Genetic-Algorithm Based Optimization for Partial Response Data Equalization Used in Advanced Recording Channels

M ABUITBEL and D KING
The Manchester School of Engineering,
University of Manchester
IT Building, Room IT 109,
Oxford Road,
Manchester M13 9PL,
UNITED KINGDOM

***Abstract*:** In this paper, an efficient and robust equalization scheme based on genetic-algorithm (GA) is developed in MATLAB simulation environment. This is to optimize the coefficients of the transfer function of the partial response equalizer, which will force the replayed signal to follow a specified target for high-density storage applications. Increasing data-density leads to substantial problems with increased inter-symbol interference (ISI) and decreased signal-to-noise ratio (SNR) that limits the capability of the signal detection scheme. Also packing more data into the storage media causes a significant reduction in the available signal energy and distortion in the recovered signal. The introduced innovative equalization optimization is successfully implemented over other equalization methodologies for the efficiency and significant performance. The presented results demonstrate the optimal capability for faster and efficient convergence that leads to enhanced system performance.

Key-words: - Higher recording density, Data equalization, Partial response signaling, Genetic algorithm.

1 Introduction

High recording density is an objective of all modern electronic data storage systems such as hard disk, magnetic tape drives and etc. In low-density storage applications the signal processing is simple and well defined. To satisfy the market requirements for high storage density and high data retrieval rates advances being made in storage materials, electronic circuitry and signal processing. As the data information are processed over a bandwidth-limited channels, increasing data-density leads to substantial problems with increased ISI and decreased SNR that limits the capability of the signal detection scheme recovered [4][5].

Packing more data into the storage media causes a significant reduction in the available signal energy and distortion in the recovered signal. The equalization process in the playback-electronics of magnetic storage channels has been the focus of much academic research and industrial development to accurately and quickly estimate the unknown system response [4][12]. Slimming individual playback pulses might improve the reliability of data recovery but it has some disadvantages. Pulse slimming equalization reduces the effect of the ISI but it also boosts the noise because of the inherent time-differentiation of the signal as shown in Fig. 1 [6].

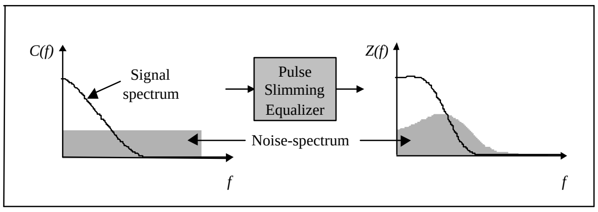

Figure 1: Pulse-slimming equalization boosts up the noise

An alternative is to reshape the replayed pulses to a specified target and this is called partial-response-signaling. Induced ISI is well-controlled using partial response. In information storage technology the problem is dealing with imprecise and uncertain information due the presence of linear and non-linear system distortions. The uncertainty led to the weakness of traditional information storage schemes by their inability sometimes to predict the original stored information data. Traditional signal processing logic is relatively simple yet introduces problems.

The performance of recording system heavily depends on the accurate design of the channel equalization. The transition response of a recording system varies with changes such as the changes in flying height and the position of the playback-head on the medium. However, the equalizer taps should be adaptively changed to account for the variations in the channel response [10][11]. Conventional adaptive filtering techniques usually involve a long convergence time and high computational complexity. Proposing innovative signal processing based on artificial intelligent systems provides a mechanism for predicting the stored data by effectively equalizing the channel playback response [2][3].

In this paper, an efficient and robust equalization scheme based on genetic-algorithm (GA) is developed in MATLAB simulation environment to optimize the coefficients of the transfer function of the partial response equalizer, which will force the replayed signal to follow a specified target. This is accomplished by minimizing the sum of squared error between the actual and desired responses. GA as a biological-based search algorithm has been successfully applied to solve practical linear and non-linear problems for finding an optimal solution according to a desired objective (fitness) function [2][3]. The fitness evaluation process that translates design specification into controller parameters, is the main contribution of this paper. The introduced equalization optimization has an advantage over other equalization methodologies for the effective adaptation process with less susceptibility to finding local-minima for an optimum equalization solution. The capability for faster and efficient convergence will lead to enhanced system performance.

2 Basics of Genetic Algorithm (GA)

Genetic Algorithms are an optimum iterative search techniques based on the principles or rules of natural selection and reproduction found in biological evolution systems. GA was developed at the University of Michigan in 1970's and successfully implemented for several applications for finding optimal solutions to numerous scientific and engineering problems (such as adaptive filtering) according to objective or fitness functions [1]. GA is well adopted as an attractive optimization tools for efficiency and robustness with simplified computational process [2][3].

