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Design of a Discrete Adaptive Equalizer for Noisy Channel using Quantum Behaved Particle Swarm Optimization Technique

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Abstract

Objectives: In this paper, we propose to develop a discrete adaptive equalizer based on Quantum behaved Particle Swarm Optimization (QPSO) technique for noisy channel. **Methods/Statistical Analysis**: Equalizers have to deal with harder and more complicated problems today due to crowded communication channels and increasing interference level. **Findings**: This work is an effort to counterbalance Inter-Symbol Interference (ISI) and other nonlinear impairments occurring in real world channels due to nonlinear devices installed in transceivers, cross talk, presence of impulsive noise, multipath propagation and the nature of physical medium itself. A simple, yet efficient optimization algorithm QPSO which belongs to a class of bare-bones PSO family is employed for this purpose. The performance of the proposed equalizer is compared with Least Mean Square (LMS) and other popular variations of PSO, namely Constant Weight Inertia (CWI-PSO) and Linear Decay Inertia (LDI-PSO) algorithms in order to investigate its efficacy. **Application/Improvements:** Mean Square Error (MSE) and Bit Error Rate (BER) are evaluated for each algorithm and a comparative study of the results reveal that QPSO enjoys an improved performance over other considered algorithms. The proposed discrete equalizer model can be widely used in communication system, especially mobile and satellite communication due to its effectiveness in noisy environment.

Keywords: Bit Error Rate, Discrete Channel Equalizer, Signal to Noise Ratio

1. Introduction

An efficient and reliable data transfer over noisy digital communication channels is the demand of present era, which has cropped up as a result of tremendous rise in internet and multimedia users. Inter-Symbol Interference (ISI), Additive White Gaussian Noise (AWGN), non-linear characteristics of electronic devices used in transceivers such as amplifiers, limited bandwidth and other effects of time varying channels are major causes that can seriously distort the symbols of transmitted data. In order to compensate these effects of physical channel in a digital communication system, a discrete adaptive equalizer offers most popular and reliable solution[1].The discrete equalizer is usually modelled on Finite Impulse Response (FIR) filter due to its linear phase characteristics and the equalization process is carried out using suitable adaptive optimization techniques. The popular gradient based LMS algorithm and its variants perform satisfactorily when the channel is assumed to be linear in nature but it fails to converge to the global minimum solution when nonlinearity arises or in case of multimodal and non-uniform objective function[2].For such situations plethora of adaptive equalizers using evolutionary methods have been proposed which works efficiently under non-linear and noisy conditions. Genetic Algorithm (GA)[3–5], Bacteria Foraging Optimization (BFO)[6], Artificial Immune System (AIS)[7], Differential Evolutionary algorithm (DE)[8], Particle Swarm Optimization (PSO)[9,10], Modified Particle Swarm Optimization (MPSO)[11],Wind Driven optimization (WDO)[12,13], constant weight inertia PSO (CWI-PSO)[14], Linear Decay Inertia PSO (LDI-PSO)[15]are few of them.

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PSO has attained increasing popularity due to its simpleness, straightforwardness, easy coding and better accomplishment. Numerousmodifications of PSO are introduced ever since the basic PSO system was proposed in 1995[14]. Like other evolutionary algorithms, a PSO system searches for the optimal solution in a complex space by continuously updating the population of random solution which is initialized at the beginning of the algorithm. However, it does not involve evolution operators, some of which are cross over and mutation probabilityused in case of GA. The credible solution referred as particles wander in the problem space guided by their own experience and the experience of current best particles i.e. through collaboration of exploration (global search) and exploitation (local search). Therefore, it sounds to be a promising optimization tool that can pave way to cheap, fast and good performance, contrary to other evolutionary methods. However, it has a major folly that particle is confined to a finite search space in each iteration, which at times, can diminish its capability to converge to global optimum. This grievance of PSO was tried to resolve by introducing the concept of inertia weight into the original PSO[15]. Constriction factor inertia PSO was reported to restrain the velocities of particles from reaching unaccepted value so as to avoid explosion[16]. Several topologies of PSO to improve its performance have been suggested henceforth[17–21].

