Biologically Inspired Evolutionary Computing Tools for Channel Equalization

Sri J Ravi Kumar[1], M S B Saithej Vaddadi [2], Sunil Kumar Penumala [3]
Department of Electronics and Communication Engineering,
National Institute of Technology-Warangal
Andhra Pradesh, India-506004
[1] ravi_ragya@yahoo.co.in
[2] saithej@gmail.com
[3] sunil.030490@gmail.com

Abstract

*One of the classical signal processing problems is the distortion of transmitted signal by the channel before reaching the receiver. Channel Equalization is the solution for the so called problem. It has got a variety of solutions in the sense that the equalizer can be trained using different algorithms. In this paper besides the two standard adaptive algorithms LMS-*Least Mean Square *Algorithm and RLS-*Recursive Least Square *Algorithm, biologically inspired evolutionary computing tools like* Standard Genetic Algorithm *and* Particle Swarm Optimization *are adopted for channel equalization problem and the consequences are thoroughly studied under the headings* convergence-rate, computational complexity ,processing time etc..

Index Terms—Channel Equalization, Genetic algorithm, LMS algorithm, Particle Swarm Optimization, RLS algorithm

1. INTRODUCTION

CHANNEL EQUALISATION is the process of compensating for the effect of the physical channel between the transmitter and a receiver.

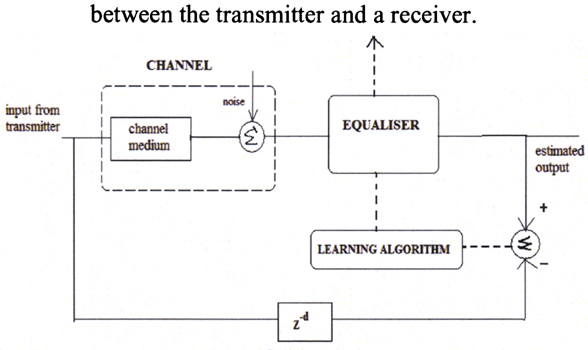

Fig.1 Channel Equalization system

It is an important area in communications as it can greatly improve the quality of transmission which in turn leads to more efficient communications. The channel is a filter with some amount of additive noise. Equalization may be linear or non-linear based on the characteristics of the channel.

Linear Equalization is based on linear systems theory and fairly a convenient one for adjusting equalizer parameters. A cost function is chosen and the equalizer is trained on this basis. Generally the cost function is Mean Square Error (MSE) which is differentiable in equalizer's parameters.

From Fig.1 it is evident that the optimal filter should have transfer function which is inverse of channel.

$$H(z) = \frac{1}{C(z)}$$

Where H(z) is the transfer function of equalizer and C(z) is the transfer function of channel.

Because of this channel equalization is also known as *inverse filtering.*

The auto-regressive modeling of the channel shows the effective transfer function of channel as

$$C(z) = \frac{1}{b_0 + b_1 z^{-1} + b_2 z^{-2} + ... + b_n z^{-n}}$$

This shows that the appropriate equalizer is an FIR filter with transfer function

$$H(z) = b_0 + b_1 z^{-1} + b_2 z^{-2} + ... + b_n z^{-n}$$

For adapting the coefficients $\{ b_i \}$of the equalizer's transfer function ,here we have dealt with two conventional algorithms *LMS and RLS* .Biologically inspired techniques such as *Standard Genetic Algorithm* and *Particle Swarm Optimization* are also implemented . These four algorithms are examined for superior signal restoration.

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2. LEAST MEAN SQUARE (LMS) ALGORITHM

LMS algorithm is one of the conventional techniques applied to channel equalization. The instantaneous error at any time-step 'k' can be represented as $e(k)$

$$e(k) = d(k) - y(k)$$

Where $d(k)$ delayed input reference is signal at time-step $'k'$and $'y(k)'$is estimated output from equalizer.The equalizer filter's impulse response vector w is adapted using the following equation.

$$w(k+1) = w(k) + 2\mu.e(k).x(k)$$

Where μ is called *Step-size* or *Convergence factor* .

$x(k)$ Is input from transmitter at time-step $'k'$.

