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Recovery of Digital Information Using Bacterial Foraging Optimization Based Nonlinear Channel Equalizers

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Abstract

Transmission and storing of high density digital information plays an important role in the present age of information technology. These binary 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. The Bacterial Foraging Optimization (BFO) is a recently developed efficient and derivative free evolutionary computing tool used for optimization purpose. In the present paper we propose a novel nonlinear channel equalizer using BFO algorithm. The recovery performance of the new equalizer is obtained through computer simulation study using nonlinear channels. It is shown that the proposed equalizer offers superior performance both in terms of bit-error-rate and convergence speed compared to the GA based equalizers. In addition it requires substantially less computation during training.

1. Introduction

Transmission and storing of high density digital information plays an important role in the present age of information technology. Digital information obtained from audio, video or text sources needs high density storage or transmission through communication channels. Communication channels and recording medium are often modeled as band-limited channel for which the channel impulse response is that of an ideal low pass filter. When a sequence of symbols are transmitted/recorded, the low pass filtering 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. In the data storage channel the binary data is stored in the form of tiny magnetized regions called bit cells, arranged along the recording track. At read back, noise and nonlinear distortions (ISI) corrupt the signal. An ANN based equalization technique has been proposed [1] to alleviate the ISI present during read back from the magnetic storage channel. Recently Sun et al have reported [2] an improved Viterbi detector to compensate the nonlinearities and media noise. Thus adaptive channel equalizers play an important role in recovering digital information from digital communication channels/storage media. Preparta had suggested [3] a simple and attractive scheme for dispersal recovery of digital information based on the Discrete Fourier Transform. Subsequently Gibson et al have reported [4] an efficient nonlinear ANN structure for reconstructing digital signals which have been passed through a dispersive channel and corrupted with additive noise. In a recent publication [5] the authors have proposed an optimal preprocessing strategies for perfect reconstruction of binary signals from a dispersive communication channels. Touri et al have developed [6] deterministic worst case frame work for perfect reconstruction of discrete data transmission through a dispersive communication channel. In recent past new adaptive equalizers have been suggested using soft computing tools such as Artificial Neural Network (ANN), PPN and the FLANN[7]. 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[8]. The drawback of these methods are that the estimated weights may likely fall to local minima during training.

For this reason Genetic Algorithm (GA) has been suggested for training adaptive channel equalizers[9].

The main attraction of GA lies in the fact that it does not rely on Newton-like gradient-descent methods, and hence there is no need for calculation of derivatives. This makes them less likely to be trapped in local minima. But only two parameters of GA, the crossover and the mutation, help to avoid local minima problem. There is still some situations when the weights in GA optimization are trapped to local minima.

In recent years Bacterial Foraging Optimization (BFO) has been proposed [10] and has been applied in many fields[11]. The BFO is an useful alternative to GA and requires less number of computations. In addition BFO is also derivative free optimization technique. The number of parameters that are used for searching the total solution space are much higher in BFO compared to those in GA. Hence the possibility of avoiding the local minimum is higher in BFO. In this scheme, the foraging (methods for locating, handling and ingesting food) behaviour of E. Coli bacteria present in our intestines is mimicked.

In this paper, chemotaxis, reproduction and elimination dispersal steps of Bacterial Foraging Optimization scheme is used for updating the weights of the proposed adaptive equalizer. The same equalizer is also trained using GA to have a comparative study.

The organization of the paper is as follows :

Section II discusses an adaptive method of data recovery either from storage medium or from the received signal. The Bacterial Foraging Optimization scheme which is used to train the adaptive equalizer is discussed in Section III. In Section IV the BFO based update algorithm is developed for the equalizer. For performance evaluation, the simulation study is carried out which is dealt in Section V. Finally conclusion of the paper is outlined in Section VI.

