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Optimal Channel Equalization using Teacher learning based optimization Technique for MPNN

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Abstract

Equalization is essential at the receiver to defeat these channel destruction to get better the original transmitted sequence. Conventionally equalization is considered as counterpart to inverse filtering and implemented using linear-perform under severe distortion conditions when Signal to Noise Ratio (SNR) is deprived Equalization can be considered as a non-linear classification problem and optimum solution is given by Bayesian solution. Non-linear techniques like Artificial Neutral Networks are very good choice for non-linear classification problems. Several non-lines are equalizers have been implemented using ANN which outperformed LTE and solved the problem of equalization to the varying degree of sources. In this paper proposed optimal channel equalization using teacher learning based optimization technique. The proposed equalization technique performs better in compression of MPNN equalizer and MPNN-ACO based equalizer in channel decoding process.

Keywords: channel equalization, MPNN and TLBO

Introduction

In real word the modern digital communication systems, the transmission of a high speed data through a channel is limited by inter symbol Interference (ISI) caused by distortion in the transmission channel. High-speed data transmission through channels with severe distortion can be achieved by designing an equalizer in the receiver that counteracts the channel distortion. Communication channels introduce linear and nonlinear distortion, secret cases of significance; they cannot be considered memory less. Inter-symbol interference (ISI), mainly a consequence of multi-path in wireless channels, accounts for the linear distortion. The existence of amplifier and converters explain the nonlinear nature of communications channels. For adaptive channel equalization need a suitable filter structure and proper adaptive approach. The very High-speed digital data transmissions mostly suffer from inter-symbol interference (ISI) and an additive noise[1,2]. An Adaptive equalization approach recursively determine the filter coefficients in order to eliminate the effects of noise and ISI. The most frequently used structure of equalizer is a transversal adaptive filter with an appropriate algorithm such as least mean square (LMS), recursive least squares (RLS), or QR-Decomposition-Based least squares lattice filter (QRD-LSL). One particular class of speech dereverberation techniques is acoustic channel equalization, which is based on estimating and inverse filtering the room impulse responses (RIRs), e.g. using the multiple-input/output inverse theorem (MINT) technique that aims to recover the anechoic speech signal. To mitigate the effects of ISI and IAI that reduce the performance and the capacity of MIMO systems, the designer has to construct a MIMO equalizer. The optimal MIMO equalizer known as the maximum-likelihood sequence estimation (MLSE) receiver was originally developed in the context of multiuser detection[3,6]. This is an various optimization algorithm that in addition to solving optimization problems, all of these algorithms are optimization techniques, some of them like ACO more successful in local and some other like PSO in global optimization problems , some of them like that (Genetic algorithm) GA , fuzzy neural systems (FNS) and Artificial Bee Colony (ABC). These algorithms in control engineering, controller designing, robotics and specially their applications in adaptive control and system identification. GA is a well studied and effective search technique used in lots of work in CDMA communications systems also been applied to UWB communications systems also the GA is a well studied and effective search technique used in lots of work in CDMA communication system. Reduction of the computational complexity of GA prompted the use of a few number of variables which resulted in medium size of search space. A genetic algorithm iteratively improves a set of candidate solutions (CSs)[4]. It uses operations inspired by genetics, such as crossover, mutation, and selection, to generate new CSs by modifying and combining existing CSs. Similar to the SGA adds to the genetic operations a local search. The SGA is substantially different from genetic algorithms previously proposed for MIMO detection. it uses the soft values provided by Stage 2 and the partial ML detection results provided by Stage 1 for an improved initialization, and it includes a local search procedure, which makes the search for improved CSs more effective. Therefore, the SGA performs well even for very small population sizes. The proposed teacher learning based optimization (TLBO) as learning algorithm in order to achieve better optimization ability. For a optimal task, MPNNs needs to be "trained"

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for the network to be able to produce the desired input-output mapping. In training phase, a set of example data are presented to the network and the connection weights of the network are adjusted by using a learning algorithm. The purpose of the weights adjustment is to enable the network to "learn" so that network would adapt to the given training data. Section-I gives the introduction of channel equalization. Section-II gives the related of channel equalization using MPNN and optimization technique. Teacher learning based optimization and MPNN filter -III. In section IV discuss simulation result in comparative manners and finally discuss conclusion and future work in section V.

II Related work

In this section described the related work in the field of channel equalization using MPNN network and optimization technique such as ANT colony optimization, particle of swarm optimization and genetic algorithm. all the optimization process perform a better optimization technique but it still needed some improvement. in the field of such optimization technique discuss here.

[1] In this paper Author proposed a new adaptive channel equalizer using Genetic Algorithm (GA) which is essentially a derivative free optimization tool. This algorithm is suitably used to update the weights of the equalizer. Genetic algorithm is based upon the process of natural selection and does not require gradient statistics. As a consequence, a GA is able to find a global error minimum. Moreover, the GA with small population Size and high mutation rates can find a good solution fast. The performance of the proposed channel equalizer is evaluated in terms of mean square error (MSE) and convergence rate and is compared with its LMS and RLS counter parts. It is observed that the new adaptive equalizer based GA offer improved performance so far as the accuracy of reception is concerned.

[2] In this paper Author tried to review briefly some parts of influence of swarm and evolutionary algorithms in control engineering, controller designing, robotics and specially their applications in adaptive control and system identification. PSO with faster convergence speed and simpler implementation than genetic algorithm has been successfully applied to solve system identification optimization problems and can be employed for on-line applications in self tuning controller design in adaptive control. In addition, swarm robots that have been inspired by the natural behavior between swarm in real word, can be useful for several applications such as rescue and planetary or underwater exploration. PSO and ACO have been applied as a navigation algorithm in robotics.