Quantum behaved PSO is based on quantum mechanics and classical trajectory philosophy[22]. Contradictory to traditional PSO paradigm, search and solution space of a particular problem are not concordant in QPSO.Rather, state of the particle in search space is defined by wave function or probability function.Since, the search space is quantized, specific statistics about the particle which is essential for evaluating fitness or cost function is not recognized. Measurement of particle position is done by collapsing or transforming quantum state to classical state. Each particle explores in anorientation beginning with individual latest position towards local attractor spot situated in betweenparticle best pbestand global best *gbest*position. So, QPSO is superior to standard PSO algorithm in search capability. Many researchers from different communities have successfully solved wide range of continuous, complex, multi-dimension and multi-modal optimization problems using QPSO. Few prominent applications are in fieldof electromagnetic devices[23,24], on-line system identification[25], image processing[26], microelectronics[27] etc. Judging by its successful applications so far, we are encouraged to exploit this algorithm to design a discrete channel equalizer.

The work presented in this paper, focuses on investigating the effectiveness of QPSO technique in developing a discrete channel equalizer for a popular channel under noisy condition, which is yet an unexplored application. The QPSO based scheme is correlated to two famous models of PSO- Constant Weight Inertia (CWI-PSO) and Linear Decay Inertia (LDI-PSO)to mark the effectiveness of QPSO among other popular variations of PSO, in developing a discrete adaptive equalizer for noisy channel. It is also compared to the benchmark LMS algorithm to bring about its efficacy. The remaining paper is executed in such a way so as to deal with the structure and principle of adaptive channel equalizer in Section 2. An overview of LMS, CWI-PSO, LDI-PSO and QPSO algorithms are presented in Section 3. The algorithm to develop new discrete equalizer through QPSO is put forth in Section 4. Simulation work is carried out in section 5 followed by vigorous discussions. Section 6 concludes and summarizes the work presented in this paper.

2. Discrete Adaptive Equalizer

For reliable digital transmission system, it is crucial to combat the effect of ISI and other impairments associated with the physical medium, it is where adaptive equalizers come into picture [1]. The equalization in digital communication system scenario is illustrated in Figure 1. A 3-tap FIR filter model is assumed as a channel and the block marked NL is inserted to include the nonlinear effect produced by physical channel.

The output of the channel a(k) is passed through nonlinear function block NL that produces output $b(k) = f(a(k))$, where $f(\cdot)$ is any mathematical nonlinear

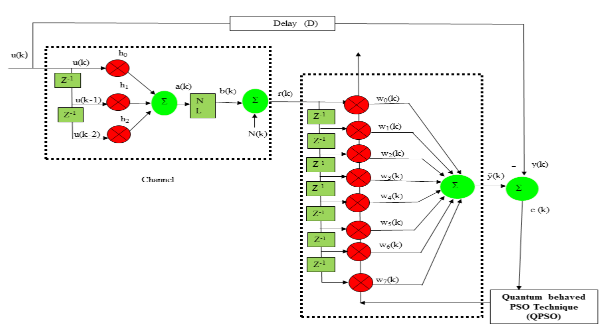

Figure 1. Schematic block diagram of QPSO based adaptive channel equalizer.

function. In order to realize real world channel AWGN noise $N(k)$ with variance σ^2 is added to $b(k)$. The signal received at the receiver side is $r(k)$, which serves as input to the discrete equalizer. The equalizer adapts its internal parameters which are weights or coefficients of the transversal filter model, using appropriate optimization methodology to produce output $\hat{y}(k)$. The desired signal is obtained by delaying input signal $u(k)$ by D samples and is represented as $y(k) = u(k - D)$. The error signal at the k^{th} sample denoted by $e(k)$ is instrumental in adapting the weights or parameters of the discrete equalizer and is defined by following equation