The successive corrections of weight vector results in minimum error output.

3. RECURSIVE LEAST SQUARE (RLS) ALGORITHM

Another most widely spread algorithm in adaptive equalization is *Recursive Least Square* algorithm. This algorithm has comparatively high convergence rate than that of *LMS* algorithm. The following set of equations are used for updating the weights of equalizer.

$$\mathbf{x}(n) = \begin{bmatrix} x(n) \\ x(n-1) \\ \vdots \\ x(n-p) \end{bmatrix}$$

$$\alpha(n) = d(n) - w(n-1)^T x(n)$$
$$g(n) = P(n-1)x^*(n)\{\lambda + x^T(n)P(n-1)x^*(n)\}^{-1}$$
$$P(n) = \lambda^{-1}P(n-1) - g(n)x^T(n)\lambda^{-1}P(n-1)$$
$$w(n) = w(n-1) + \alpha(n)g(n)$$

Where P(0)=$\delta^{-1}I$ is a (p+1)th order matrix.p is filter order. λ is forgetting factor.The above set of equations show the level of mathematical computational complexity in the algorithm.

4. STANDARD GENETIC ALGORITHM

The Standard Genetic Algorithm (SGA) is inspired by Charles Darwin's evolutionary theory of evolution. Typically Genetic Algorithm maintains a population of candidate solutions for problem at hand and makes it evolve by iteratively applying a set of stochastic operations.

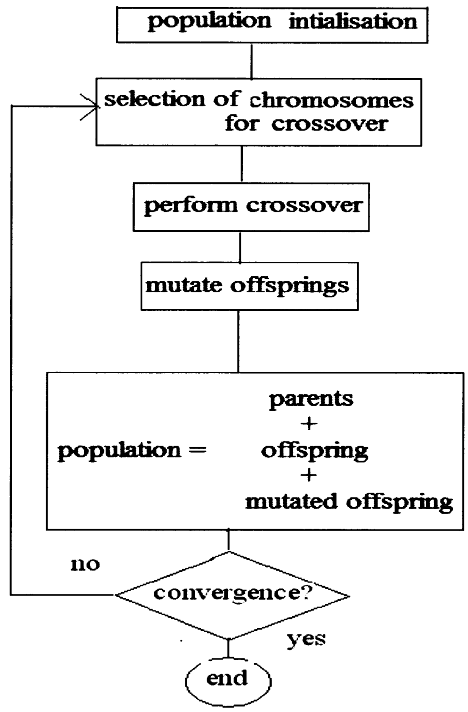

Fig.2 Block diagram of Genetic Algorithm

Applied to channel equalization problem, at first the equalizer's impulse response vector is initialized to a random set of weights (population initialization) and trained using the algorithm as shown in the block diagram.

Usually the probability of cross-over is kept high (more than 0.8) and the probability of mutation –low (less than 0.2).

The evaluation function is often referred as *fitness function*. The selection of chromosomes for mating is based on fitness function. Knowledge of function is not of much importance.

Here we use SGA for optimizing the fitness function i.e. *Mean Square Error.*

5. PARTICLE SWARM OPTIMIZATION

PSO is population based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling etc.

The Swarm of particles indicates estimates of multiple parameters involved in the problem. We can begin with initializing a random swarm of particles like in SGA. During each iteration fitness of the particle is evaluated with the help of fitness function (Mean Square Error in our problem).

The algorithm progressively replaces most fit parameters of each particle i.e.*pbest.* Pbest is the best position of the particle itself.

There exist another best position *gbest* which is the global best i.e. the best position in the swarm. Each particle has the influence of these two bests in their trajectories. The parameters of each particle are updated with the following equations

Velocity updation

$$v_i(t+1) = w.v_i(t) + c_1.rand.(pbest(t) - x(t))$$

$$+ \quad c_2.rand.(gbest(t) - x_i(t))$$

Position updation

$$p = p + v$$

Where

p-instantaneous position of the particle
v-instantaneous velocity of the particle
Pbest-positional best of the particle
gbest-global best position of the swarm of particles
W – Inertial weight factor
C1, C2 – acceleration coefficients

