QPSO for Training of Ann in Channel Equalization

Padma Charan Sahu, Sunita Panda

Abstract: ***This basic aim of this article is to find the optimal solution by the use of QPSO for training of Artificial Neural Network channel Equalization. As Particle Swarm Optimization techniques cannot find optimum value easily and also the rate of convergence is low. To overcome this drawback, QPSO is evolved which is capable of finding the optimal solution easily as well as increase the convergence speed. By using the QPSO the parameter like neurons, numbers of segmants etc are optimized. The outcomes guarantee that quantum based particle swarm optimization technique is better than PSO technique.***

Keywords: QPSO, PSO, Channel Equalization, and Neural Network.

I. INTRODUCTION

Particle swarm optimization (PSO) techniques applied to find the solution of for the problems in signal processing, which is basically a meta-heuristic algorithms. These methods emulate the social conduct of feathered creatures running and fishes tutoring. Beginning structure a haphazardly appropriated set of particles, the calculations attempt to improve the arrangements as indicated by wellness work. The ad lib is performed through moving the particles around the pursuit space by methods for a lot of basic numerical articulations which demonstrate some inter particle correspondences. The scientific articulations are least complex and most essential structure propose the development of every molecule toward its own best experienced position and the swarm's best position up until now, alongside some irregular bothers. There is a bounty of various variations utilizing diverse refreshing standards.

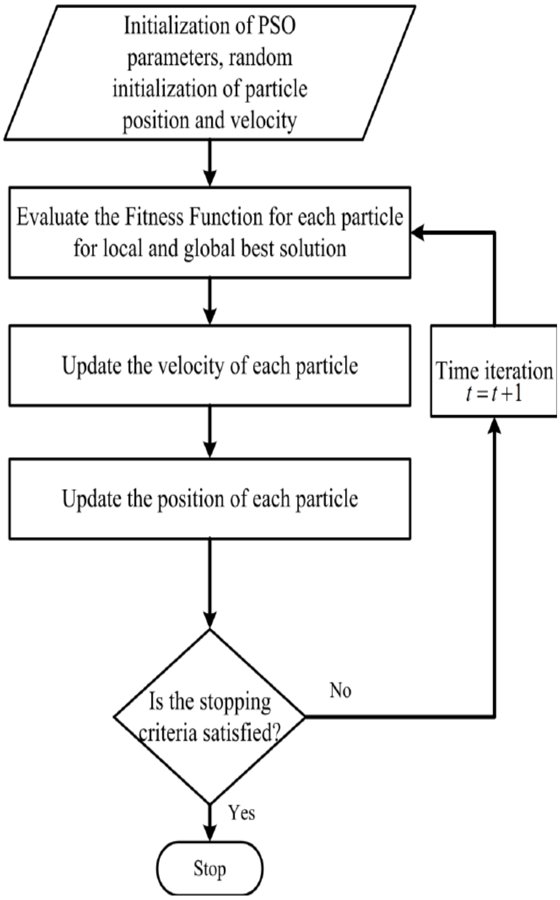

Fig 1

The principle favorable position of PSO is its capacity to accomplish sensibly great arrangements moderately quick. While examining PSO versus other developmental techniques, demonstrated that despite the fact that PSO finds great quality and a lot quicker than transformative calculations, it doesn't improve the nature of the solution as the quantity of particles is expanded. This is a direct result of the particles getting bunched in a little area of the inquiry space and in this manner the loss of diversity. Increasing the investigation capacity of PSO has been a functioning examination theme lately. PSO Algorithm Attempts have been made so as to improve the calculation's investigation abilities and also improve the convergence speed. Engelbrecht and van den Bergh presented an GCPSO stands for Guaranteed convergence PSO in which particles play out an irregular inquiry around best inside a range characterized by a scaling factor. The calculation is accounted for to perform superior to unique PSO in unimodal issues while delivering comparative outcomes in multimodal ones. The scaling factor anyway is another parameter for which earlier information might be required to be ideally set. Krink et al. proposed an impact free PSO where particles endeavoring to assemble

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about a problematic arrangement bob away. An irregular course changer, a reasonable bob, and an arbitrary speed changer were utilized as three ricocheting methodologies. The last two are accounted for to altogether improve the investigation capacities of the calculation and get better outcomes particularly in multimodal issues.

Aside from that the equalizers dependent on PSO are renowned on account of simple usage [1].Due to some drawback of PSO, GCPSO a new technique is used commonly known as QPSO. In QPSO [5], preferences of Quantum mechanics is an expansion to PSO. QPSO establishes effective use in improvement issues [8] additionally in adjustment .Most popular Back Propagation trained Artificial Neural Network algorithm provides slow Convergence which may develop PSO trained Artificial Neural Network. Here the fundamental utilization of QPSO is expansion of quantum mechanics to the system swarms which gives better results when contrasted with the current calculations.