$$e(k) = y(k) - \hat{y}(k); \qquad 0 < k < n \tag{1}$$

where, n is the number of input samples. As illustrated in Figure 1, the channel is modeled as a three tap FIR filter whose transfer function is $h(z)$. The equalizer modelled as 8-tap delay transversal filter is connected in series with the channel. Conventionally, the order of equalizer is greater than or equal to twice the order of the channel. Therefore, its transfer function is 1/h(z). Output of the communication channel at the k^{th} instant is represented by

$$a(k) = \sum_{L=0}^{2} h_L * u(k) \tag{2}$$

where, $h_L = [h_0, h_1, h_2]$ represents the weight vector of linear channel h(z) and $u(k) = [u(k), u(k-1), u(k-2) \ldots \ldots u(k-n)]$ is the transmitted data sequence assumed to be independent taking values from [1, -1] with an equal probability. Received input to the discrete equalizer is

$$r(k) = b(k) + N(k). \tag{3}$$

After compensating for distortion, the discrete equalizer produces an output represented by

$$\hat{y}(k) = \sum_{Q=0}^{7} r(k-Q) * w(k) \tag{4}$$

where, $w = [w_0, w_1, \ldots . w_7]$ is the associated weight vector which is to be optimized and Q is the length of equalizer. The desired signal is obtained by delaying the input signal by m samples (m = 4 in this case) as conventionally m is either Q/2 (for even Q) or (Q+1)/2 (for odd Q). Here, mean square error serves as the cost/objective function (J) and is given by

$$J_i(k) = \frac{1}{n}\sum_{k=1}^{n} e_{ji}^{\,2}(k); \qquad 1 < i < R \tag{5}$$

where, e_{ji} is the j^{th} error for the i^{th} particle. R is the population size or number of particles and j varies between 1 and number of iterations.

Main goal of the presented work is to minimize(5), representing the cost function for the problem formulated here. This is done by optimizing the weights of equalizer through QPSO algorithm. The performance of QPSO is compared with those of LMS, CWI-PSO and LDI-PSO to investigate the efficacy of QPSO based discrete equalizer.

3. Overview of the Optimization Algorithm Employed for the Equalization Task

3.1 LMS Algorithm

LMS is the benchmark algorithm for adaptive filters and is popular due to its distinctive traits like computational simplicity, guaranteed convergence and stability in stationary circumstances[28]. This stochastic gradient method employs distinctive estimate of the gradient called as wiener solution to arrive at the optimal values of FIR filter weights used in adaptive discrete equalizer depicted in Figure 1. The update equation for the filter coefficient or weight vector w at $(k+1)^{th}$ instant is postulated as[2]

$$w(k+1) = w(k) + 2\mu e(k)u(k) \tag{6}$$

where, μ is the step size.

3.2 Constant Weight Inertia PSO (CWI-PSO) Algorithm

CWI-PSO proposed by Shi and Eberhart is essentially a swarm intelligence paradigm that utilizes etiquette of the swarm in searching for global optimum solution[14]. The trajectory followed by individual particle is basically a consequence of previous best *pbest*which resembles autobiographical memory of the individual gathered out of its own experience and global best*gbest*analogous to publicized or group understanding which individual strives to acquire.The algorithm begins with a population of swarm consisting of R individuals. Individual particle in the swarmis assumed to be infinitesimally small and volume less. $X_i(k) = [X_{i1}(k), X_{i2}(k) \ldots \ldots \ldots \ldots X_{iR}(k)]$ and $V_i(k) = [V_{i1}(k), V_{i2}(k) \ldots \ldots . V_{iR}(k)]$stands for the position and velocity vectors of i^{th} particle respectively. These vectors are updated on dimension 'd' during the evolution of swarm population by[14]

$$\begin{aligned} V_{id}(k+1) &= \omega * V_{id}(k) + C_1 * \text{rand}() \\ &* \left(P_{id} - X_{id}(k)\right) + C_2 * \text{rand}() \\ &* \left(P_{gd} - X_{id}(k)\right); 1 \le d \le R \end{aligned} \tag{7}$$

