International Journal of Fuzzy Logic and Intelligent Systems, vol. 4, no. 3, December 2004 pp. 259-265

A New Hybrid Genetic Algorithm for Nonlinear Channel Blind Equalization

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Abstract

In this study, a hybrid genetic algorithm merged with simulated annealing is presented to solve nonlinear channel blind equalization problems. The equalization of nonlinear channels is more complicated one, but it is of more practical use in real world environments. The proposed hybrid genetic algorithm with simulated annealing is used to estimate the output states of nonlinear channel, based on the Bayesian likelihood fitness function, instead of the channel parameters. By using the desired channel states derived from these estimated output states of the nonlinear channel, the Bayesian equalizer is implemented to reconstruct transmitted symbols. In the simulations, binary signals are generated at random with Gaussian noise. The performance of the proposed method is compared with those of a conventional genetic algorithm(GA) and a simplex GA. In particular, we observe a relatively high accuracy and fast convergence of the method.

Key Words : nonlinear channel, blind equalization, genetic algorithm, simulated annealing

1. Introduction

In digital communication systems, data symbols are transmitted at regular intervals. Time dispersion caused by non-ideal channel frequency response characteristics, or by multipath transmission, may create inter-symbol interference (ISI), and it has become a limiting factor in many communication environments. Furthermore, the nonlinear ISI that often arises in high speed communication channel degrades the performance of the overall communication system[1]. To overcome the effects of nonlinear ISI and to achieve high-speed reliable communication, nonlinear channel equalization is necessary.

The conventional approach to linear or nonlinear channel equalization requires an initial training period with a known data sequence to learn the channel characteristics. In contrast to standard equalization methods, the so-called blind (or self-recovering) equalization methods operate without a training sequence[2]. Because of its superiority, the blind equalization method has gained practical interest during the last few years. Most of the studies carried out so far are focused on linear channel equalization and this is required by the simplicity of the channel[3]-[7]. Only a few papers have dealt with nonlinear channel models. The blind estimation of Volterra kernels which characterize nonlinear channel was derived in [8], and a maximum likelihood (ML) method implemented via expectation-maximization (EM) was introduced in [9]. The Volterra approach suffers from its enormous complexity. Furthermore the ML approach requires some prior knowledge of the nonlinear channel structure to estimate the channel parameters. Major progress in nonlinear channel blind equalization was made by Lin et al.[10], in which they estimated the optimal channel output states instead of direct estimation of channel parameters by using hybrid simplex GA. The desired channel states were constructed from these estimated channel output states, and placed at the center of their RBF equalizer. With this method, the complex modeling of the nonlinear channel can be avoided, and it has turned out that the nonlinear channel blind equalization problem can be transformed to the problem of determining the optimal channel output states. In [10], it was shown that the mathematical relation between the nonlinear channel output states and the Bayesian likelihood for fitness (or cost) function is too complex to be formulated or cannot be derived when the structure of the nonlinear channel is unknown. Subsequently the authors in [10] presented an optimization method on hybrid genetic algorithm (hybrid simplex GA) as a possible alternative. In our study, a new hybrid genetic algorithm(GA merged with simulated annealing(SA): GASA) to find optimal output states of a nonlinear channel is investigated. GA[11][12] and SA[13][14], each of which represents a powerful optimization method, have complementary strengths and weaknesses. While GA explores the search space by means of the population of search points, it suffers from poor convergence properties. SA, by contrast, has good convergence properties, but it cannot explore the search space by means of population. The proposed GASA is constructed to obtain the synergy effect between them, and shows a high estimation accuracy with fast convergence speed in search of the optimal channel output states. Its performance is compared with those of conventional GA and a simplex GA. In the experiments, the Bayesian equalizer is implemented to reconstruct the transmitted symbols with each

Manuscript received Aug. 20, 2004; revised Oct. 28, 2004.

of three different styles of GA algorithm.

The organization of this paper is as follows: Section 2 includes a brief introduction to the equalization of nonlinear channel and the Bayesian equalizer, and section 3 shows the relation between the desired channel states and the channel output states. In section 4, GASA with a Bayesian fitness function is introduced. The simulation results including the comparisons with the two other algorithms and the conclusions are provided in section 5 and 6 respectively.