As an optimization tool, GA is random search algorithm that uses random choice as a tool to guide a highly exploitative search through a coding of parameter space and its different from more normal optimization and search procedures in the following respects:

1 GA's work with a coding of the parameter set, not the parameters themselves.
2 GA's search from a population of points, not a single point.
3 GA's use objective function information, not derivative or other auxiliary knowledge.
4 GA's use probabilistic transition, not deterministic rules.

As the name indicates, GA's attempt to solve problem in a fashion similar to the way in which biological processes seems to operate guided by the principles of evolution and natural genetics, where stronger individuals would likely be the winners in a competing environment. Figure (2) simplifies the operational search cycle for a typical GA algorithm numbered (1) to (7) [2] [3]. GA iterative cycle starts by creating a constant size of population of individuals represented by symbols called chromosomes or genomes. A chromosome represents one solution to a given problem this solution may not be the optimal one, however. An evaluation procedure is used to give the fitness values of each chromosome. Then, genomes are paired off in a mating pool using selection operation. Applying genetic operations such as crossover, mutation, inversion…etc, determines new individuals (off-spring) that fitness values are calculated replacing old population members. The cycle of fitness evaluation genomes, selection, and genetic operations is continuously repeated until the best solution of the given problem is achieved [3].

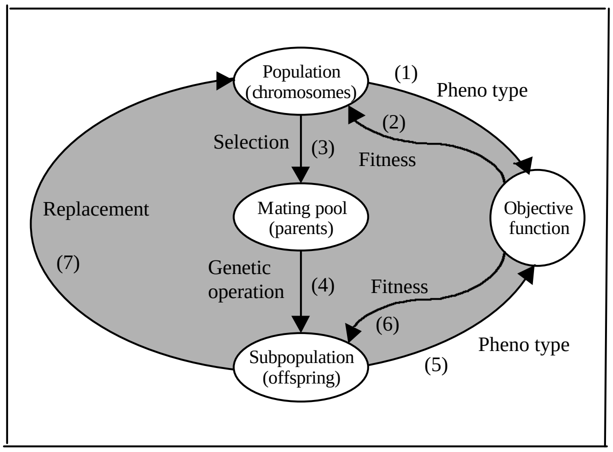

Figure 2: GA iterative process cycle

GA adaptive criterion	*Other adaptive criterion*
Generate an initial population.	Initiate the filter tap coefficients.
Evaluate the fitness function of each chromosome in the current population.	Calculate the mean square error (*MSE*) between the filter output and the target response.
Create new chromosomes by mating current chromosomes using genetic operation (mutation and crossover).	$C_{new} = C + meS_i$ C = desired filter coefficients m = adaptation step size. e = the difference between filter output and the desired target. S_i= filter sampled input data.
Replace the original chromosomes with new offspring.	Replace the filter coefficients with new calculated ones.
Compute the fitness function for the new chromosomes and to be fed back into population.	Use the new obtained coefficients to compute the new *MSE*.
Continue the procedure until the best chromosome is obtained.	Stop the iterations when no further improvements in the MSE value.

Table 1: Iterative cycle for different adaptive filtering

Many types of tap coefficient adaptation algorithms have been proposed for use in adaptive filtering. The adaptive training is based on minimizing the mean square error (*MSE*) criterion between the desired output and the output of the equalizer [11]. Table 1 summarizes the adopted iterative cycle of GA compared with other utilized procedures for optimizing the equalizer tap coefficients.

In summary, genetic algorithms are perhaps the most widely known types of evolutionary computation methods that have proved to be able to cope with a wide range of difficult optimization problems. The main reason for the success of genetic algorithms is due to their simplicity and competence, and also because they perform multidirectional search in parallel by a population of candidate solutions to a specific problem. However, the main disadvantage of GA's is in their computational time. They can be slower than some other methods, but with today's very high-speed computation facilities this problem is well controlled. The simple classical genetic algorithm implementation is inadequate in solving some optimization problems. This motivated the use of more advanced genetic operators such as fitness sharing, elite preserve, constraint handling, etc., in order to maintain the population genetic diversity and avoid premature convergence.

