International Journal of Fuzzy Logic and Intelligent Systems, vol. 4, no. 3, December 2004 pp. 283-287

An Efficient Low Complexity Blind Equalization Using Micro-Genetic Algorithm

Sung-Soo Kim, Jee-Hye Kang

School of Electrical and Computer Engineering Chungbuk National University, Cheongju Chungbuk, Republic of Korea

Abstract

In this paper, a method of designing the efficient batch blind equalization with low complexity using a micro genetic algorithm (GA), is presented. In general, the blind equalization techniques that are focused on the complexity reduction might be carried out with minor effect on the performance. Among the advanced various subjects in the field of GAs, a micro genetic algorithm is employed to identify the unknown channel impulse response in order to reduce the search space effectively. A new cost function with respect to the constant modulus criterion is suggested considering its relation to the Wiener criterion. We provide simulation results to show the superiority of the proposed techniques compared to other existing techniques.

Key Words : Blind equalization, Micro Genetic Algorithm, Constant Modulus Criterion, Wiener criterion.

1. Introduction

In order to develop faster and more reliable communication systems, many efforts are required for the efficient digital communication techniques[1]. Especially, intersymbol interference (ISI) is usually the primary impairment in high-speed digital communication systems. There are different techniques for combating ISI. Linear equalization, employed at the receiver, is performed by using a simple transversal filter. The advantage of linear equalization is that a transversal filter has low computational complexity. However, when the channel contains nulls, linear equalization may become inadequate as a compensator for the ISI encountered. One of the most powerful techniques of nonlinear equalization methods is the maximum likelihood sequence estimation (MLSE) [1], which has been shown to be the optimum method for the detection of data in the presence of ISI and additive white Gaussian noise provided that the channel impulse response (CIR) is known or can be precisely estimated. Despite its high performance, the practical implementation of MLSE is limited by the enormous computational complexity as well as is required essentially channel parameters.

These classical equalization techniques employ a time-slot during which a training signal, which is known in advance by the receiver, is transmitted to estimate the channel impulse response. Since the inclusion of such signals sacrifices valuable channel capacity, the adaptation without resort to training, the blind adaptation, is preferred. Blind equalization improves systems bandwidth efficiency by avoiding the use of a training sequence. Furthermore, for multi-point communication systems, training is infeasible and blind equalizer provides a practical means for combating the detrimental effects of channel intersymbol interference. Recently, blind equalization techniques have been studied very richly [3]-[6] where the performance and the complexity are known to be important parameters at the blind equalization.

An efficient model for stochastic signal processing is not easy to obtain and is often accomplished with the aid of an optimization scheme [7]. One of the powerful optimization methods is the genetic algorithm (GA)[8]. GA has the properties related to signal processing and a number of applications that are being successfully implemented. The micro-Genetic Algorithm (μGA) has small size of population, in contrast to the more classical genetic algorithm, which requires a large amount of computational time. By using this simple characteristics of the μGA, new effective blind equalization method is proposed.

The paper is divided as follows. Section 2 overviews the conventional adaptive equalization methods including the blind adaptation techniques, and an efficient version of GA known as the micro-genetic algorithm is summarized briefly also. In Section 3, we propose the effective channel identification method with complexity reduction scheme based on the use of μGA. Then Section 4 shows the superiority of the proposed method through several experimental results and discusses these simulation analysis comparing with conventional blind equalization techniques. Finally, Section 5 states the conclusion and final remarks.

2. Preliminaries

2.1 System Description

We consider a common baseband communication system model as shown Fig. 1.

Manuscript received Aug. 22, 2004; revised Oct. 25, 2004.

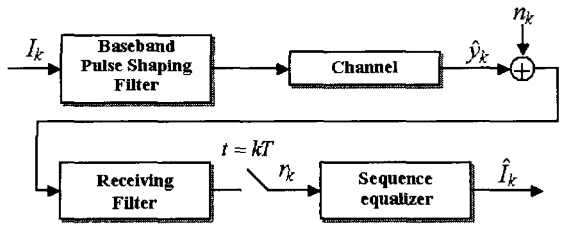


Fig. 1 A common baseband communication model.

