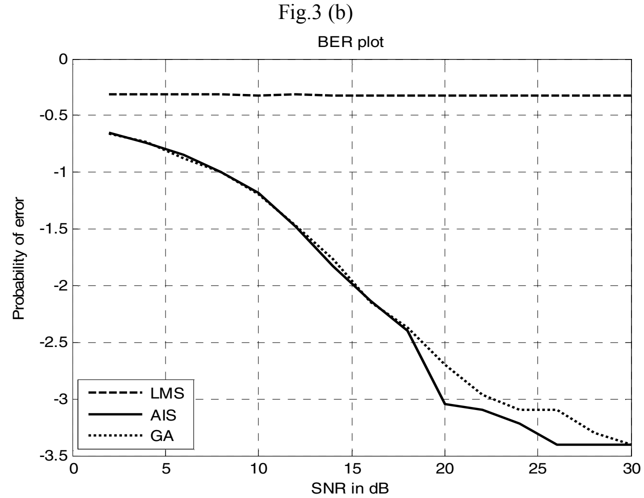

Fig.3 (c)

Fig.3 BER plot of CH1 at 5dB SNR: (a) using f_1 (b) using f_2 (c) using f_3

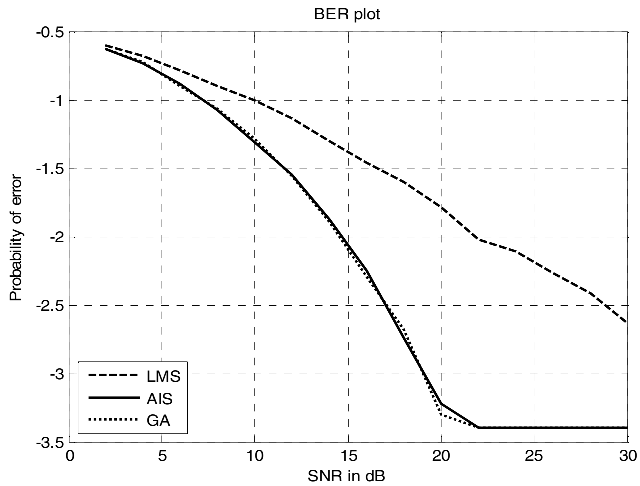

Fig. 4 (a)

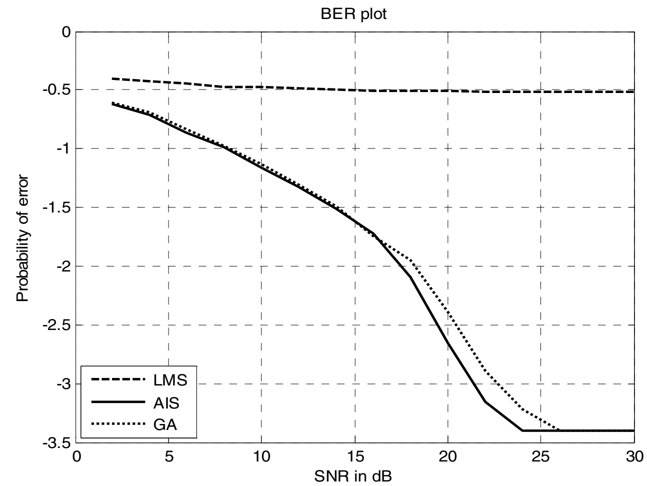

Fig.5 (a)

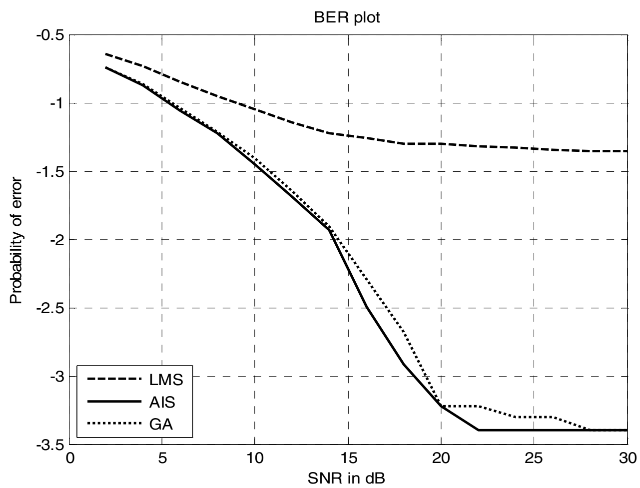

Fig.4 (b)