2. Modeling for nonlinear channel equalization and Bayesian equalizer

A nonlinear channel equalization system is shown in Fig. 1.

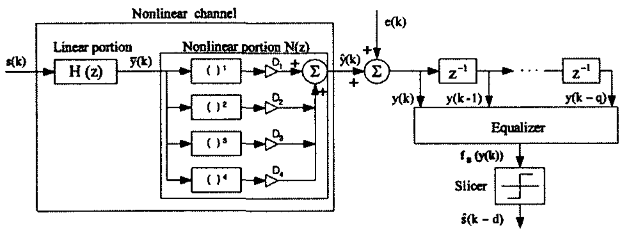

Fig.1. The structure of nonlinear channel equalization system.

A digital sequence s(k) is transmitted through the nonlinear channel, which is composed of a linear portion H(z) and nonlinear portion N(z) governed by the following expressions.

$$\bar{y}(k) = \sum_{i=0}^{p} h(i)s(k-i) \tag{1}$$

$$\tilde{y}(k) = D_1\bar{y}(k) + D_2\bar{y}(k)^2 + D_3\bar{y}(k)^3 + D_4\bar{y}(k)^4 \tag{2}$$

where p is the channel order and D_i is the coefficient of the ith nonlinear term. The transmitted symbol sequence s(k) is assumed to be an equiprobable and independent binary sequence taking values from ±1, and the channel output is corrupted by an additive white Gaussian noise e(k). Thus the channel observation y(k) can be written in the form of

$$y(k) = \tilde{y}(k) + e(k) \tag{3}$$

If q denotes the equalizer order(number of tap delay elements in the equalizer), then there exist $M = 2^{p+q+1}$ different input sequences

$$\mathbf{s}(k) = [s(k), s(k-1), \ldots, s(k-p-q)] \tag{4}$$

that may be received (where each component is either 1 or -1). For a specific channel order and equalizer order, the number of input patterns that influence the equalizer is M, and the input vector of equalizer without noise is

$$\tilde{\mathbf{y}}(k) = [\tilde{y}(k), \tilde{y}(k-1), \ldots, \tilde{y}(k-q)] \tag{5}$$

The noise-free observation vector $\tilde{\mathbf{y}}(k)$ is referred to as the desired channel states, and can be partitioned into two sets, $Y^{+1}_{q,d}$ and $Y^{-1}_{q,d}$, as shown in equations (6) and (7), depending on the value of s(k-d), where d is the desired time delay.

$$Y^{+1}_{q,d} = \tilde{\mathbf{y}}(k)|s(k-d) = +1 \tag{6}$$

$$Y^{-1}_{q,d} = \tilde{\mathbf{y}}(k)|s(k-d) = -1 \tag{7}$$

The task of the equalizer is to recover the transmitted symbols s(k-d) based on the observation vector y(k). Because of the additive white Gaussian noise, the observation vector y(k) is a random process having conditional Gaussian density functions centered at each of the desired channel states, and determining the value of s(k-d) becomes a decision problem. Therefore, the Bayes decision theory[15][16] can be applied to derive the optimal solution for the equalizer, and this optimal Bayesian equalizer solution is given by equations (8) and (9) in [17].

$$f_B(\mathbf{y}(k)) = \sum_{i=1}^{n_s^{+1}} \exp(-\| \mathbf{y}(k) - \mathbf{y}_i^{+1} \|^2 / 2\sigma_e^2) - \sum_{i=1}^{n_s^{-1}} \exp(-\| \mathbf{y}(k) - \mathbf{y}_i^{-1} \|^2 / 2\sigma_e^2) \tag{8}$$

$$\hat{s}(k-d) = \operatorname{sgn}(f_B(\mathbf{y}(k))) = \begin{cases} +1, & f_B(\mathbf{y}(k)) \geq 0 \\ -1, & f_B(\mathbf{y}(k)) < 0 \end{cases} \tag{9}$$

where $\mathbf{y}_i^{+1}$ and $\mathbf{y}_i^{-1}$ are the desired channel states belong to $Y^{+1}_{q,d}$ and $Y^{-1}_{q,d}$, respectively, and their numbers are denoted as n_s^{+1} and n_s^{-1}, and σ_e^2 is the noise variance. The desired channel states, $\mathbf{y}_i^{+1}$ and $\mathbf{y}_i^{-1}$, are derived by using their relationship with the channel output states, which will be explained in the next section. In our study, the optimal Bayesian decision probability shown in equation (8) is used to construct the fitness function of the proposed GASA algorithm in section 4, and it is also utilized as an equalizer along with equation (9) for the reconstruction of the transmitted symbols.