In systems design, an efficient mathematical model is desirable. Optimization algorithms are used to search for and identify the system parameters. In order to find a solution to a given problem that involves an iterative search and an adaptive criterion, intelligent computer-based systems such as GA that resemble the real-time hypothesis are selected for the following:

1. Guarantees an optimal solution (avoiding to stuck in local-minima) as long as the problem has got one.
2. Intelligent optimization is understandable technique with very little mathematics.
3. Fast convergence (kangaroo movement) to the optimal solution with low estimating error and less number of iterations compared to other non-artificial intelligent optimization methods.
4. Intelligently adaptive parameters are typically iterated a number of times in optimization process in order to achieve an overall desired system response [12].

5. Intelligent systems can be easily interfaced to other simulation models with less complex realization constraints.
6. Implementing equalization method in MATLAB simulation environment allows the flexibility of investigating the recording channel performance without having to build frequent expensive hardware.

3 Recording Channel Equalization

The digital signal is subjected to increased ISI, non-linear distortions and other impairments such as noise. Channel equalizations are used to compensate for the introduced effects and restore the stored data [4]. The channel equalization is divided to two main tasks as illustrated in Fig.3. Firstly, continuous-time low pass filter (CTF) attenuates the high frequency noise also it provides anti-aliasing before the sampling stage. Secondly, the sequence of the playback signal samples at the output of the sampling device is reshaped to a partial response signaling by use of the partial-response equalization. Partial-response equalizer has been implemented using a linear transversal filter (LTF) [10][11].

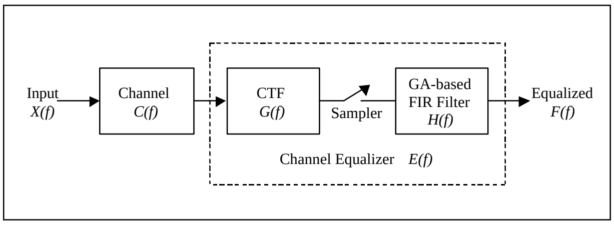

Figure 3: Recording channel equalization

LTF is normally specified by the transfer function $H(z)=\sum_{n=0}^{N} a_n z^{-n}$ with a_n being the filter tap coefficients ($a_0\ a_1 \ldots a_N$) and N is the filter order. The filter forces the channel replayed signal to follow a specified partial response target by calculating the filter tap coefficients through adaptive iterations as shown in Fig.4. Then the set of coefficients (a_n), which would give a best reasonable signal match with minimum error difference, is kept constant. GA has been selected as an optimization tool to generate the optimal set of filter tap coefficients. Normally in practical applications the adaptive filtering is widely used [10][11]. This is to accurately and quickly estimate the unknown system response.

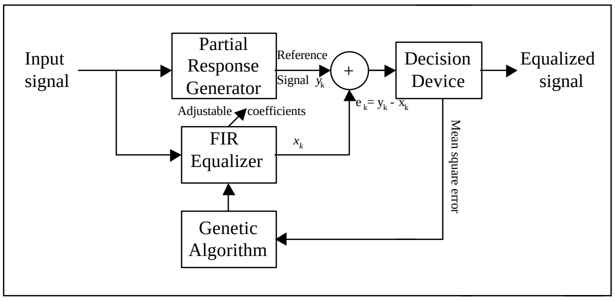

Figure 4: Configuration of GA-based adaptive equalization

4 Partial Response Signaling

Partial response signaling equalized to the form $P_n(D)=(1\text{-}D)(1+D)^n$, $n \geq 1$ and D is the delay operator has been introduced in magnetic storage applications as a substantial replacement to conventional data detection systems with the goal of maximizing the storage capacity (*bits/inch*^{2}). This will provide a significant improved system performance [7][8]. Fig.5 shows the most commonly used partial response targets for higher storage density applications. When n=1, the system called *PR4*, n=2 is referred to *EPR4* and n=3 is referred to E^2PR4. Partial-response polynomials with higher orders (n>1) provide a better match to the magnetic recording channel natural response as shown in Fig.6 [6][9]. However, fast and efficient digital circuitry has to be utilized to compensate for the increased computational complexity of the implemented detector after the equalization [9].