where, C_1 and C_2 are the acceleration constants equivalent to step size of an adaptive algorithmand are usually assigned same value to emphasize equal weightage to both social and cognitive component, rand( ) is a random number from uniform distribution in the range [0,1]. $P_{id} = (P_{i1}, P_{i2} \ldots P_{iR})$, is the best position found so far for the i^{th} particle and the global best position $P_{gd} = (P_{g1}, P_{g2} \ldots P_{gR})$ is the best particle in the neighborhood. The position of i^{th} particle is then updated as[14],

$$X_{id}(k+1) = X_{id}(k) + V_{id}(k) \; ; \qquad 1 \le d \le R. \quad (8)$$

The velocity of particle plays significant role converging the algorithm to global minimum and therefore, it must be clamped to the range $[-V_{max}, V_{max}]$.This clamping facilitates in taking reasonable step size to comb the search space thoroughly and stay well within the boundary, without exploding. The inertia weight ω is introduced in (7) to control the momentum of particle by adjusting the influence of previous velocities at every iteration. In fact, it is considered to replace the maximum velocity V_{max} and helps the swarm to converge more efficiently and accurately. The swarm diverges when $\omega \geq 1$, reaches better solution when $\omega \ll 1$, and moves in a chaotic manner for $\omega = 1$. In CWI-PSO, a fixed optimum value of inertia weight is assumed to implement the algorithm for specific application.

3.3 Linear Decay Inertia PSO (LDI-PSO) Algorithm

Since, exploration and exploitation of search space is controlled by the inertia weight ω, dynamically varying values of ω is preferred now a day. Value of ω is usually kept high at the beginning and then subsequently decreased at every iteration. This results in better coverage of search space. Inertia weight in (7) is expressed as[15]

$$\omega\,(k+1) = \omega_{max} - \frac{(\omega_{max} - \omega_{min})iter}{iter_{max}} \qquad (9)$$

where, ω decreases linearly from maximum value ω_{max} to minimum value ω_{min}, $iter_{max}$ is the maximum number of iterations and $iter$ is the current iteration.

Usually, ω linearly falls from 0.9 to 0.4 over the entire run and it should satisfy the following condition for ensured convergence

$$\omega > \frac{1}{2}(C_1 + C_2) - 1 \qquad (10)$$

3.4 QPSO Algorithm

In QPSO, a particle is represented in quantum mechanics unlike standard PSO where it is determined by $X_i(k)$ and $V_i(k)$ following the Newtonian mechanics. Heisenberg's uncertainty principle claims that both the position and velocity of the particle cannot be found at the same time. Therefore, the quantum state of a particle is described by wave function or probability density function (PDF) denoted by $\Psi(X,k)$ instead of position vector **X** and velocity vector **V**of standard PSO[19-22]. The probability of the particle occupying position $X_i$can be known from PDF $|\Psi(X,k)|^2$. The form of PDF depends upon the type of potential field, whether delta potential well or harmonic oscillator field, the particle is located in. PDF is expressed as

$$|\Psi(X)|^2 = \frac{1}{L}\exp(-2\,\|P - X\|/L) \qquad (11)$$

where, L is the learning inclination point (LIP) or creativity or imagination and P is the centre of delta potential well. Here, each particle formulated by (11) preserves itsbest position *pbest* in the entire feasible search space and compares with other existing particles to evolve *gbest* at every iteration. Random numbers φ_1 and φ_2 are generated to establish the center of gravity of delta potential well.The particles get attracted and converges to this equilibrium point described by

$$P_d = (\varphi_{1d}P_{id} + \varphi_{2d}P_{gd})/(\varphi_{1d} + \varphi_{2d}) \qquad (12)$$

so that *pbest* of all particles in a swarm will arrive at unique *gbest* when$t \to \infty$. Next knowledge seeking step is executed by evaluating the control parameter L given by

