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Survey on Adaptive Channel Equalization Techniques using Particle Swarm Optimization

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Abstract- ***In digital communication system, symbols are generated in a source and transmitted over a channel to a receiver. Noise gets added during the transition of symbols over the channel from source to the destination. In practice the symbols are corrupted with nonlinear distortion, Inter Symbol Interference (ISI) and noise. One possibility to reduce the effect of this problem is to use a channel equalizer at the receiver. The function of the equalizer is to reconstruct the original signal from the received signal or to generate a reconstructed version of the transmitted signalo as close as possible to it. The addition of an equalizer usually reduces the bit error rate (BER): the ratio of received bits in error to total transmitted bits. The most preferred technique is adaptive equalization. Traditional adaptive equalization uses linear transversal filter to reduce the effect of ISI. This filter is generally adjusted using a known training sequence at the beginning of the transmission and Least Square Estimation or gradient descent to determine the optimal set of coefficients for the filter. In the literature many adaptive algorithms such as Least Mean Square Algorithms have been developed which are effective under the assumption that the output is a linear function of the inputs. In practice this situation is rare and when nonlinear distortion and ISI are severe, nonlinear equalizers such as neural nets, the use of particle swarm optimization (PSO) can give a better performance. The objective of this paper is to discuss some of the adaptive equalization techniques available in the literature and put forth some ideas to improve the performance of PSO based adaptive equalization techniques.***

Keywords— Particle Swarm Optimization, PSO, adaptive channel equalization, adaptive equalization.

I. Introduction

Adaptive equalization is important due to the fact that the effect of ISI in digital communication systems is reduced, where an adaptive algorithm will adjust the coefficients of the equalizer. Many efficient adaptive algorithms such as the least mean squares (LMS) algorithm have been developed. The LMS Algorithm is a linear adaptive filtering algorithm that consists of two basic processes namely a filtering process which involves computation of the output of a transverse filter produced by a set of tap inputs, and generating an estimation error by comparing this output to a desired response. The second step being an adaptive process, which involves the automatic adjustment of the tap weights of the filter in accordance with the estimation error. However, the use of a linear adaptive algorithm was successful occasionally when the output is a linear function of the inputs. In such scenarios, nonlinear adaptive equalization techniques were required and a number of such techniques have already been proposed in the literature. Alternatively, heuristic techniques have also been employed for adaptive equalization. Particle Swarm Optimization (PSO) is more suitable for the general are of optimizing engineering systems. The use of PSO in adaptive equalization is gaining success in the area of digital communication. For example the use of PSO in adaptive IIR phase equalization and interference cancellation in CDMA systems are some of the successful application areas.

Kennedy and Eberhart first introduced particle swarm optimization. The authors used this optimization technique for studying the social behaviour of the movement of organisms in a bird flock or fish school. The algorithm was simplified and it was observed to be performing optimization. The book by Kennedy and Eberhart describes many philosophical aspects of PSO and swarm intelligence. An extensive survey of PSO applications is made in the literature. This new approach features many advantages; the most important ones being that it is simple and fast, can be coded in few lines, and requires minimum storage. Actually speaking PSO is a computational method that optimizes a problem by iteratively improving a candidate solution with reference to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best-known position and is also guided toward the best-known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions. Moreover, this approach is advantageous over evolutionary algorithms in more than one way. One key advantage is that PSO has memory, i.e., every particle remembers its best solution (local best) as well as the group's best solution (global best).

As such PSO is well suited to tackling dynamical problems, another advantage of PSO is that its initial population is maintained fixed throughout the execution of the algorithm, and so, there is no need for applying operators to the population, a process that is both time- and memory-storage-consuming. In addition, PSO is based on a “constructive cooperation” between particles, as opposed to the other artificial algorithms that are based on “the survival of the fittest”. The choice of PSO parameters can have a large impact on optimization performance. Selecting PSO parameters that yield good performance has therefore been the subject of much research.

In relation to PSO the word convergence typically means one of two things, first convergence may refer to the swarm's best-known position approaching the optimum of the problem, regardless of how the swarm behaves. Secondly, convergence may refer to a swarm collapse in which all particles have converged to a point in the search-space, which may or may not be the optimum.

II. Survey on Adaptive Channel Equalization Techniques using PSO

As discussed earlier, in digital communication systems, source generates symbols and is transmitted to the receiver through the communication channel. During transition the information is corrupted and as a result ISI occurs. In [1], S. Qureshi discussed the use of channel equalizer in the receiver to reconstruct the original signal from the received signal, which in turn reduces the BER.

In [2], N. C. Peng, M. and J. Proakis dicussed the use of nonlinear equalizers, which can give, better performance. In the traditional techniques, the system is trained with a training sequence to decide the optimal set of coefficients to get better results. This type of systems may not be suitable for cases when non linear distortion and ISI are severe. The author has proposed the use of neural nets for better performance [2]. The training of these structures generally involves the use of back propagation or other related, computational expensive, supervised techniques.