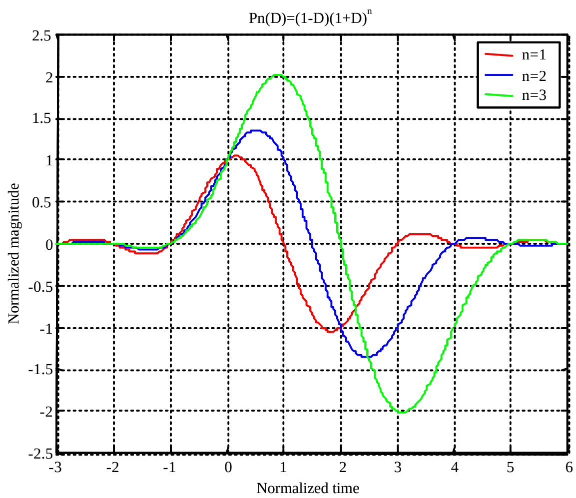

Figure 5: Dibit-response for commonly used partial response signaling

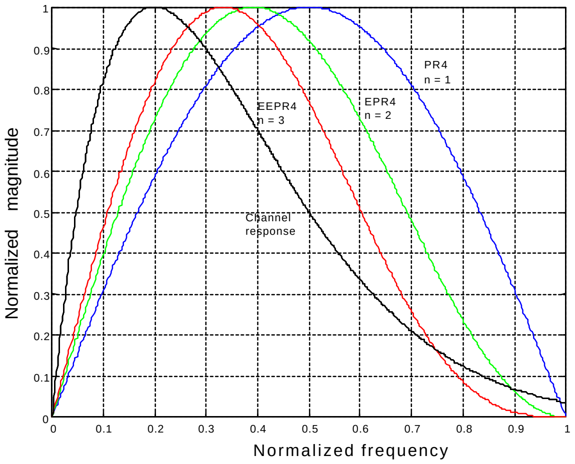

Figure 6: Higher partial signalings provide a resenable spectral match to magnetic recording channel spectrum

5 Simulation Results

Through a MATLAB programming language, a biological evolution based scheme called genetic algorithm has been implemented to optimize the performance of a digital equalizer used in magnetic recording systems by optimizing channel impulse response to partial-response signaling and to provide the required input-output signal processing. The introduced equalizer enforces the spectral properties by allowing a controlled amount of ISI at the channel playback electronics hence achieving higher storage capacity. Basic GA operation involves three main processes, which are selection, genetic operation (such as crossover and mutation) and replacement. These operations have been developed in computer programming as shown in Fig.7 and through iteration cycle, the best effective solution is selected as described in the following main steps:

1. The program reads in the playback signal stored in the implemented medium that will be equalized.
2. Produces the desired partial response pattern using mathematical models.
3. Simulates the behavior of the GA by programming the corresponding iterative operations.
4. Finally through an iterative cycle selects the set of the equalizer coefficients that will provide the best equalization performance.

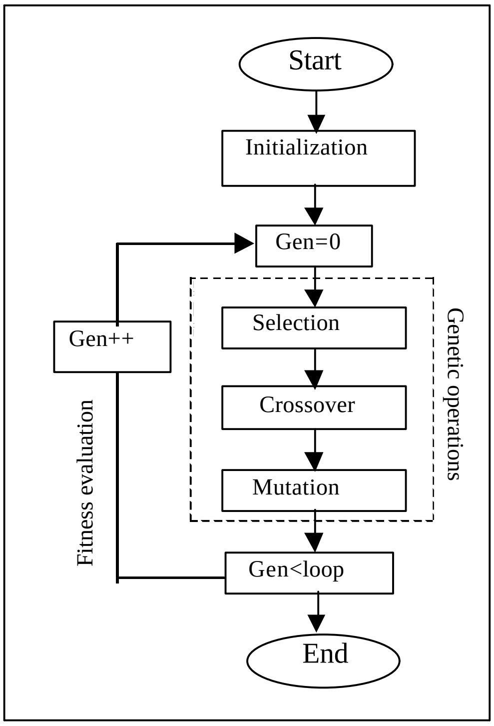

Figure 7: Programming the basic cycle of genetic algorithm

Fig.8 demonstrates the performance of the equalizer using the proposed iterative equalization scheme. The presented results of the current methodology indicate that the GA would precisely establish the required real-time mechanism for equalizing the replayed data to a known target signaling and effectively controls the signal at the equalizer output.