The channel is modeled as a baseband time-dispersive channel with the finite impulse response h_i spanned over L consecutive transmitted symbol, which is assumed to be unknown and slowly time-variant. The equivalent low-pass kth received observation r_k is sampled at a rate $1/T$ samples/sec, as shown in Fig. 1. Several different types of digital modulation schemes have the common form,

$$r_k = \sum_{i=0}^{L-1} I_{k-i} h_i^* + n_k = \boldsymbol{h}^H \boldsymbol{I}_k + n_k \qquad (1)$$

where $\boldsymbol{I}_k$ represents the kth discrete information-bearing sequence of symbols which is independent and identically distributed (i.i.d), the n_k is the additive white noise. In the form of matrix, $\boldsymbol{h} = [h_0, h_1, \ldots, h_{L-1}]$ is the vector of the L taps of the channel impulse response. The superscripts T, H and * denote transposition, Hermitian and conjugation respectively.

The main question is how to adjust the equalizer in order to obtain the best estimates $\hat{I}_k$. In the next section, this subject will be considered in detail.

2.2 Adaptive Blind Channel Equalization

As the data rate increases, the communication channel particularly wireless mobile environment brings more distortion. To keep acceptable levels of distortion, one may use an equalizer, a countermeasure device that filters the received signal, in order to recover the desired information.

If it is impossible to count on the priori knowledge of the channel impulse response, a suitable optimization criterion must be employed for equalization. Very recently, a new equalization-based blind identification method suggested in [6]. This method uses the relation between the Winer criterion and the Constant modulus (CM) criterion. CM criterion is the blind or non-supervised criteria to employ the equalizer. the authors obtained a channel estimate by using the convolution commutative property[6]. They used a long length equalizer that is a conventional proper blind adaptive search method to obtain best channel information. However, when the system is time-varying, this method has some problems. There exists the offline Whiner analysis to derive the best equalizer and the search to obtain the long-length equalizer weights using the genetic algorithm. The GA has the disadvantage of slow convergence, which may prevent its use in some communication systems that are characterized by fast time-varying channels. Hence, many procedures and times are required in the system with GA's.

In this paper, in order to reduce the complexity and convergence, a new method to reduce time during the blind search is proposed by using the micro-genetic algorithm.

2.3 Micro-Genetic Algorithm(μGA)

Genetic algorithm searches the solution space of a function through the use of simulated evolution, i.e., the survival of the fittest strategy. In general, the fittest individuals of any population tend to reproduce and survive to the next generation improving successive generations. However, inferior individuals can, by chance, survive and also be reproduced. Genetic algorithm has been shown the capability of solving the linear and nonlinear problems by exploring all regions of the state space and exponentially exploiting promising areas through mutation, crossover, and selection operations applied to individuals in the population [8].

In general, the macro-genetic algorithm (μGA) is considered as an advanced evolutionary computing technique to solve an optimization problem. Also, μGA is called a small population genetic algorithm. In contrast to the classical genetic algorithm, which requires a large number of individuals in each population, the μGA uses a μ-population of five individuals. This is the very convenient property for systems, but it require a large amount of computational time. This feature significantly reduces the amount of elapses that is required to achieve the best-fit solution. Thus, we used a simple μGA optimization technique to estimate the unknown channel.

GA works with the population of individuals, each of which represents a candidate solution to a given optimization problem. Just as organisms in nature compete for resources, the population's individuals are assigned a fitness based on a defined objective, or merit, junction. Individuals with higher fitness prove to be more effective having the higher probability of survival and reproduction. A simple GA usually consists of three operations, namely, selection, crossover, and mutation, at each cycle.

In summary, the μGA optimization is performed as follows: 1) A μ-population of five chromosome is generated randomly. 2) The fitness of each chromosome is determined and the fittest individual is carried to the next generation. This is called the elitist strategy. 3) The parents of the remaining four individuals are determined using a tournament selection strategy. In this strategy, designs are paired randomly and adjacent pairs compete to become the parents of the remaining four individuals in the following generation. 4) Convergence of the μ-population is checked. If the population converges, we go to step 1, keeping the best individual and generating the other four randomly. If the population has not converged, we go to step 2.

After the search converges in a μGA, the population is re-initialized with random values, whereas the best individual found up to that point is automatically copied to the newly generated population. A population size of five was suggested in [8] for the μGA. Generally speaking, however, the more complex the search space is, the larger the population size should be. An appropriate population size also depends on the application problem. In our case, the population size Np is given by $Np=5\times q$, where q is the equalizer taps. This is still considerably smaller than a typical population size used by standard GA's. In our μGA implementation, the crossover rate is set to 1.0 to facilitate a high rate of information exchange, whereas the mutation rate is set to 0.0 (no mutation) as the re-initialization of the population will keep the diversity of potential solutions fairly well. Due to the small population size of μGA, the convergence rate is very fast, and the tournament selection is used in choosing parents for reproduction. Fig. 2 represents the procedure of μGA as mentioned above.