In [3], Murakawa et al. presented a system, which is purely based on the usage of an hardware set up to implement adaptive channel equalization. The authors proposed a GRD chip and used it for adaptive channel equalization. The GRD chip is a group of 15 DSPs connected in a binary-tree network that implement a feed forward neural network. The net is reconfigured and trained by a genetic algorithm and steepest gradient descent running in an embedded RISC processor. The population of solutions does not have material existence: the network of DSPs implements only one physical net, with each individual being downloaded for evaluation. The performance was solid due to the fact that it is a hardware implementation. But the proposed system presents two limitations namely the need of a training sequence to be transmitted from the source and the solution is rather expensive, since a single neuron is implemented in a dedicated DSP. Nowadays, commercially available FPGAs benefit from large amounts of configurable resources, allowing the implementation of very complex circuits.

In [4] Jorge Pena et al. found that self-reconfigurable adaptive systems have the possibility of adapting their own hardware configuration. This feature provides enhanced performance and flexibility, reflected in computational cost reductions. Self-reconfigurable adaptation requires powerful optimization algorithms in order to search in a space of possible hardware configurations. If such algorithms are to be implemented on chip, they must also be as simple as possible, so the best performance can be achieved with the less cost in terms of logic resources, convergence speed, and power consumption. The authors presented an hybrid bio-inspired optimization technique that introduces the concept of discrete recombination in a particle swarm optimizer, obtaining a simple and powerful algorithm, well suited for embedded applications. The proposed algorithm is validated using standard benchmark functions and used for training a neural network-based adaptive equalizer for communications systems.

In [4] the authors introduced an approach wherein the authors introduced the FPGA implementation of a whole population of very simple neural networks (e.g, BRBF nets), along with an embedded soft-processor responsible for running the adaptation mechanism (e.g, the proposed PSODR) and the reconfiguration of the population of nets. The setup of the complete system used by the authors consists of a self-reconfigurable platform as the one described in [5]. Based on hardware synthesis reports, a single 15-neuron BRBF-network with 8-bit data resolution, implemented in a Virtex-II 2v4000 FPGA from Xilinx, requires 2% of the FPGA's logic resources. Therefore, it is reasonable to imagine a self-reconfigurable platform with a MicroBlaze soft processor reconfiguring a population of until 30 BRBF networks embedded in a single Virtex-II 2v4000 FPGA The authors planned to use this platform for the solution of adaptive channel equalization. In order to do this without the need of a training sequence, the BER of each neural network based equalizer will be estimated by means of an error detection code. Using these measures, the PSODR will adapt the different parameters of the nets in the population, finding incrementally a good solution in the search space, and decreasing the BER of the whole system. The best solution found so far will be always physically present, giving the actual output of the equalizer. For the sake of comparison, the authors used the communication system proposed in [3], where the source transmits a randomly generated sequence of bipolar symbols through a linear channel with additive, zero-mean Gaussian noise. Finally the author performed a comparison with the other schemes and found that for the population size of 10, the improvement is of 5 times, whereas for 20 and 30 particles the improvement is of about 2 orders of magnitude. This is a significant result, specially when comparing the population sizes and the computational complexity of the two approaches.

In [6], Xueming Yang proposed a modified particle swarm optimization algorithm with dynamic adaptation. In this algorithm, a modified velocity updating formula of the particle is used, where the randomness in the course of updating particle velocity is relatively decreased and the inertia weight of each particle is different. Moreover, this algorithm introduces two parameters describing the evolving state of the algorithm, the evolution speed factor and aggregation degree factor. By analyzing the influence of two parameters on the PSO search ability, a new strategy is presented that the inertia weight dynamically changes based on the run and evolution state. In the strategy the inertia weight is given by a function of evolution speed factor and aggregation degree factor, and the value of inertia weight is dynamically adjusted according to the evolution speed and aggregation degree. The authors analyzed the proposed algorithm and several testing functions are performed in simulation study. Experimental results show that, the proposed algorithm have better convergence towards an optimum value. The improved PSO algorithm proposed in this paper is easy to implement, without additional computational complexity and the convergence precision is also good.

In [7], Ai-min Miao et al. proposed a new adaptive equalization technique with dynamical Inertia Weight to increase the convergence speed and prevent the prematurity of the particle swarm optimizer, the idea of which is entirely different from the traditional linearly decreasing weight. The inertia weight was dynamically updated by two factors namely the dispersion degree and advance degree factors which have significant impact on the evolutionary state of the PSO. Comparison studies were done for three PSOs. The experimental results for eight test functions demonstrated good performance of the proposed method in both the optimization speed and computational accuracy.