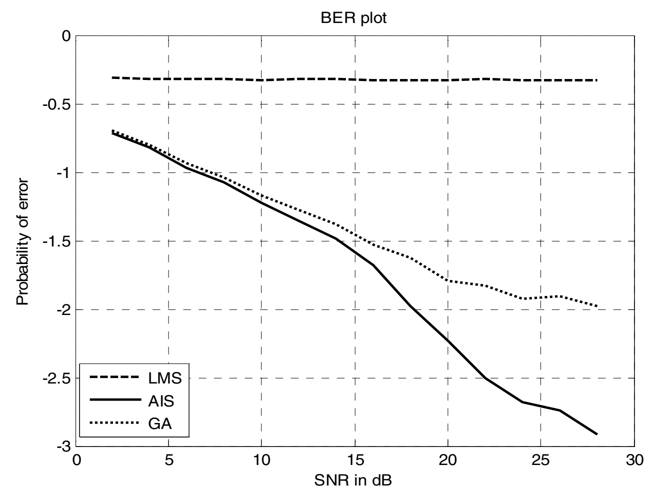

Fig.5 (b)

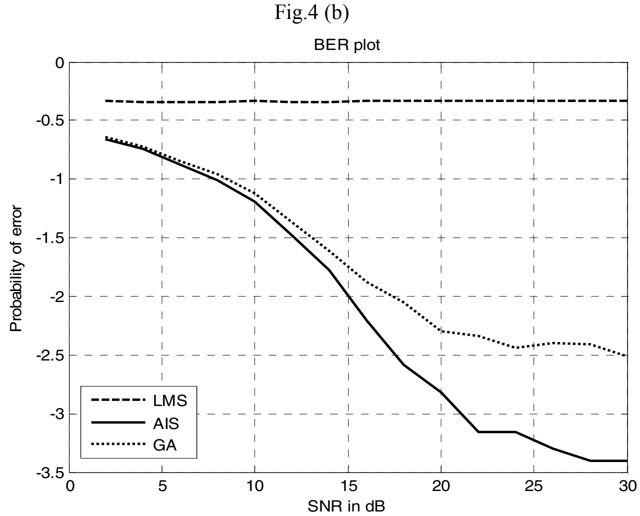

Fig. 4 (c)

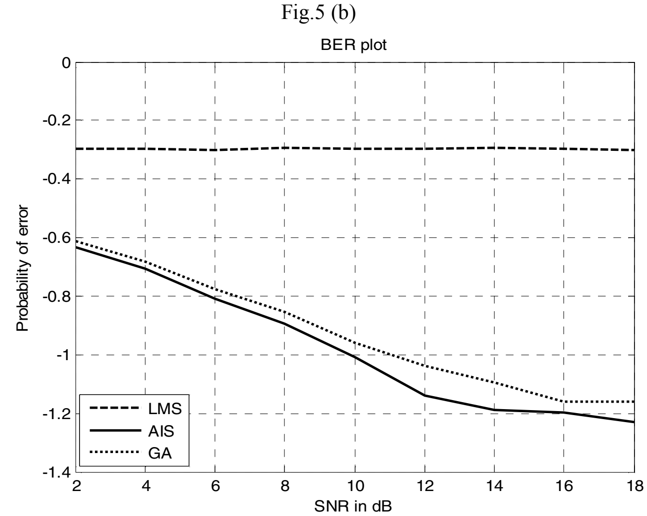

Fig.5 (c)