3. Proposed New Method for Blind Identification

In this paper, new method with low complexity in order to identify the unknown channel impulse response is proposed. In the stage of searching the channel parameters, micro-genetic algorithm (μGA), which is mentioned in section 2, is used. The μGA to be presented here works in the following way: a population is used the floating encoding scheme [8] and goes through the multiple cross over points in the crossover operation. The number of crossover points in our case is equal to the number of the parameters.

The fitness function in the genetic algorithm is very important to reach the global solution. It is the best to find out the proper fitness function according to its applications. For adaptive blind identification, several stochastic-gradient algorithm such as the constant- modulus algorithm (CMA), the reduced-constellation algorithm (RCA), and the multi-modulus algorithm (MMA) are considered [4]. Our application is adopted the constant-modulus (CM) criterion,

$$J_{GA}=\frac{1}{1+J_{CM}} \tag{2}$$

where, $J_{CM}=E\left(\,|r_k|^2-\frac{E(|I_k|^4)}{E(|I_k|^2)}\right)$.

It is possible that the re-initialization of the population may sample the same regions of the search space as the previous population does. Convergence properties of the proposed μGA scheme are extremely difficult to analyze due to the complexity of the underlying optimization problem. Since GA's are global optimization techniques, the method proposed in this paper is likely to find a global optimal solution that is more effective than the conventional methods.

4. Experimental Results and Analysis

In order to evaluate the performance of the proposed new blind channel equalization, we have conducted computer simulations under different channel and SNR conditions. Computer simulations are conducted to test the proposed μGA scheme using three non-minimum phase channels in order to compare with the classical blind techniques. The impulse response of these three channels is given by Fig. 3

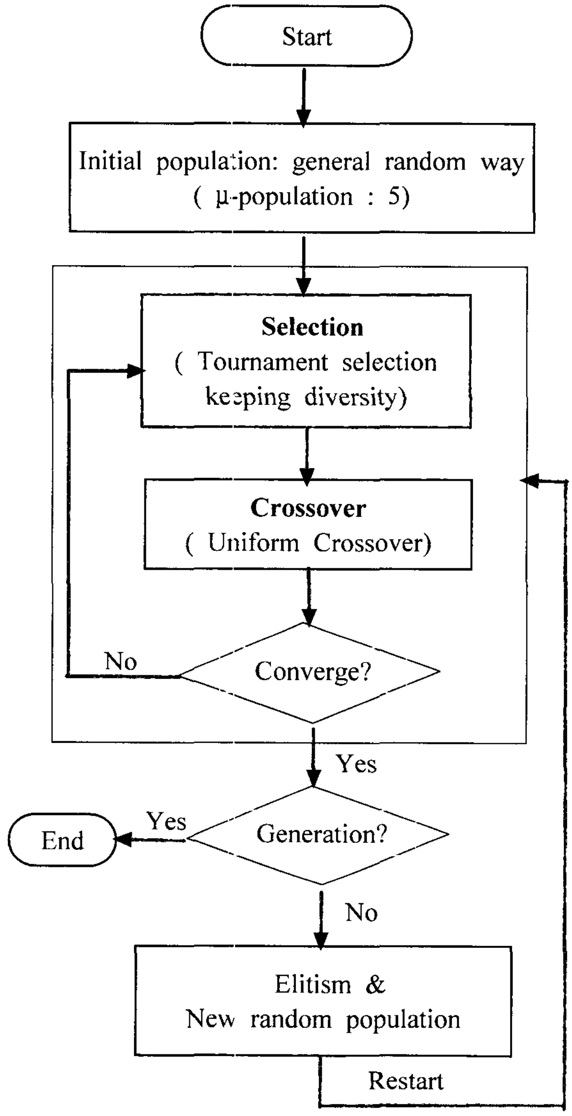


Fig.2 Procedure of Micro-genetic algorithm (μGA)

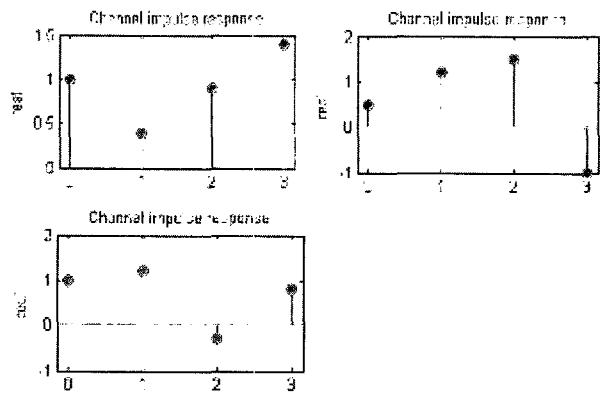


Fig. 3 channel impulse response in experiments channel 1, channel 2 and channel 3, respectively.