$$L = 2 * \beta * |P - X(k)| \qquad (13)$$

where, β is an important control parameter for delta potential field. Deviation of particle's current position from its LIP, gives a measure of L. The probability of finding new knowledge or solution greatly increases for high value of L. At last, new position is obtained by mapping search space into solution space and is given by

$$X_i(k+1) = P + \beta * |P_i - X(k)| * \ln\left(\frac{1}{u}\right) \text{ if } u > 0.5 \qquad (14a)$$

$$X_i(k+1) = P - \beta * |P_i - X(k)| * \ln\left(\frac{1}{u}\right) \text{ if } u < 0.5 \qquad (14b)$$

where, u is a random number distributed in range [0,1]. To generate convergence, following condition must be satisfied

$$\lim_{t \to \infty} L(t) = 0. \qquad (15)$$

That is, when $L \to 0$, then $X \to P$ at $t \to \propto$. If the latest position portrays more desirable information than it is restored until termination criteria is met.

4. Realization of the Equalizer using QPSO Algorithm

The adaptive channel equalizer modelled on FIR filter is realized using the optimization algorithms considered in the previous section. The main goal of the algorithms is to change the filter weights iteratively so that the Mean Square Error (MSE) is minimised to an optimum value. The updating of weights of the equalizer using QPSO algorithm is carried out according to the steps enumerated in Table 1.

5. Simulation Results and Discussions

A Simulation example is presented in this section for the performance evaluation of the proposed discrete adaptive equalizer for noisy channel. To realize the effect of noisy environment two values of AWGN is considered, 5dB and 10dB.

Linear channel:

The channel taken for simulation is given by following transfer function

Table 1. QPSO algorithm for channel equalizer

Step#	Description
1.	Define the problem space and set the boundaries i.e. inequality constraints of the tap weights (position of particles) defined by their maximum and minimum limits.
2.	Initialize an array of particles, X_i with random positions (tap weights) and their associated velocities inside the D- dimensional (D=8) problem space.
3.	Check if the current position is inside the problem space or not. If not, adjust the positions so as to be inside the problem space.
4.	Evaluate the fitness value $J_i(k)$ of each particle using (5).
5.	Compare the current fitness value with the particle's previous best value, pbest. If MSE (X_i) < MSE ($pbest_i$); then $pbest_i = X_i$ If MSE (X_i) < MSE ($gbest_i$); then g= X_i
6.	Update the global point P according to (10) and particle's position X_i using (12a) and (12b).
7.	Terminate if a good fitness value or maximum number of iterations is met, otherwise repeat from step# 4.

$$h(z) = 0.3410 + 0.8760z^{-1} + 0.3410z^{-2} \tag{16}$$

Nonlinear channel:

The channel is made acutely nonlinear by adopting following nonlinear mathematical function

$$b(k) = a(k) + 0.2 \times (a(k))^2 - 0.1(a(k))^3 + 0.5cos\pi(a(k)) \tag{17}$$

Two vital parameters, convergence characteristics measured in terms of normalized MSE and BER are considered for performance assessment. The results obtained by QPSO are compared with those achieved by conventional LMS and two successful variants of PSO, CIW-PSO and LDI-PSO to validate the efficacy of QPSO. Parameters of all the algorithms are chosen such that the algorithm converges to the same steady state. The selected parameters corresponding to the best performance exhibited by the considered algorithm is mentioned in Table 2.

Comparison of convergence characteristics of linear and nonlinear channel at 5dB and 10dB AWGN is shown in Figure 2 and Figure 3 respectively. Numerical results of simulation are recorded in Table 3, which gives a lucid picture of performance comparison. When channel is

Table 2. QPSO, PSO, WDO and LMS parameters

Parameters	QPSO	CWI-PSO	LDI-PSO	LMS
Population size	60	60	60	-
Iteration cycles	200	200	200	200
No.of input samples	500	500	500	500
Accl. constant, C_1	1.49	1.49	1.49	–
Accl. constant, C_2	1.49	1.49	1.49	–
Control parameter, β	0.54	–	–	–
Inertia weight, ω	–	0.2081	$0.9 - \frac{0.4i}{200}$	–
Step size, μ	–	–	–	0.01