Problem Statement:

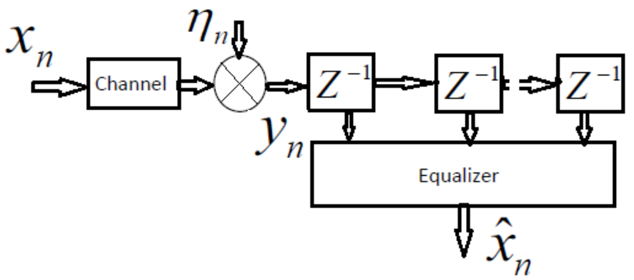

Fig-2 Models of Digital Communication System

The above figure shows the communication channel with equalizer whose channel Impulse response is

$$H_k(z) = \sum_{j=0}^{P_k-1} a_{k,j} \; Z^{-j} \qquad 0 \leq i \leq n \qquad (1)$$

Where P_k and $a_{k,z}$ are length and weight of the channel.

The output of the channel i.e $Y(n) = r(n) + r_\infty(n) + Noise$ (2)

$r_\infty(n)$ *be the interfering signal .*

r (n) be the required signal . The noise is assumed to be Gaussian

The required signal is

$$r(n) = \sum_{j=0}^{P_0-1} a_{0,j}\, x_0(n-j) \qquad (3)$$

The interfering signal is

$$r_\infty(n) = \sum_{i=1}^{n} \sum_{j=0}^{P_i-1} a_{i,j}\, x_i\,(n-j) \qquad (4)$$

Based on channel observation vector, the equalizer recovers the transmitted sequence $x_0\;(n-k)$

The error signal $e(n) = r(n) - y(n)$ (5)

The primary point of this paper is to limit this mistake by utilizing some calculation (QPSO) just as adjust the ideal loads of the equalizer.

QPSO (Quantum Behaved Particle Swarm Algorithm.)

QPSO brings quantum figuring into the particle swarm calculation, beginning from the mechanical perspective that the particle in the space has quantum conduct. This calculation defeats the impediments while safeguarding the benefits of particle swarm enhancement calculation, which can viably improve the execution of streamlining calculation.

PSO is established by certain particles speaking to an answer vector to the issue. Particles are capable of memorizing their past best position and velocity. Each particle in K-dimensional space and meant by $X_i = (x_{i1}, x_{i2}, \ldots\ldots x_{iK})$ and the velocity is $V_i = (v_{i1}, v_{i2}, \ldots\ldots\ldots v_{iK})$ is along each dimension. In this paper the velocity and the position is to be updated by certain number of iteration.

Algorithm Flow .

Step 1 : Initialize algorithm parameters (Population Size n, Particle Dimension ,Max Iteration).

Step 2 : Determine individual fitness function.

Step 3: Update optimal population in history. The particle fitness is better than the particle history itself, with the current value of the replacement; otherwise the history optimal particles remain unchanged.

Step 4: Update the history global optimal particle in a population, the best wellness estimation of the considerable number of particles in the populace.

Step 5: Calculate particles by using QPSO method.

Step 6: If the algorithm reaches the maximum number of iteration then the output of optimal solution and the calculation ends generally go to stage 2

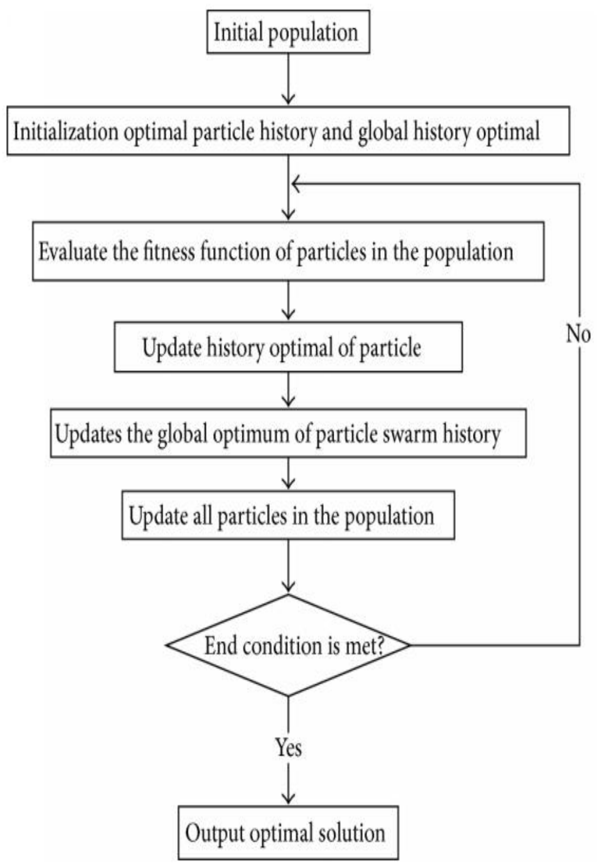

Fig 3

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For updating the particle i, at $(s+1)^{th}$ iteration

$$v_{ij}^{s+1} = w.v_{ij}^{s} + c_1.r_{1j}^{s}\left(P_{ij}^{s} - X_{ij}^{s}\right) + c_2.r_{2j}^{s}\left(P_{gj}^{s} - X_{ij}^{s}\right) \quad (6)$$

c_1 is cognitive coefficient and C_2Social Coefficient which can used for controlling the particles. The best position of the particle is P_b and is denoted by the vector $P_i = P_{i1}, P_{I2} \ldots \ldots \ldots P_{IK}$ $.g_b$ be the best previous solution and is denoted by $P_g = P_{g1}P_{g2} \ldots \ldots \ldots . P_{gk}$.