2. Data recovery by adaptive channel equalization

Reading out of high density data from the recording medium or recovery of binary data from the noisy digital channel needs ISI compensation. This is achieved by employing an adaptive equalizer shown in Fig. 1. The transmitted symbols are represented as $x(k)$ at time instance, k. They are then passed into the channel model which may be linear or nonlinear. An FIR filter is used to model a linear channel whose output at time instant k may be written as

$$y(k) = \sum_{i=0}^{N-1} w(i)x(k-i) \tag{1}$$

where $w(i)$ are the channel tap values and N is the length of the FIR channel. The "NL" block represents the nonlinear distortion of the symbols in the channel and its output may be expressed as

$$z(k) = \psi(x(k), x(k-1), \ldots\ldots x(k-N+1);$$
$$w(0), w(1), \ldots\ldots\ldots\ldots w(N-1)), \tag{2}$$

where $\psi(.)$ is some nonlinear function generated by the "NL" block.

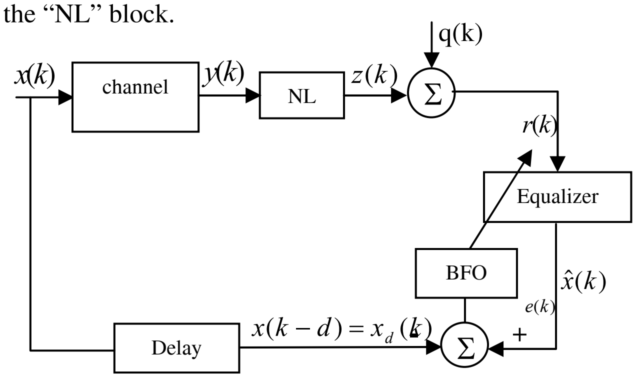


Figure 1. A Digital Communication System with BFO based adaptive channel equalizer

The channel output $z(k)$ is corrupted with additive white Gaussian noise $q(k)$ of variance σ^2. This corrupted received signal is given by $r(k)$. The received signal $r(k)$ is then passed into the digital channel equalizer to produce $\hat{x}(k)$ which recovers the transmitted symbol $x(k)$. From initial tap values (at $t = 0, w(i) = 0$), the weights are updated until the cost function, $\sum_{k=1}^{N} e^2(k)$, is minimized. Where $N =$ No. of input samples used for training and $e(k) = x_d(k) - \hat{x}(k)$. The minimization of this cost function is iteratively performed by BFO scheme which is dealt in the next section.

3. Bacterial Foraging Optimization

Bacterial Foraging is a new evolutionary computational method proposed by Passino[10]. In this scheme, the foraging (methods for locating, handling and ingesting food) behavior of E. coli bacteria present in our intestines is mimicked. They undergo different stages such as chemotaxis, swarming, reproduction and elimination and dispersal.

A. Chemotaxis

This process in the control system is achieved through swimming and tumbling via Flagella. An E. coli bacterium can move in two different ways; it can run (swim for a period of time) or it can tumble, and alternate between these two modes of operation in the entire lifetime. To represent a tumble, a unit length random direction, say $\phi(j)$, is generated; this will be used to define the direction of movement after a tumble.

In particular $\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\phi(j)$ (3)

where $\theta^i(j,k,l)$ represents the i th bacterium at j th chemotactic k th reproductive and l th elimination and dispersal step. $C(i)$ is the size of the step taken in the random direction specified by the tumble (run length unit).

B. Swarming

When a group of E. coli cells is placed in the center of a semisolid agar with a single nutrient chemo-effecter (sensor), they move out from the center in a traveling ring of cells by moving up the nutrient gradient created by consumption of the nutrient by the group. Moreover, if high levels of succinate are used as the nutrient, then the cells release the attractant aspartate so that they congregate into groups and, hence, move as concentric patterns of groups with high bacterial density.The spatial order results from outward movement of the ring and the local releases of the attractant; the cells provide an attraction signal to each other so they swarm together.

C. Reproduction

The least healthy bacteria die and the other healthier bacteria each split into two bacteria, which are placed in the same location. This makes the population of bacteria constant.

D. Elimination and Dispersal

It is possible that in the local environment, the lives of a population of bacteria changes either gradually or suddenly due to some other influence. Events can occur such that all the bacteria in a region are killed or a group is dispersed into a new part of the environment. They have the effect of possibly destroying the chemotactic progress, but they also have the effect of assisting in chemotaxis, since dispersal may place bacteria near good food sources. From a broad perspective, elimination and dispersal are parts of the population-level long-distance motile behavior. The detailed mathematical treatment of this new concept are presented in [10].