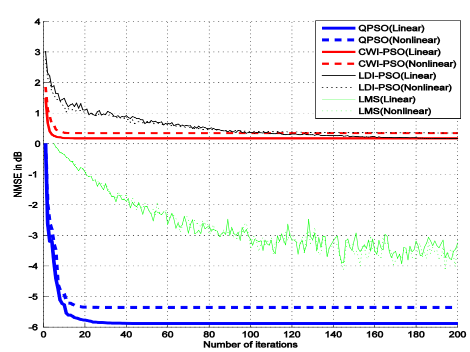

Figure 2. Comparison of convergence plot of linear and nonlinear channels at 5dB.

severely noisy at 5dB, QPSO achieves minimum NMSE of –5.88dB at 40^{th} iteration for linear channel as compared to 0.184dB at 10^{th} iteration, 0.2262dB at 167^{th} iteration for CWI-PSO and LDI-PSO respectively. Similarly, even for nonlinear channel QPSO outperforms other algorithms by converging to –5.359dB at 26^{th} iteration as compared to 0.349dB at 16^{th} iteration and 0.3597dB at 153^{rd} iteration for CWI-PSO and LDI-PSO respectively. But, LMS converges beyond 200 iterations. When channel is less noisy at 10dB, NMSE achieved by QPSO is -8.33dB at 70^{th} iteration for linear channel and –7.039dB at 23^{rd} iteration for nonlinear channel. Other algorithms in this work fail to be even near about these results, as can be clearly read out from Table 3.

Testing of different training algorithms is done by evaluating BER performed on 10^5 bits of input data and is shown in Figure 4 and Figure 5 at 5dB and 10dB respectively.

Comparative BER performance of various algorithms for 10^5 samples at 20dB SNR and 5dB and 10dB AWGN is summarized in Table 4.

QPSO outperforms other algorithms for both linear and nonlinear channel as the error is only 14 bits and 69 bits respectively at AWGN 10dB and 13 bits and 80 bits at AWGN 5dB. Performance improvement of QPSO is 3dB over CWI-PSO and 2dB over LDI-PSO for linear channel. It is 2dB over CWI and 1dB over LDI-PSO for nonlinear channel at 10dB AWGN. This improvement drops to 1dB

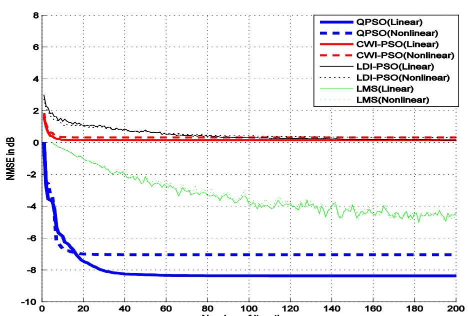

Figure 3. Comparison of convergence plot of linear and nonlinear channels at 10dB.

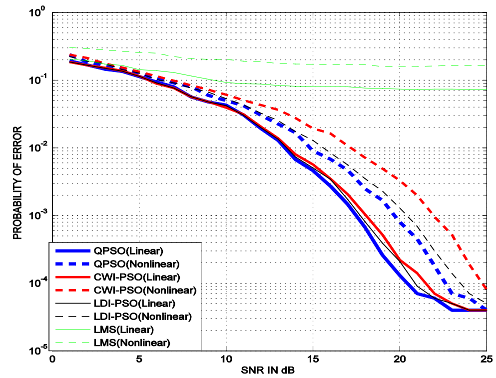

Figure 4. Comparison of BER Plot of linear and nonlinear channels at 5dB.

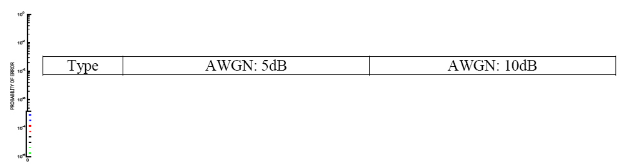

Figure 5. Comparison of BER Plot of linear and nonlinear channels at 10dB.