3. Relation between desired channel states and channel output states

The desired channel states, $\mathbf{y}_i^{+1}$ and $\mathbf{y}_i^{-1}$, must be known for the Bayesian equalizer in equations (8) and (9) to reconstruct the transmitted symbols. If the channel order p=1 with H(z) by equation (10), the equalizer order q=1, the time delay d=1, and the nonlinear portion $D_1 = 1$, $D_2 = 0.1$, $D_3 = 0.05$, $D_4 = 0.0$ in Fig. 1, then the eight different channel states($2^{p+q+1} = 8$) may be observed at the receiver in the noise-free case, and the output of the equalizer should be $\hat{s}(k-1)$ as shown in Table 1.

$$H(z) = 0.5 + 1.0z^{-1} \tag{10}$$

From Table 1, it can be seen that the desired channel states $[\tilde{y}(k), \tilde{y}(k-1)]$ can be constructed from the elements of the dataset, called "channel output states", a_1, a_2, a_3, a_4, where $a_1 = 1.89375$, $a_2 = -0.48125$, $a_3 = 0.53125$,

$a_4 = -1.44375$. The length of dataset, $\tilde{n}$, is determined by the channel order, p, such as $2^{p+1}=4$. In general, if q=1 and d=1, the desired channel states for $Y^{+1}_{1,1}$ and $Y^{-1}_{1,1}$ are (a_1, a_1), (a_1, a_2), (a_3, a_1), (a_3, a_2), and (a_2, a_3), (a_2, a_4), (a_4, a_3), (a_4, a_4), respectively. In the case of d=0, the channel states, (a_1, a_1), (a_1, a_2), (a_2, a_3), (a_2, a_4), belong to $Y^{+1}_{1,1}$, and (a_3, a_1), (a_3, a_2), (a_4, a_3), (a_4, a_4) belong to $Y^{-1}_{1,1}$. This relation is valid for the channel that has a one-to-one mapping between the channel inputs and outputs[10]. Thus the desired channel states can be derived from the channel output states if we assume p is known, and the main problem of blind equalization can be changed to focus on finding the optimal channel output states from the received patterns.

Table 1. The relation between desired channel states and channel output states.

Nonlinear channel with $H(z)=0.5+1.0z^{-1}$, $D_1=1$, $D_2=0.1$, $D_3=0.05$, $D_4=0.0$ and $d=1$						
Transmitted symbols			Desired channel states			Output of equalizer
$s(k)s(k-1)s(k-2)$			$\hat{y}(k)$	$\hat{y}(k-1)$	By channel output states a_1, a_2, a_3, a_4	$\hat{s}(k-1)$
1	1	1	1.89375	1.89375	(a_1, a_1)	1
1	1	-1	1.89375	-0.48125	(a_1, a_2)	1
-1	1	1	0.53125	1.89375	(a_3, a_1)	1
-1	1	-1	0.53125	-0.48125	(a_3, a_2)	1
1	-1	1	-0.48125	0.53125	(a_2, a_3)	-1
1	-1	-1	-0.48125	-1.44375	(a_2, a_4)	-1
-1	-1	1	-1.44375	0.53125	(a_4, a_3)	-1
-1	-1	-1	-1.44375	-1.44375	(a_4, a_4)	-1

It is known that the Bayesian likelihood(BL) defined in equation (11) is maximized with the channel states derived from the optimal channel output states[10][17][18]. Therefore, it is utilized as the fitness function(FF) of the proposed algorithm to find optimal channel output states after taking the logarithm, which is shown in equation (12).