We adopted BPSK and QPSK signaling to modulate digital informations. In this paper, the latter case results are considered. For the simulation, the µGA parameters set as following below:

Population Size : 5,
Selection : Elitist.
Crossover : Uniform crossover with rate 1.0,
Mutation rate : 0.0,
Max terminated generation : 2000.

In practice, the performance of the algorithm can only be observed through the best estimated mean square error (MSE) defined by

$$\mathrm{MSE} = \frac{1}{N}\sum_{k=1}^{N}\left(r_k - \sum_{i=0}^{L-1}\widetilde{h}_i\widetilde{I_{k-i}}\right)^2 \tag{3}$$

where $\hat{\boldsymbol{h}}_{best} = [\,\widetilde{h}_0\ \widetilde{h}_1 \ldots \widetilde{h_{L-1}}]$ is the best channel model in the population. In simulation, the performance of the algorithm can also assessed by the mean tap error (MTE)

$$\mathrm{MTE} = \|\hat{\boldsymbol{h}}_{best} - \boldsymbol{h}\|^2 \tag{4}$$

Table 1. and Table 2. show the performance results by the classical blind equalization techniques and by the proposed new method using µGA optimization.

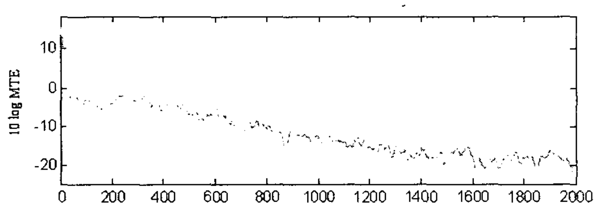
Table 1. Performance comparison w.r.t Average MSE

MSE	Channe 1	Channel 2	Channel 3
CMA	4.38×10-2	1.14×10-2	3.57×10-3
RCA	3.69×10-2	0.56×10-2	2.41×10-3
MMA	1.35×10-2	0.72×10-2	2.16×10-3
Proposed	1.07×10-4	1.28×10-5	1.03×10-6

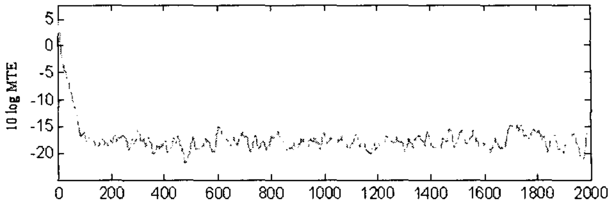
Table 2. Performance comparison w.r.t Average MTE

MTE	Channe 1	Channel 2	Channel 3
CMA	0.082	0.052	0.039
RCA	0.065	0.042	0.028
MMA	0.055	0.047	0.025
Proposed	0.005	0.003	0.002

Fig 4 represents the performance of channel 1 and channel 2 corresponding to generation numbers (termination number: 2000) using the proposed method. The new method ensures the fast convergence and the good performance.



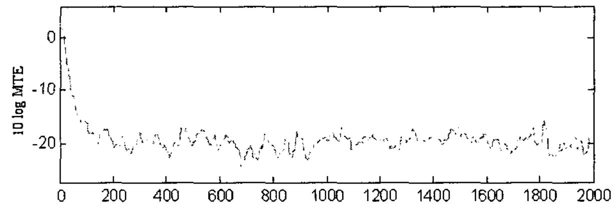
(a) channel 1



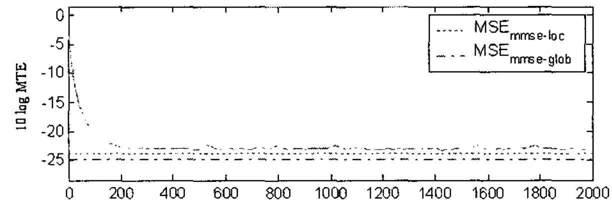
(b) channel 2

Fig. 4 Performance of proposed method w.r.t 10logMTE of channel 1 and channel 2.