Table 4. Comparison of BER ($\times 10^{-5}$) at 20dB

Type of algorithm	AWGN: 5dB		AWGN: 10dB	
	Linear channel	Nonlinear channel	Linear channel	Nonlinear channel
QPSO	13	80	14	69
CWI-PSO	21	329	69	155
LDI-PSO	21	128	24	69
LMS	7358	16080	9794	9794

Table 3. Comparison of convergence characteristics under different noise condition

Type of algorithm	AWGN: 5dB				AWGN: 10dB			
	Linear channel		Nonlinear channel		Linear channel		Nonlinear channel	
	NMSE (in dB)	Iteration no.	NMSE (in dB)	Iteration no.	NMSE (in dB)	Iteration no.	NMSE (in dB)	Iteration no.
QPSO	–5.881	40	–5.359	26	–8.338	70	-7.039	23
CWI-PSO	0.184	10	0.349	16	0.1677	14	0.3251	16
LDI-PSO	0.2262	167	0.3597	153	0.3434	147	0.3313	115
LMS	Beyond 200 iteration		Beyond 200 iteration		Beyond 200 iteration		Beyond 200 iteration	

over both CWI-PSO and LDI-PSO for linear channel at 5dB AWGN. For nonlinear channel the improvement is 2dB over CWI-PSO. However, it shows no improvement with respect to LDI-PSO. LMS does not work when noise level is high in the environment, as can be seen from Figure 4 and Figure 5.

In summary, QPSO comes out as a better option as compared toLMS, CIW-PSO and LDI-PSO at 5dB and 10dB which is supposedly a noisy environment. Thus, QPSO based design of discrete channel equalizer can be boldly adopted for digital communication system.

6. Conclusion

A novel FIR based channel equalizer using quantum behaved PSO is employed to develop a discrete adaptive equalizer which works efficiently, specifically under noisy channel conditions. The efficacy of this methodology is validated by comparing with benchmark LMS and two successful variations of PSO, CIW-PSO and LDI-PSO. The simulation results confirm that the presented approach paves way to build a fast and easy discrete equalizer by smart quantum depiction of PSO system. It is extremely reliable for applications exploiting real time processing and is potentially a better choice for constructing linear and non-linear discrete channel equalizers. It is also to be noted that the update equation of QPSO adopts adaptive strategy with lesser number of parameters to be optimized guiding to an improved overall performance without increase in the computation complexity.