Fig.4 BER plot of CH1 at 10dB SNR: (a) using f_1 (b) using f_2 (c) using f_3

Fig.5 BER plot of CH2 at 5dB SNR: (a) using f_1 (b) using f_2 (c) using f_3

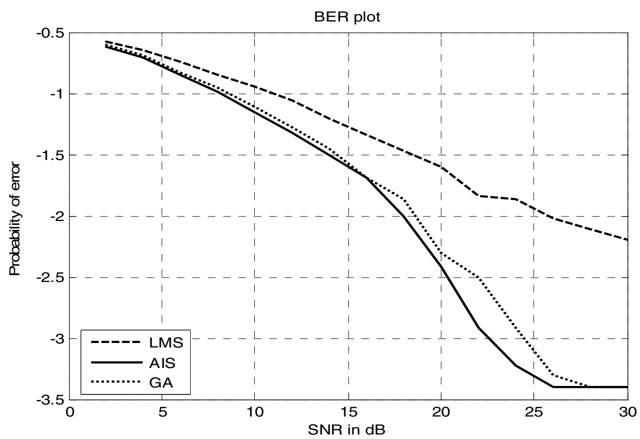

Fig.6 (a)

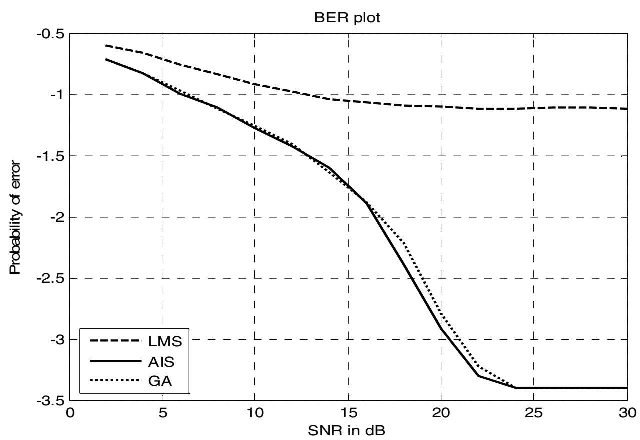

Fig.6 (b)

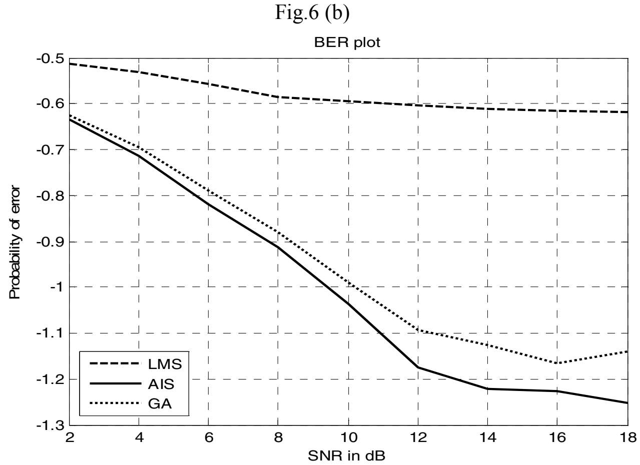

Fig.6 (c)

Fig.6 BER plot of CH2 at 10dB SNR: (a) using f_1 (b) using f_2 (c) using f_3

The CPU time required for training a typical equalizer is 0.047 sec for LMS, 23.02 sec for GA and 16.265sec for AIS. Although LMS is much faster, from the BER plot it is observed that when the channel is highly noisy and nonlinear in nature it fails to equalize the transmitted output completely. Examination of BER plots Figs 4 -7 and the CPU time reveals that AIS is a much better candidate for channel equalization as compared to its GA counter part.

VI. CONCLUSION

The present paper proposes a novel application of the AIS to equalization of noisy nonlinear channels. Exhaustive simulation study of the proposed equalizer is carried out using benchmark examples to demonstrate its improved performance. The computed results show its superior performance compared to the LMS and GA based equalizers in terms of lower probability of error in BER plot. The CPU time required for training of AIS equalizer is also less as compared to the GA based equalizer. Thus it is concluded that the AIS is a potential learning tool for efficient equalization of complex nonlinear channels under high noise conditions.

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