$$BL = \prod_{k=0}^{L-1} \max(f_B^{+1}(k), f_B^{-1}(k)) \qquad (11)$$

where

$f_B^{+1}(k) = \sum_{i=1}^{n_s^{+1}} \exp(-\mid y(k) - y_i^{+1} \mid^2 / 2\sigma_e^2)$,

$f_B^{-1}(k) = \sum_{i=1}^{n_s^{-1}} \exp(-\mid y(k) - y_i^{-1} \mid^2 / 2\sigma_e^2)$ and L is the length of received sequences.

$$FF = \sum_{k=0}^{L-1} \log(\max(f_B^{+1}(k), f_B^{-1}(k))) \qquad (12)$$

The optimal channel output states which maximize the fitness function FF can not be obtained with the conventional gradient methods, because the mathematical formulation between the channel output states and FF cannot be accomplished without knowing the channel structure. These are shown in [10]. Thus, genetic algorithm(GA) and simulated annealing(SA), each of which has shown the successful performance in complex high dimensional optimal problems, are considered in order to find the optimal solution of equation (12). They have complementary strengths and weaknesses, which are explained in the next section. Therefore, in our approach, a new hybrid genetic algorithm that combines the recombinative power of GA and the local selection of SA to get the synergy effect between them, called GASA, is applied to search for the optimal output states, and is compared with conventional GA and the simplex GA introduced in [10].

4. Algorithm for GASA to find optimal channel output states

The basic idea of SA comes from the physical annealing process done on metals and other substances. In metallurgical annealing, a metal body is heated to near its melting point and then slowly cooled back down to room temperature. This process will cause the global energy function of the metal to reach an absolute minimum value eventually. If the temperature is dropped too quickly, the energy of the metallic lattice will be much higher than this minimum because of the existence of frozen lattice dislocations that would otherwise eventually disappear because of thermal agitation. Analogous to this physical behavior, SA allows a system to change its state to a higher energy state occasionally so that it has a chance to jump out of local minima and seek the global minimum. The function to be minimized, i.e., the performance index, is analogous to the energy of the metal, and the control parameter, called temperature, is analogous to the temperature of metal. Downhill moves are always accepted, whereas uphill moves are accepted with an acceptance probability that is a function of temperature. Its mathematical representation and detail optimization mechanism are given in [13] and [14]. In our particular application. the typical selection of SA is reversed to have its fitness function maximized, which means uphill moves are always accepted, whereas downhill moves are accepted depending on the acceptance probability.

Another powerful optimization algorithm, GA, is a search algorithm based on an analogy with the process of natural selection and evolutionary genetics. It combines the survival of the fittest among string structures with a structured yet randomized information exchange to form a search algorithm with some of the innovative flair of a human search. It is guided largely by the machinations of three operators: selection, crossover, and mutation. In every generation, a new set of artificial creatures is created using bits and pieces of the old; an occasional new part is tried for good measure. More details of the conventional GA algorithm can be found in [11] and [12].

GA and SA have complementary strengths and weaknesses. While GA explores the search space by means of the population of search points, it suffers from poor convergence properties. SA, by contrast, has good convergence properties, but it cannot explore the search space by means of population. However, SA does employ a completely local selection strategy where the current candidate and the new modification are evaluated and compared. To get the synergy effect between GA and SA, many literatures have been considered as the combination of each other and other optimization algorithms [19]-[21]. Therefore, in this study, a new hybrid genetic algorithm, which combines GA with SA to improve the performance of GA, is investigated and applied to find the optimal channel output states for nonlinear channel blind equalization. The proposed GASA algorithm has the following pseudo-code. In the proposed GASA, the Bayesian likelihood shown in equation (12) is utilized as the fitness function, and thus GASA searches the channel output states which maximize the Bayesian likelihood.

Step 1: Initialize population at random.
Step 2: Random generate the initial temperatures T[i] in a specified region, where i is an index of individual.
Step 3: Calculate the fitness function shown in eq. (12) for the initial population.
Step 4: Save the current population as parents.
Step 5: Apply crossover and mutation operators to current population in order to get offsprings.
Step 6: Find the best-fit individual among parents, offsprings, and current best solution, and then update best solution.
Step 7: Apply the selection function to all individuals as:ith-individual = SA-selection(SA-selection(offspring[i], parent[i], T[i]), best solution, T[i])
Step 8: Update the fitness of ith-individual
*Step 9: T[i]=T[i]*cooling rate*
Step 10: When the criterion is satisfied stop the algorithm. Otherwise, go to Step 4.