4. Bacterial Foraging Optimization based equalization : The Algorithm

In adaptive equalizers the parameters which can vary during training are weights of a 8-tap FIR filter. The objective of an adaptive algorithm is to change the filter weights iteratively so that the squared error, $e^2(k)$ is minimized and subsequently reduced to a minimum. The updating of the weights of the BFO based equalizer is carried out using the training rule as outlined in the following steps:

Step -1 Initialization of various parameters

(i) S_b = No. of bacteria to be used for searching the total region

(ii) N_{is} = Number of input sample

(iii) p = Number of parameter to be optimized

(iv) N_s = Swimming length after which tumbling of bacteria will be undertaken in a chemotactic loop.

(v) N_c = Number of iterations to be undertaken in a chemotactic loop. Always $N_c > N_s$.

(vi) N_{re} = Maximum number of reproduction to be undertaken

(vii) N_{ed} = Maximum number of elimination and dispersal events to be imposed over the bacteria.

(viii) P_{ed} = Probability with which the elimination and dispersal will continue.

(ix) The location of each bacterium P (1- p , 1- S_b , 1) is specified by random numbers on [0,1].

(x) The value of $C(i)$ (i.e. runlengthunit). It is assumed to be constant for all bacteria.

Step-2 Generate desired signal

(i) Random binary input [1,-1] is applied to the channel..

(ii) The output of the channel is contaminated with white Guassian noise of known strength to produce the input signal for the equalizer.

(iii) The binary input is delayed by half of the order of the equalizer to act as the desired signal, $x_d(k)$.

Step -3 Iterative Algorithm for optimization

This section models the bacterial population, chemotaxis, reproduction, elimination and dispersal. Initially $j = k = l = 0$

(i) Elimination dispersal loop $l = l + 1$

(ii) Reproduction loop $k = k + 1$

(iii) Chemotaxis loop $j = j + 1$

(a) For $i = 1,2,............S_b$, the cost function, (in this case mean squared error) $J(i, j, k, l)$ for each i th bacterium is calculated as follows :

(1) N_{is} number of binary input are passed through the equalizer.

(2)The output is then compared with the corresponding desired signal, $x_d(k)$ to calculate the error, $e(k)$.

(3)The sum of squared error averaged over N_{is} is finally stored in $J(i,j,k,l)$.

(4)End of For Loop.

(b)For $i = 1,2,............S_b$ the tumbling/swimming decision is taken.

Tumble : Generate a random vector $\Delta(i)$, with each element, $\Delta_m(i)$, $m = 1,2,.........p$, a random number in the range of [-1, 1].

Move: Let $P^i(j+1,k,l) = P^i(j,k,l) + C(i) \times \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$

This results in an adaptable step size in the direction of tumble for bacterium i. The cost function (mean squared error) $J(i, j+1, k, l)$ is computed.

Swim – (i) Let c =0; (counter for swim length)

(ii) While $c < N_s$ (have not climbed down too long)

Let $c = c+1$

If $J(j) < J(j-1)$ then

$P^i(j+1,k,l) = P^i(j,k,l) + C(i) \times \frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$ and the $P(j+1,k,l)$ is used to compute the new $J(i, j+1, k, l)$

ELSE let $c = N_s$. This is the end of the WHILE statement.

(c)Go to next bacterium $(i+1)$ if $i \neq S_b$ to process the next bacterium.

(d)If $\min(J)$ {minimum value of J among all the bacteria} is less than the tolerance limit then break all the loops.

Step-4. If $j < N_c$,go to (iii) i.e. continue chemotaxis loop since the life of the bacteria is not over.

Step-5 Reproduction

(a) For the given k and l, and for each $i = 1,2,.........S_b$ let J^i be the health of the i th bacterium. Sort bacteria in ascending order of cost J (higher cost means lower health).

(b) The $S_r = S_b/2$ bacteria with highest J value die and other S_r bacteria with the best value split and the copies that are made are placed at the same location as their parent.