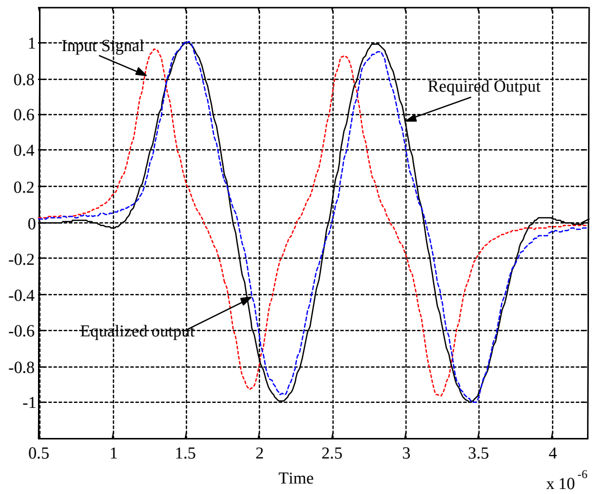

Figure 8: GA equalization response

6 Summary and Conclusion

Usually, in high density magnetic recording applications, sampled replayed signals are often equalized to partial-response targets of the form $(1-D)(1+D)^n$ instead of slimming the individual pulses which results in system noise enhancement. Then by applying appropriate maximum likelihood detection, significant system performance can be achieved [7][8][9]. Knowing precisely the recording system characteristics, successful sampled data equalization could be maintained [7].

Introducing partial-response equalization in storage channels allows a better handling of ISI hence more efficient utilization of the given channel bandwidth can be permitted. Thus the linear superposition of isolated pulses to form the replayed signal at very high density does not affect the system performance. An efficient model for a signal processing through designed circuitry is often obtained with use of adaptive optimization schemes in which the accuracy is normally governed by a set of parameters that are optimized through a search methodology to achieve an objective task [10][11].

This paper presents a biological-based search scheme called genetic algorithm to be implemented for optimizing the tap coefficients (chromosomes) for a digital partial-response equalizer in MATLAB simulation environment. GA provides a flexible direct manipulation of data to solve different real-world optimization problems [1]. For efficient data equalization, the introduced search algorithm has been made as adaptive as possible for a better solution convergence time, to produce an overall response as close as possible to that required and allows compensation for changes in the unknown recording system characteristics due to component variations. Adaptive equalization precisely maintained the desired shape at the storage channel output based on minimizing the sum of squared error between a desired equalized signal and an ideal reference target [10][11]. Finally, the optimization cycle is terminated when no further improvements in the value of the error signal are observed at the equalizer output.

References

[1] J. H. Holland, *Adaptation in Natural and Artificial Systems*, University of Michigan Press, USA 1975.

[2] K. S. Tang, K. F. Man, S. Kwong and Q. He, Genetic Algorithms and Their Applications, *IEEE Signal* Processing *Magazine*, November 1996, p22-37.

[3] K. F. Man, K. S. Tang and S. Kwong, Genetic Algorithms: Concepts and Applications, *IEEE Trans. On Industrial Electronics*, Vol. 43, No. 5, October 1996, p519-534.

[4] S. K. Nair, H. Shafiee and J. Moon, Equalization and Detection in Storage Channels, *IEEE Trans. On Magnetics*, Vol. 32, No. 5, September 1996, p5206-5217.

[5] G. V. Jacoby, Signal Equalization in Digital Magnetic Recording, *IEEE Trans. On Magnetics*, Vol. Mag-4, September 1968, p302-305.

[6] N. D. Mackintosh, A Superposition-Based Analysis of Pulse Slimming Techniques for Digital Recording, *The Radio and Electronic Engineer*, Vol.50, No.6, p307-314, June 1980, p307-314.

[7] D. Cideciyan, F. Dolivo, R. Hermann, W. Hirt, and W. Schott, A PRML System for Digital Magnetic Recording, *IEEE Journal on Selected Areas in Communications*, Vol. 10, No. 1, January 1992, p38-56.

[8] D. T. Tyner and J. G. Proakis, Partial Response Equalizer Performance in Digital Magnetic Recording Channels, *IEEE Trans. On Magnetics*, Vol. 29, No. 6, November 1993, p4194-4208.

[9] H. Thapar, and A. Patel, A Class of Partial Response Systems for Increasing Storage Density in Magnetic Recording, *IEEE Trans. On Magnetics*, Vol. 23, No. 5, September 1987, p3666-3668.

[10] J. M. Cioffi, W. L. Abbott, H. K. Thapar, C. M. Melas, and K. D. Fisher, Adaptive Equalization in Magnetic-Disk Storage Channels, *IEEE On Communications Magazine*, Vol. 28, No.2, February 1990, p14-29.

[11] S. Haykin, *Adaptive Filter Theory*, *2nd* Edition, Prentice-Hall International Inc., 1991.

[12] D. Woods, Comparison and Optimization of Digital Read Channels Using Actual Data, *1993 Conference Record of the Twenty- Seventh Asilomar on Systems and Computers*, Vol. 2, 1993, p1474-1478.