7. References

1. Haykin S. Communication systems. John Wiley & Sons; 2008.
2. Bernard W, Stearns SD. Adaptive signal processing. Englewood Cliffs, NJ, Prentice-Hall, Inc. 1985; 1:491
3. Merabti H, Massicotte D.Nonlinear adaptive channel equalization using genetic algorithms.New Circuits and Systems Conference (NEWCAS), IEEE 12th International. IEEE; 2014.
4. Effatnejad R, Rouhi F. Unit Commitment inpower system by combination of Dynamic Programming (DP), Genetic Algorithm (GA) and Particle Swarm Optimization (PSO). Indian Journal of Science and Technology. 2015 Jan; 8(2).
5. Venkateswaran K, Shree TS, Kousika N, Kasthuri N. Performance analysis of GA and PSO based feature selection techniques for improving classification accuracy in remote sensing images. Indian Journal of Science and Technology. 2016 Apr; 9(16).
6. Majhi B,Panda G, Choubey A. On the development of a new adaptive channel equalizer using bacterial foraging optimization technique. Annual IEEEConference. IEEE, India;2006. p.1–6.
7. Nanda SJ, Panda G, Majhi B.Development of novel digital equalizers for noisy nonlinear channel using artificial immune systems.IEEE Region 10 and the Third International Conference on Industrial and Information Systems, 2008. ICIIS 2008;2008. p.1–6.
8. Karaboga N, Cetinkaya B. Design of digital FIR filters using differential evolution algorithm.Circuits, Systems and Signal Processing. 2006; 25(5):649–60.
9. Kumar DD, Meenakshipriya B, Ram SS. Design of PSO based I-PD controller and PID controller for a spherical tank system. Indian Journal of Science and Technology. 2016 Mar; 9(12).
10. Hasan IJ, Gan CK, Shamshiri M, Ab Ghani MR, Bin Omar R. Optimum feeder routing and distribution substation placement and sizing using PSO and MST. Indian Journal of Science and Technology. 2014 Jan; 7(10).
11. Al-Awami A, Ali T. A new modified particle swarm optimization algorithm for adaptive equalization. Digital Signal Processing. 2011; 21(2):195–207.
12. Mahto SK, Choubey A. A novel hybrid IWO/WDO algorithm for interference minimization of uniformly excited linear sparse array by position-only control.IEEE Antennas and Wireless Propagation Letters. 2016; 15:250–4.
13. SinhaR, Choubey A., Mahto SK. A novel efficient transversal channel equalizer based on nature inspired Wind Driven Optimization (WDO) technique.Kasmera Journal.2016; 44(1):423–36.
14. Eberhart RC,Kennedy J. A new optimizer using particle swarm theory. Proceedings of the Sixth International Symposium on Micro Machine and Human Science. 1995; 1:1–5.
15. Shi S, Yuhui Y, Eberhart RC. A modified particle swarm optimizer. The IEEE International Conference onEvolutionary Computation Proceedings, IEEE World Congress on Computational Intelligence,USA;1998.
16. Clerc M. The swarm and the queen: towards a deterministic and adaptive particle swarm optimization. Proceedings of the Congress onEvolutionary Computation, CEC. 1999; 3:1–4.
17. Eberhart RC,Shi S. Comparing inertia weights and constriction factors in particle swarm optimization. Proceedings of the Congress onEvolutionary Computation.2000. 1:4–9.
18. Hu X, Russell C,Eberhart RC. Adaptive particle swarm optimization: detection and response to dynamic systems. Proceedings of the IEEE Congress on Evolutionary Computation, CEC,USA;2002.p.1–5.
19. Bratton D, Kennedy J. Defining a standard for particle swarm optimization. IEEE Swarm Intelligence Symposium,USA;2007.

20. Janson S, Middendorf M. A hierarchical particle swarm optimizer and its adaptive variant. IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics). 2005; 35(6):1272–82.
21. Renato A,Krohling K, Coelho LDS. PSO-E: Particle Swarm with exponential distribution. IEEE International Conference on Evolutionary Computation; 2006.
22. Sun J, Feng B,Xu W. Particle swarm optimization with particles having quantum behaviour. Congress on Evolutionary Computation; 2004.p.23–71.
23. Coelho DS,Leandro L, Alotto P. Global optimization of electromagnetic devices using an exponential quantum-behaved particle swarm optimizer. IEEE Transactions on Magnetics. 2008;44(6):1074–7.
24. Said M, Mikki M, Ahmed A,Kishk K. Quantum particle swarm optimization for electromagnetics. IEEE Transactions on Antennas and Propagation.2006; 54(10):2764–75.
25. Gao F, Tong HQ. Parameter estimation for chaotic system based on particle swarm optimization. Acta Physica Sinica. 2006; 55(2):577–82.
26. Li S. A new QPSO based BP neural network for face detection. Fuzzy Information and Engineering. 2007;40:355–63.
27. Samrat L,Sabat S, Coelho LDS, Abraham A. MESFET DC model parameter extraction using quantum particle swarm optimization. Microelectronics Reliability. 2009; 49(6):660–6.
28. Raviteja GV, Sridevi K, Rani AJ. An insight into adaptive elliptical and hexagonal array synthesis using normalized fractional least mean squares algorithm. Indian Journal of Science and Technology.2016 Jul; 9(26).