In this pseudo-code, the selection of SA shown in "*SA-selection(SA-selection(offspring[i], parent[i], T[i]), best solution, T[i])*" had been modified to have its fitness function maximized as mentioned before. For example, the function "*SA-selection(new, old, T)*" calculates the acceptance probability "*P=exp(-(old-new)/T)*". If "*new>old*", a "*new*" solution is selected, which means that an uphill move is always accepted. And also, if "*new≤old*" and "*P>random number in [0, 1]*", a "*new*" solution will be selected, which means that a downhill move is occasionally accepted depending on P. An "*old*" solution will be selected for all other cases. This selection of SA allows a downhill move(same as uphill move in typical SA which minimizes the fitness function) to explore the search space at higher temperatures, and to exploit the search space accepting the best solution's individual at lower temperatures. Thus in our algorithm, the GA-selection is effectively replaced with an SA-selection without increasing the number of fitness evaluations per generation. This means that the population stores a diversity of annealing schedules, and the proposed GASA can reach the optimum global solution with a relatively high speed even when it is trapped in local solution. Additionally, it is not necessary to tune the initial temperature, which should be done by a trial and error process in traditional SA, because in GASA, it is set randomly for the purpose of simplicity.

5. Experimental results and performance assessments

The blind equalizations with GA, simplex GA, and GASA are taken into account to show the effectiveness of the proposed hybrid algorithm. Three nonlinear channels in [10] and [22] are evaluated in the simulations. Channel 1 is shown in Table 1, and the other two channels are as follows.

Channel 2: $H(z)=0.5+1.0z^{-1}$, $D_1=1$, $D_2=0.1$, $D_3=-0.2$, $D_4=0.0$ and $d=1$
Channel 3: $H(z)=0.5+1.0z^{-1}$, $D_1=1$, $D_2=0.0$, $D_3=-0.9$, $D_4=0.0$ and $d=1$

The parameters of the optimization environments for each of the algorithms are included in Table 2, and these are fixed for all experiments. The choice of these specific parameter values is not critical in the performance of the proposed GASA. It is shown that the same quantities of population size, crossover rate, and mutation rate are used for the performance comparisons. For genetic optimization, a standard form of GA with real number encoding is used, and the same structures of chromosome (channel output states, a_1, a_2, a_3, a_4, coded as chromosome) and fitness function (defined by equation (12)) are utilized for all of three algorithms.

Table 2. Parameters of the optimization environments.

GA	Population size	50
	Maximum number of generation	100
	Crossover rate	0.8
	Mutation rate	0.1
Simplex GA	Population size	50
	Maximum number of generation	100
	Crossover rate	0.8
	Mutation rate	0.1
	Elitist number	4
	Ω in the concurrent simplex method	4
GASA	Population size	50
	Maximum number of generation	100
	Crossover rate	0.8
	Mutation rate	0.1
	Random initial temperature	[0, 1]
	Cooling rate	0.99

In our experiments, 10 independent simulations for each of three channels with five different noisy levels (SNR=5,10,15,20 and 25db) are performed with 1000 randomly generated transmitted symbols, and the results are averaged. The three algorithms, GA, simplex GA and proposed GASA, have been implemented in a batch way in order to obtain an accurate comparison among them. The averaged fitness functions in successive generations with 25db are shown in Figs. 2-4 for each of the three channels. It is observed that the proposed GASA converges with the highest speed because of its diversity of annealing schedules as mentioned in the previous section. Fig. 5 shows the averaged convergence speed (generation no.) for simplex GA and GASA to reach within a 10% difference of the fitness function driven by optimal channel output states (conventional GA does not reach within 100 generations).