The trajectory of the particle is dependent on three factors : its previous position , pbest and gbest.Greater the strain of the particle in searching food, smaller are the acceleration coefficients.The inertial weight factor w signifies the importance of the particle's previous position in further search

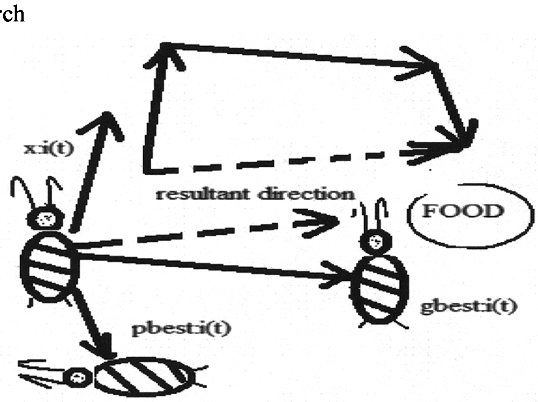

Fig.3 Trajectory of particle after velocity updation

Thus each particle tend to move towards *gbest* to reach food early. If *gbest* has less number of values then the particles will reach the food early. The algorithm comes to an end when all the particles converge at that gbest i.e. food position. In our problem i.e. attaining minimum possible value for *MSE.*The block diagram of PSO can be shown like this:

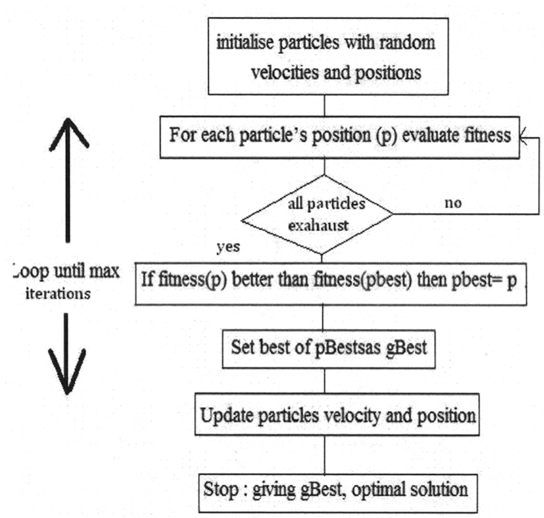

Fig.4 Block Diagram of PSO

6. SIMULATIONS AND RESULTS

In our simulations we have employed a channel whose impulse response is given by

$$C(z) = 0.26 + 0.93z^{-1} + 0.26z^{-2}$$

For LMS and RLS algorithms a binary random signal is fed to the channel and its output is corrupted by a zero mean white Gaussian noise. In case of nonlinear channels the noise is added to the nonlinear output of channel.

Using the weight vector adaptation equations Mean Square Error is calculated and optimized.