The design of linear adaptive filters is well developed and widely applied in practice. However, the same is not true for more general classes of adaptive systems such as nonlinear adaptive systems. This situation results because nonlinear structures tend to produce multi-modal error surfaces for which stochastic gradient optimization strategies may fail to reach the global minimum. In [8], D.J.Krusienski and W. K. Jenkins paid attention to non-linear adaptive systems for potential use in echo cancellation, channel equalization, acoustic channel modeling, nonlinear prediction, and nonlinear system identification. Structured stochastic optimization algorithms that are effective on multimodal error surfaces are then introduced, with particular attention to the Particle Swarm Optimization (PSO) technique. The authors demonstrated the PSO algorithm on some nonlinear filter structures, and both performance and computational complexity are analyzed for these types of nonlinear systems which showed better results.

In [9], A. T. Al-Awami et al. presented an improved version of the existing particle swarm optimization technique and discussed the advantage of the proposed modified technique over other PSO-based techniques, with an application to the important area of adaptive channel equalization. The author has proposed a novel technique to decide upon the optimal values of the parameters under assumption. In this proposed technique PSO is employed to find the optimum value of the tap weights for which the Mean Square Error is minimum. The performance of various PSO algorithms, including proposed algorithm, is compared with respect to adaptive channel equalization to that of the LMS algorithms. The comparative analysis revealed that the proposed modification is superior on both linear and nonlinear channels.

In [10], Lipika Gupta and Rajesh Mehra proposed a new filter with modified Particle Swarm Optimization (PSO) Algorithm. The speciality is that the proposed Filter is capable of finding the global optimum solution for system identification problem in less number of iterations. The authors developed a modified PSO algorithm has been developed and simulated using MATLAB. The result shows the enhanced speed of purposed design in terms of number of iterations it takes to identify the unknown system. The same algorithm has also been realized on various Xilinx FPGA devices and performances have also been analyzed. The area utilization by the proposed design on different FPGA devices has been compared. The results show that proposed filter is consuming very less area in terms of LUTs and Slices to provide enhanced area efficiency. Here the authors basically concentrated on the three PSO parameters. The parameters c1 and c2 are called cognitive and social acceleration constants and help to guide the particles towards the best optimal value. These constant are equal and have the values from 0 to 2 but studies have shown their values set to 2 gives the best results. So the values are set purposely to 2 in the proposed system. Another parameter of PSO is w called the inertia weight. For unconstrained PSO, w is linearly decreasing from wmax=0.9 to wmin=0.4 over iterations. Further the inertia weight (w) control the influence of the current velocity on the new velocity. A large inertia weight compels large exploration through the search space; a smaller inertia weight causes reduced exploration. The use adaptive updation to w leads to sufficient exploration of search space, thus finding out the global optimum solution. In addition to this maximum velocity is also limited using Signum function. As velocity update leads to acceleration of particles, the limitation is that the smaller the acceleration, the smoother the trajectory of the particle is. However, too small an acceleration may lead to slow convergence, whereas too large an acceleration drives the particles towards infinity.

The techniques so far discussed gave an insight idea about how particle swarm optimization can be applied for adaptive channel equalization in digital communication systems. Different approaches were discussed both in terms of hardware and software implementation keeping in mind the storage and the computational capacity. The general understanding of PSO from the concepts so far discussed is that a problem space need to defined with some predetermined boundaries, i.e., in the case of adaptive equalization it is nothing but the inequality constraints of the tap weights defined by their maximum and minimum limits. Then it is required to initialize an array of particles with random positions and their associated velocities inside the problem space. In our case it is nothing but the tap weights related to the equalizer. Then the current positions of the particles are checked, i.e., it is determined whether the particles are well within the space, if not their positions are adjusted so that they are well within the space. Finally the fitness value of each particle is evaluated and compared with the previous value and if the current fitness value is better than that is assigned as the best fitness value of the particle. Likewise the global minimum among particle’s best position is determined. Finally the velocities are changed as discussed earlier by moving each particle to a new position and repeating the same set of steps until the stopping criterion is satisfied. The performance of the system using PSO is purely based on how effectively the positions of the particles in the space are varied and the convergence to the best optimal value is achieved.

III. Conclusions and Future work

The paper discussed few adaptive equalization techniques based on particle swarm optimization. The performance of each system is discussed based on the parameters like computational complexity, computation accuracy, convergence precision, optimization speed etc. It is understood that in particle swarm optimization the word convergence typically means one of two things, first convergence may refer to the swarm's best-known position approaching the optimum of the problem, regardless of how the swarm behaves. Secondly, convergence may refer to a swarm collapse in which all particles have converged to a point in the search-space, which may or may not be the optimum. The objective of the future work is to find a novel method to vary the tap weights of the phenomenon under assumption so that the velocity of the particles in space is varied in a required manner and finally best convergence is achieved.

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