Fig. 5 shows the performance according to the generation number and the comparison betwen the global and the local solutions. The optimization result of channel 3 is very close to optimum solution.



(a) channel 3



(b) Smoothed MSE of channel 3 compared with both the global and the local solutions

Fig. 5 Performance of the proposed method w.r.t 10logMTE of channel 3

By using results of the proposed blind channel identification, the performance of adaptive equalizer is presented in Fig. 6. This performance is applied to channel 2.

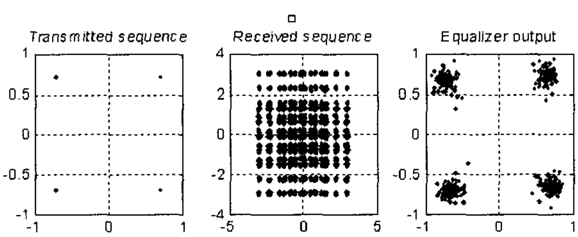


Fig.6 The results of the proposed method of channel 2

5. Conclusions

Intersymbol interference is considered as a primary impediment to reliable high-speed communications. In order to mitigate this distortion, many equalization techniques have been developed. Especially, blind optimization algorithm has been used to estimate the unknown channel impulse response in time-varying channels. However, its use is practically limited to the slow varying channels and has the high complexity that increases with the length of channel memory.

Throughout this paper, we have presented a technique to reduce the complexity of blind channel identification while preserving its performance by using a micro-genetic algorithm. A considerable complexity reduction is achieved comparing with the classical blind equalization methods. The improvement of performance is achieved according to adopt proper fitness function in μGA. Finally, we have demonstrated the superior performance achieved by the proposed method through simulations under various channel conditions.

Reference

[1] J. G. Proakis, *Digital Communications*. McGraw-Hill, Singapore, third edition, 1999.

[2] G. D. Forney "Maximum-likelihood sequence estimation of digital sequence in the presence of intersymbol interference,", *IEEE Trans. Inform. Theory*, vol. IT-18, no. 3, pp. 363-378, May, 1972.

[3] D.N. Godard, "Self-recovering Equalization and Carrier Tracking in Two-dimensional Data Communication Systems", *IEEE Trans. on Comm.*, Vol. COMM-28, No. 11, pp. 1867-1875, 1980.

[4] C.R. Johnson, P. Schniter, T.J. Endres, et al,, "Blind Equalization using the Constant Modulus Criterion: a Review", *Proc. of the IEEE*, Vol. 86, No. 10, pp. 1927-1950, 1998.

[5] Y. Li and Z. Ding, "Convergence analysis of finite length blind adaptive equalizers", *IEEE Trans. Signal Processing*, vol. 43, pp. 2120-2129, Sept. 1995.

[6] A. M. Costa, Romis Ribeiro de Faissol Attux, "A New Method for Blind Channel Identification with Genetic Algorithms", *ITS 2002*, Natal, Brazil.

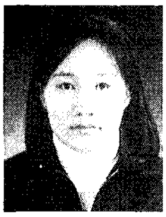
[7] J. H. Holland, *Adaptation in Natural and Artificial Systmes*, Univ. of Michigan Press, 1975.

[8] K. S. Tang, K. F. MAn and Q. He, "Genetic algorithms and their applications", *IEEE Signal Processing Magazine*, vol. 13, no. 6, pp. 22-37, 1996.

김성수(Kim Sung Soo)

1983.2 : 충북대 전기공학과(B.S).
1989.2 : University of Arkansas-Payetteville(M.S)
1997.12 : University of Central Florida (Ph.D)
1998.2~1999.3 : 시스템 공학연구소/전자통신연구원
1999.3~2001.8 우석대학교 전기공학과 조교수.
2001.9~현재 충북대학교 전기공학과 부교수.

관심분야 : 퍼지 이론, 신경회로망, 인공지능
Phone : 261-2421
E-mail : sungkim@chungbuk.ac.kr



강지혜(Kang Jee Hye)

2003년 : 충북대 전기전자컴퓨터공학부과 졸업.
2003년~현재 : 동 대학원 전기학과 석사과정

관심분야 : 신경회로망, 인공지능, 신호 처리
Phone : 011-9407-157
E-mail : k23511181@hotmail.com