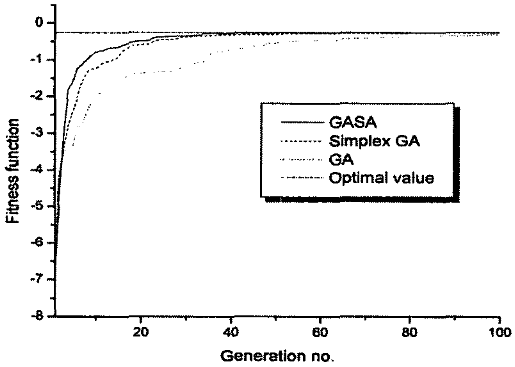

Fig. 2. Averaged fitness functions in successive 100 generations for channel 1.

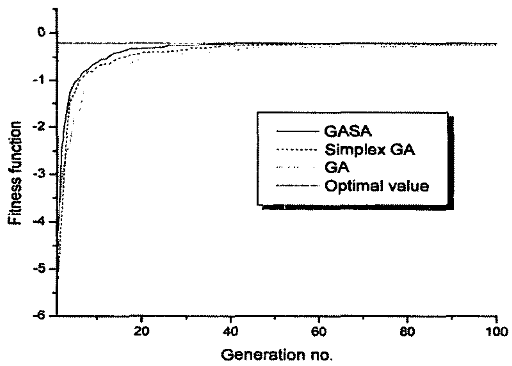

Fig. 3. Averaged fitness functions in successive 100 generations for channel 2.

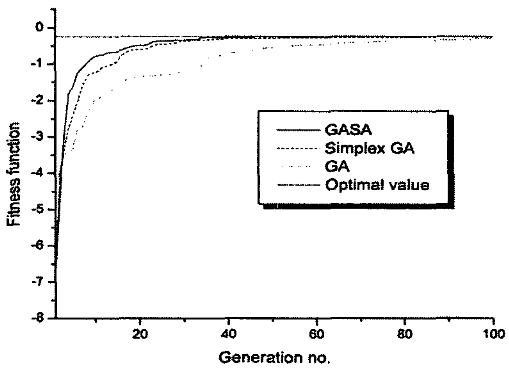

Fig. 4. Averaged fitness functions in successive 100 generations for channel 3.

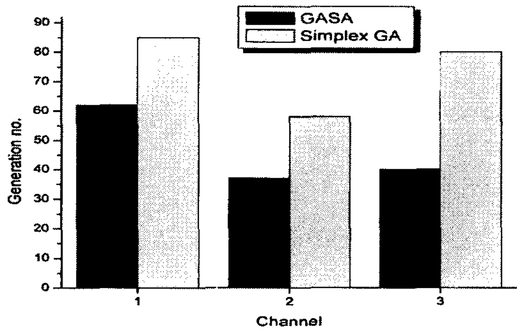

Fig. 5. Averaged generation no. to reach within a 10% difference of optimal fitness function.

We also measure the normalized root mean squared errors (NRMSE) for the estimation of channel output states, defined by equation (10), and they are shown in Figs. 6-8. GASA presents the lowest NRMSE over all of the SNR ranges, and it means that the proposed hybrid genetic algorithm is a very effective way to find optimal output states for nonlinear channel blind equalization. A sample of 1000 received symbols under 5db SNR for channel 1 and their desired channel states constructed from the estimated channel output states by GASA is shown in Fig. 9.

$$NRMSE=\frac{1}{|\boldsymbol{a}|}\sqrt{\frac{1}{m}\sum_{i=1}^{m}|\boldsymbol{a}-\hat{\boldsymbol{a}}_i|^2} \qquad (10)$$

where $\boldsymbol{a}$ is the dataset of optimal channel output states, $\hat{\boldsymbol{a}}_i$ is the dataset of estimated channel output states, and m is the number of simulations performed(m=10). Finally, the bit error rates (BER) are checked by a conventional Bayesian equalizer as mentioned in section 2, with the desired channel states constructed from the estimated channel output states. They are summarized in Table 3. It is shown that the BER with the estimated channel output states by GASA is almost same as the one with the optimal output states for all of three channels.

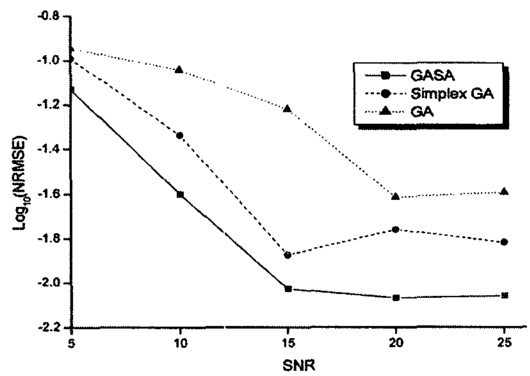

Fig. 6. NRMSE for channel 1.