In QPSO a new term is used called as contraction expansion (CE) α which is responsible for determining the wider space search. For M particles in K-dimensional space, the location of particle i at $(t+1)^{th}$ steps is calculated by

$$x_{ij}^{t+1} = P_{ij}^{t} \pm \alpha.\left(x_{ij}^{t} - MP_{j}^{t}\right) \quad (7)$$

Where MP_j^t *be the* mean of P_b for all particle in the entire population.

Simulations: From [29] the simulation parameters are to be chosen. Thus beginning qualities set were M=5, N=25, C1=C2=2 and the speed factors was set at 0.8. The transfer function of the channel picked likewise same as of [29] is :

$$H(Z) = 1 - 0.9Z^{-1} + 0.385Z^{-2} + 0.771Z^{-3} \quad (8)$$

and the nonlinearity is $y(n) = \tanh[x(n)]$

As it has been already stated that as compared to existing ANN based equalizers, PSO trained ANN performs superior. The fundamental utilization of this exploration work demonstrates that the proposed QPSO trained ANN performs superior than results compared to PSO. Here two parameters are taken in to consideration that is Bit Error Rate (BER) and Mean Square Error (MSE).

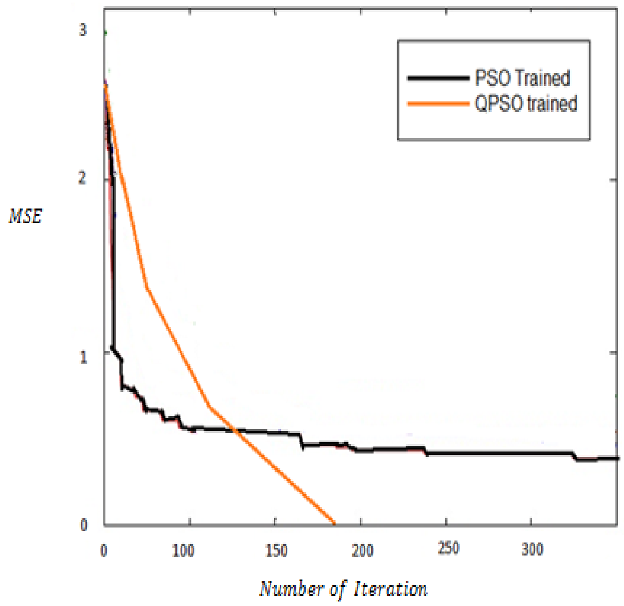

Fig 4

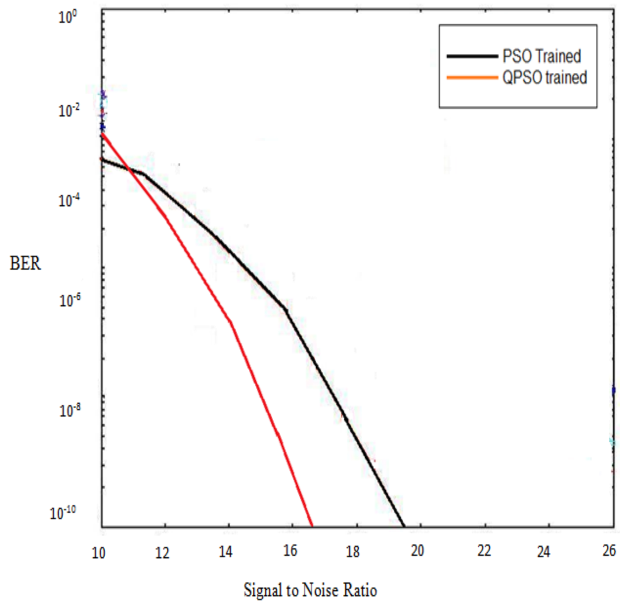

Fig 5

From figure 4 it is seen that, the proposed equalizer merges nearly about 180 iterations while 400 iterations is required for PSO based equalizer. Similarly BER curve shows that QPSO trained equalizer perform better then PSO trained equalizer in all noise conditions.

Outlines

In this paper Artificial Neural Network equalizer trained with QPSO is introduced. As compared to PSO based equalizer the proposed equalizer gives the advantage by comparing with their simulation results. Apart from that, the proposed method is easy to use.

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