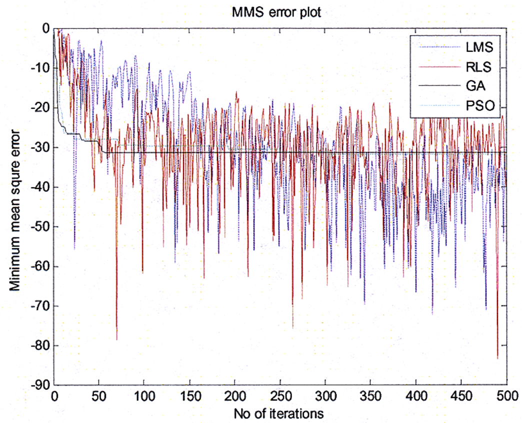

Fig.5 MMS error plot for linear channel at SNR=30dB

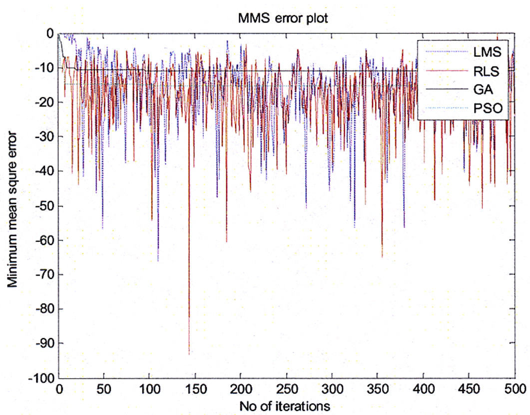

Fig.8 MMS error plot for linear channel at SNR=10dB

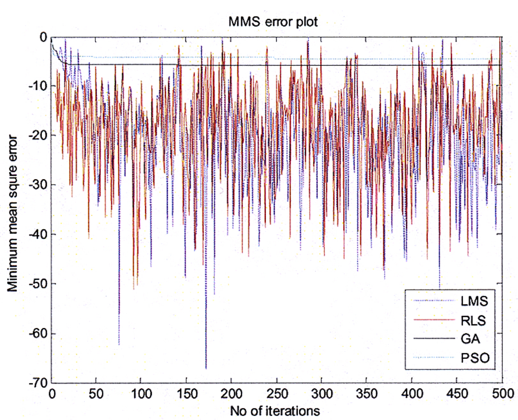

Fig.9MMS error plot for linear channel at SNR=0dB

From the results we can say that particle swarm optimization is giving better results in the worst case of noises (0db) also.

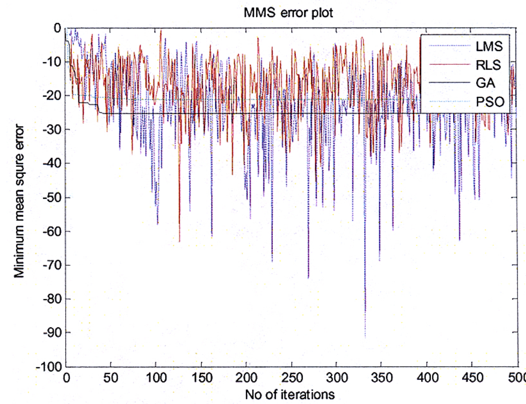

Fig.6 MMS error plot for non-linear channel at SNR=30dB.

The nonlinear channel function is tanh(x).

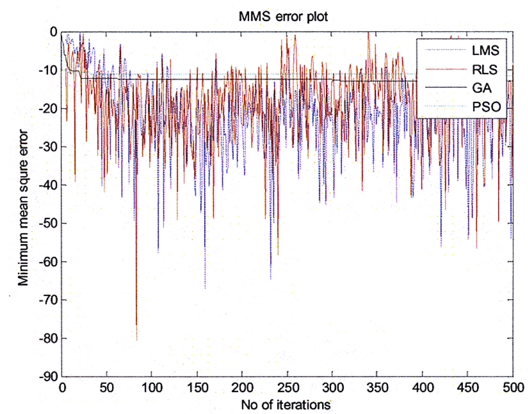

Fig.7 MMS error plot for non-linear channel at SNR=10dB.

The nonlinear channel function is tanh(x).

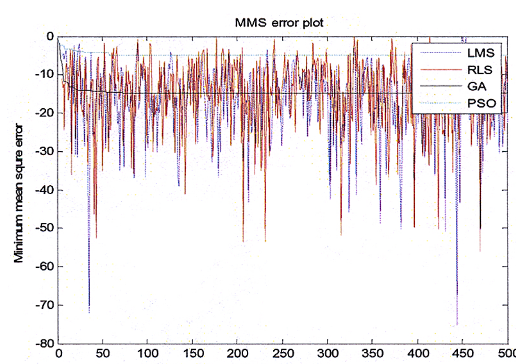

Fig.10 MMS error plot for non-linear channel at SNR=0dB

(non-linearity is hyperbolic tangent)

From the above figures, it is observed that Particle Swarm Optimization algorithm converges excatly to -30dB and -10dB and even in the worst noise condition (SNR=0dB) PSO has the best convergence when compared to the rest of the three algorithms.