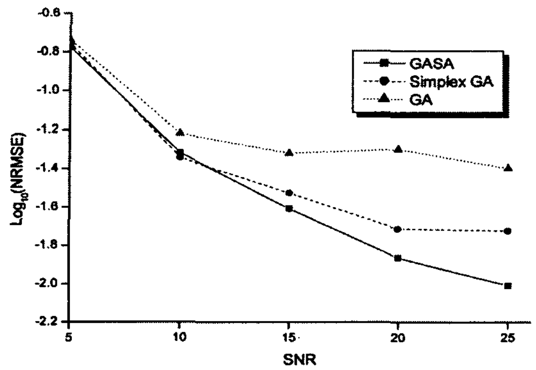

Fig. 7. NRMSE for channel 2.

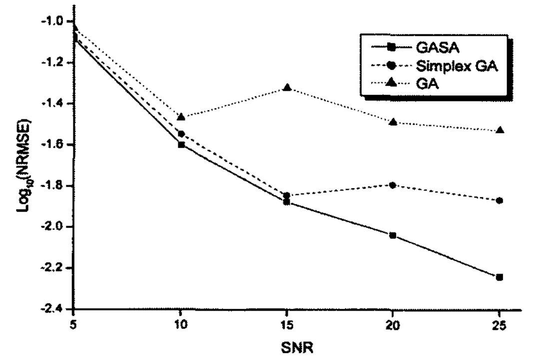

Fig. 8. NRMSE for channel 3.

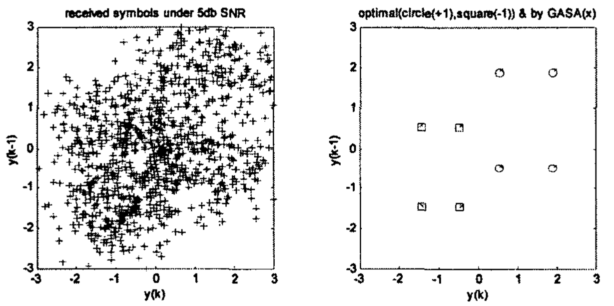

Fig. 9. A sample of received symbols for channel 1 and their desired channel states by GASA.

Table 3. Averaged BER(no. of errors/no. of transmitted symbols) for channel 1 to 3.

SNR	Estimation	with optimal state	GASA	Simplex GA	GA
Channel 1	5 db	0.0797	0.0815	0.0824	0.0816
	10 db	0.0120	0.0120	0.0128	0.0136
	15 db	0	0	0	0.0003
	20 db	0	0	0	0
	25 db	0	0	0	0
Channel 2	5 db	0.1515	0.1529	0.1557	0.1561
	10 db	0.0480	0.0484	0.0484	0.0490
	15 db	0.0032	0.0034	0.0034	0.0039
	20 db	0	0	0	0
	25 db	0	0	0	0
Channel 3	5 db	0.1091	0.1095	0.1109	0.1113
	10 db	0.0284	0.0283	0.0283	0.0288
	15 db	0.0008	0.0008	0.0008	0.0008
	20 db	0	0	0	0
	25 db	0	0	0	0

6. Conclusion

In this paper, a new genetic algorithm merged with SA (GASA) is presented for nonlinear channel blind equalization. The complex modeling of an unknown nonlinear channel becomes unnecessary by constructing the desired channel states directly from the estimated channel output states. The proposed GASA with the Bayesian likelihood as the fitness function successively estimates the channel output states with relatively high speed and accuracy. Its superiority to conventional GA and hybrid simplex GA makes the implementation of a nonlinear channel Bayesian equalizer based on GASA feasible. For further research, more complex optimization environments such as those with high dimensional channels and equalizer orders should be considered.

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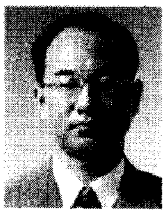

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