Step-6 If $k < N_{re}$ go to 2. In this case, we have not reached the number of specified reproduction steps, so we start the next generation in the chemotactic loop.

Step-7 Elimination –Dispersal

Eliminate each bacterium which has an elimination-dispersal probability above a preset value P_{ed} is eliminated by dispersing to a random location. By this the total population is maintained constant.

5. Simulation study and discussions

In this Section we carry out the simulation study of the proposed channel equalizer. Fig. 1 is simulated for various linear and nonlinear channels using the algorithm given in Section-4. Three different channels used in the simulation study are :

$$CH1: 0.209 + 0.995z^{-1} + 0.209z^{-2}$$
$$CH2: 0.260 + 0.930z^{-1} + 0.260z^{-2}$$
$$CH3: 0.304 + 0.903z^{-1} + 0.304z^{-2} \qquad (4)$$

To study the effect of nonlinearity on the equalizer performance, nonlinear channel models with the following types of nonlinearity are used :

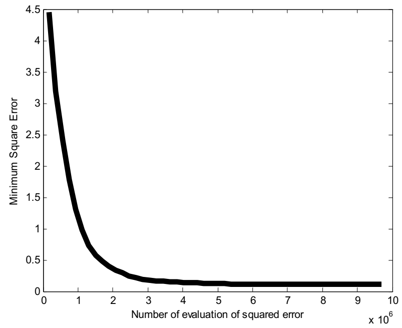
$$NL0: z(k) = y(k)$$
$$NL1: z(k) = \tanh(y(k))$$
$$NL2: z(k) = y(k) + 0.2y^2(k) - 0.1y^3(k)$$
$$Nl3: z(k) = y(k) + 0.2y^2(k) - 0.2y^3(k) + 0.5\cos(\pi y(k)) \qquad (5)$$

where $y(k)$ is the output of each of these linear channels (CH1 through CH3). The additive noise is white Gaussian with -30dB and -15dB 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 (4 in this case) of the equalizer. In this simulation work, we have considered the following parameters of BFO :

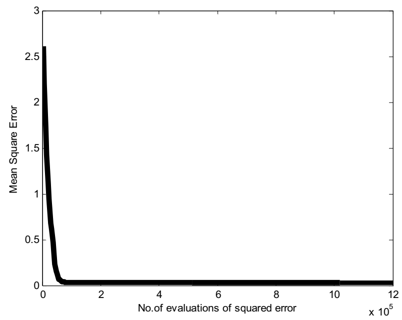
S_b = 8, N_{is} = 100, p =8, N_s=3, N_c=5, N_{re}=30, N_{ed}=10, P_{ed} = 0.25, $C(i)$ = .075

The number of evaluation of squared error to reach the minimum squared error using BFO and GA based learning are given in Figs. 2(a) and (b) respectively. Table -1 represents the variation of MSE with number of evaluations of squared error in BFO and GA based learning corresponding to -15dB additive noise. Figs. 2(a & b) and Table-1 show that the BFO algorithm requires significantly less number of evaluations of squared error (10, 400) compared to its GA counterpart (53, 85, 000) to achieve the minimum MSE level of (0.0289) in BFO in contrast to (0.1241) in GA. This results show that the BFO based equalizer shows faster convergence compared to that of its GA counter part. In addition it is observed that the BFO equalizer attains much lower MSE (0.0289) after training compared to that offered by GA equalizer. This observation is true for all linear and nonlinear channels and also for both low and high noise conditions. Thus the proposed BFO based adaptive equalizer is capable of providing more accurate reconstruction of binary signal compared to that of GA method.

The bit error (BER) plot of BFO equalizer pertaining to different nonlinear channels are also obtained through simulation and are plotted in the Figs. 3(a) to (d). These figures also reveal that the BFO based equalizer offers much superior BER performance compared to GA based equalizer.