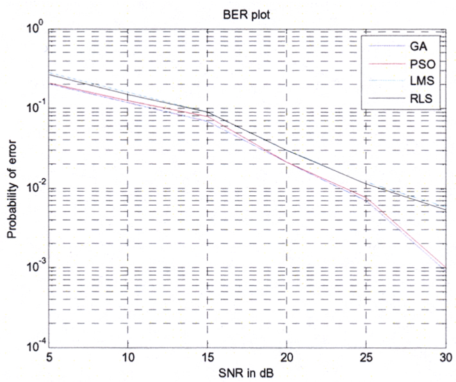

Fig.11 Bit Error Ratio Pot for linear channel against SNR

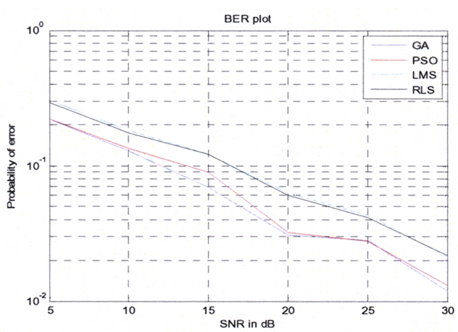

Fig.12 Bit Error Ratio Plot for non-linear channel against SNR.

(The non-linear channel function is hyperbolic tangent i.e.tanh(x)).

The BER plots are the fantastic evidences to study the degree of signal restoration achieved by the learning algorithm.Fig.11 and Fig.12 indicate the BER plots for linear and non-linear channels .A set of input samples (about 10,000)are sent from transmitter to channel. The equalizer's estimated output signal is compared with the delayed input reference singnal.BER is evaluated with this comparision at various SNRs'.SGA's performance goes with PSO and LMS's with RLS's. Initially when high noise prevails the SGA and PSO handles the situation better. Also in the less noise situations they had their upper hand than LMS and RLS.

7. CONCLUSIONS

The quality of a learning algorithm depends on factors like high convergence rate, less mathematical complexities, low tracking time, low processing time, and steady state error etc. The very purpose of the paper is to convey that it is mandatory to compromise between disparate requirements which cannot be satisfied simultaneously. Hence an algorithm which satisfies most of the requirements is to be picked up.

Though LMS deals with comfortable computations, it has its own disadvantages like slow convergence rate and higher steady state error. From high convergence point of view, RLS can be treated as a better option in spite of its high mathematical complexities. Especially for non-linear channels these two algorithms show poor performance.

It can be noticed that SGA and PSO show many a similarity in aspects like random weight initialization, fitness evaluation, derivative free approach to avoid local minima etc.

For linear channels, PSO shows better performance than others and also exhibit faster convergence.

For non-linear channels, SGA slightly dominates over PSO in performance but PSO takes the lead with faster convergence.

Considering the processing time durations taken by these algorithms during simulations it can be conclude that LMS and RLS responses are quite appealing where as the others require practically a greater amount of time.

S.No	Algorithm	Processing time taken by CPU*	Mean square error
1	LMS	0.294	1.986
2	RLS	0.184	1.837
3	SGA	26.266	1.432
4	PSO	12.348	0.688

*Time is measured in seconds(these times may vary as it also depends on processor speed).The measurements are as per 'AMD Duron ™ p 1.61 GHz'.

Thus PSO can be regarded as the better learning algorithm as it can satisfy many requirements of a qualitative adaptive algorithm like high convergence, less compexity in computations, optimum processing time,maintaince of steady state error etc.It can be used as a substitute for SGA..SGA's major disadvantage is consumption of more time.

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BIOGRAPHIES

Ravi Kumar Jatoth was born in Warangal, India on October 13 1980. He received his B.E degree in Electronics and communications Engineering from Osmania University, Hyderabad in 2003; M.Tech in Instrumentation and Control Systems from Jawaharlal Nehru Technological University Hyderabad in 2005. He is currently working as Lecturer in National Institute of Technology-Warangal. His research areas include Digital Signal Processing, Tracking Algorithms and Embedded Systems.

M S B SAITHEJ VADDADI, currently an undergraduate of Electronics and Communication Engineering stream in NIT,Warangal born in Ramachandrapuram,India on August 27th ,1990.

SUNIL KUMAR PENUMALA, currently an undergraduate of Electronics and Communication Engineering stream in NIT,Warangal is from VIshakapatnam,India and was born on April 3rd ,1990.