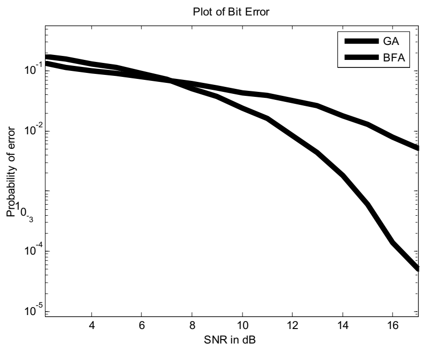


(a) GA-Equalizer

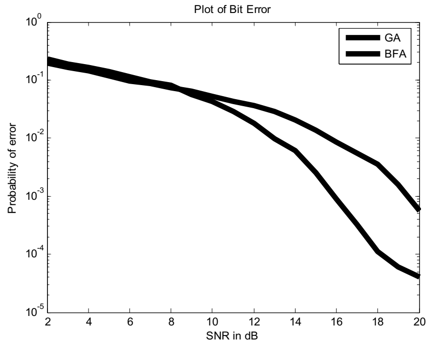


(b) BFO-Equalizer

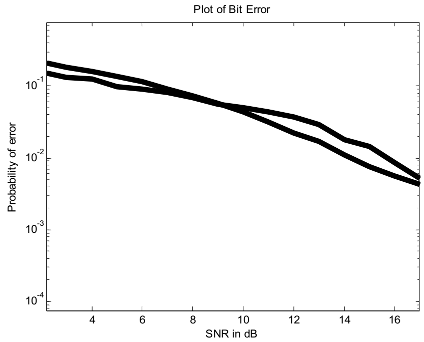
Figures 2. Variation of MSE with number of evaluations of squared errors at -15dB noise



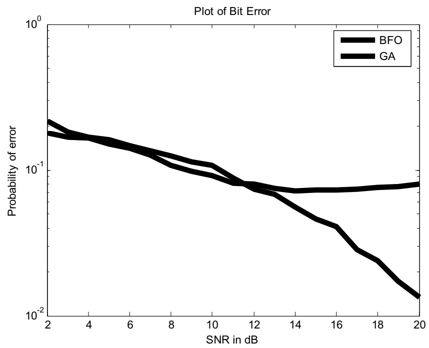
(a) NL0



(b) NL1



(c) NL2



(d) NL3

Figures 3. Comparison of bit errors of BFO and GA based linear and nonlinear equalizers using CH3

6. Conclusion

Faithful reconstruction of digital information is an important issue. The adaptive channel equalizer circumvents the ISI of the channel and aids to recover the transmitted data. To achieve this objective the present paper proposes an efficient adaptive nonlinear channel equalizer using BFO based training. The BFO is basically a derivative free optimization tool and has the potentiality to avoid local minima. Using this tool the weights of the equalizer are updated to achieve lowest possible MSE. Two distinct advantages obtainable from the proposed equalizers are

(i) less computational complexity compared to GA based equalizer.

(ii) improved BER plot which shows that the proposed equalizer yields more accurate reconstruction of transmitted data compared to its GA counter part.

Table 1. Variations of MSE with number of evaluations of squared error in GA and BFO based learning at -15db noise

No. of evaluations of squared error to converge		MMSE	
BFO	GA	BFO	GA
4000	182000	2.6071	4.4499
8000	365000	2.1956	3.1954
12000	553000	1.7259	2.3980
16000	741000	1.4258	1.7812
20000	930000	1.1201	1.3070
24000	1120000	0.9473	0.9841
28000	1310000	0.6834	0.7364
32000	1501000	0.6176	0.5766
36000	1693000	0.4716	0.4839
40000	1885000	0.3466	0.4031
44000	2078000	0.2337	0.3345
48000	2271000	0.1565	0.2908
52000	2464000	0.1290	0.2492
56000	2657000	0.0655	0.2176
60000	2850000	0.0622	0.1919
64000	3045000	0.0462	0.1739
68000	3240000	0.0380	0.1645
72000	3435000	0.0380	0.1599
76000	3630000	0.0352	0.1563
80000	3825000	0.0341	0.1505
84000	4020000	0.0328	0.1563
88000	4215000	0.0299	0.1505
92000	4410000	0.0299	0.1446
96000	460500	0.0296	0.1397
100000	4800000	0.0294	0.1352
104000	4995000	0.0289	0.1316
108000	5190000	0.0289	0.1280
112000	5385000	0.0289	0.1241

7. References

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