[3] Author proposes to measure the performance of this equalizer after a low-density parity-check channel decoder has detected the received sequence. Typically, most channel equalizers concentrate on reducing the bit error rate, instead of providing accurate posterior probability estimates. We show that the accuracy of these estimates is essential for optimal performance of the channel decoder and that the error rate output by the equalizer might be irrelevant to understand the performance of the overall communication receiver. In this sense, GPC is a Bayesian nonlinear classification tool that provides accurate posterior probability estimates with short training sequences. In the experimental section, we compare the proposed GPC based equalizer with state-of-the-art solutions to illustrate its improved performance.

[4] This paper presents the development of novel type-2 neuro-fuzzy system for identification of time-varying systems and equalization of time varying channels using clustering and gradient algorithms. It combines the advantages of type-2 fuzzy systems and neural networks. The type-2 fuzzy system allows handling the uncertainties associated with information or data in the knowledge base of the process. The structure of the proposed type-2 TSK fuzzy neural system (FNS) is given and its parameter update rule is derived, based on fuzzy clustering and gradient learning algorithm. The proposed structure is used for identification and noise equalization of time-varying systems. The effectiveness of the proposed system is evaluated by comparing the results obtained by the use of models seen in the literature.

[5] Author propose a genetic algorithm (GA) based equalization approach for direct sequence Ultra-wideband (DS-UWB) wireless communications, where GA is combined with a RAKE receiver to combat the inter-symbol interference (ISI) due to the frequency selective nature of UWB channels for high data rate transmission. Simulation results show that the proposed GA based structure significantly outperforms the RAKE receiver. It also provides a close bit error rate (BER) performance to the optimal maximum likelihood detection (MLD) approach, while requiring a much lower computational complexity. The impact of the number of RAKE fingers on the algorithm and the speed of convergence in terms of the BER against the number of generations are also presented.

[6] In this work, the equalization of the very frequency selective UWB channel is carried out in frequency domain without any GI inserted, and this is assisted by the use of GA as an optimization technique. Reduction of the computational complexity of GA prompted the use of a few number of variables which resulted in medium size of search space. Meanwhile, the use of GI with a few number of variable leads to very high GI overhead which is not desirable in wireless communication. Our work is different from other research work in FDE because of the absence of GI and also combining GA with FDE is a novel contribution as at the time of this work.

[7] Author propose an equalization approach using GA in DS-UWB wireless communication, where GA is combined with a RAKE receiver to combat the ISI due to the

frequency selective nature of UWB channels for high data rate transmission. We also compare our proposed RAKE-GA equalization approach with the MMSE based linear equalization approach and the optimal MLD approach to demonstrate a trade-off between performance and computational complexity. Moreover, we employ a data aided approach to estimate the channel amplitudes and delays using a sliding window method, which has lower complexity than ML based channel estimation methods.

[8] Author proposes a low-complexity detector for multiple-input multiple output (MIMO) systems using BPSK or QAM constellations. The detector operates at the bit level and is especially advantageous for large MIMO systems. It consists of three stages performing partial ML detection, generation of soft values, and soft-input genetic optimization. we present a genetic programming algorithm that uses the soft values computed by the second stage. Simulation results demonstrate that for large systems, our detector can outperform state-of-the-art methods, and its complexity scales roughly cubically with the system dimension. For large MIMO systems, the proposed MIMO detector is demonstrated through simulation to outperform detectors based on nulling-and-canceling, semi definite relaxation, and likelihood ascent search. The computational complexity scales roughly cubically with the system dimension and constellation size.

[9] Author investigates robust turbo equalization over the frequency selective channels in the presence of channel uncertainties. The turbo equalization framework investigated in here contains a linear equalizer to combat ISI and a trellis based decoder. However, instead of completely tuning the linear equalizer parameters to the available inaccurate channel information, a mini max scheme and a competitive scheme are studied, which incorporate the uncertainty in channel information to equalizer design in order to improve robustness. Approximate implementations of these methods are also presented with reduced computational complexity.

[10] This paper presents the ability of Functional Link Neural Network (FLNN) to overcome the complexity structure of MLP by using single layer architecture and propose an Artificial Bee Colony (ABC) optimization for training the FLNN. The proposed technique is expected to provide better learning scheme for a classifier in order to get more accurate classification result. we describe an overview of FLNN and the proposed Artificial Bee Colony (ABC) as learning algorithm in order to achieve better classification ability.

III. Teacher learning based optimization and MPNN filter

This optimization method is based on the effect of the influence of a teacher on the output of learners in a class. It is a population based method and like other population based methods it uses a population of solutions to proceed to the global solution. A group of learners constitute the population in TLBO[11]. In any optimization algorithms there are numbers of different design variables. The different design variables in TLBO are analogous to different subjects offered to learners and the learners' result is analogous to the 'fitness', as in other population-based optimization techniques. As the teacher is considered the most learned person in the society, the best solution so far is analogous to Teacher in TLBO. The process of TLBO is divided into two parts. The first part consists of the "Teacher phase" and the second part consists of the "Learner phase". The "Teacher phase" means learning from the teacher and the "Learner phase" means learning through the interaction between learners. In the sub-sections below we briefly discuss the implementation of TLBO.

Initialization

Following are the notations used for describing the TLBO

N: number of learners in class i.e. "class size"

D: number of courses offered to the learners

MAXIT: maximum number of allowable iterations

The population X is randomly initialized by a search space bounded by matrix of N rows and D columns. The jth parameter of the ith learner is assigned values randomly using the equation

$$x^{0}_{(i,j)}=x_j^{min}+rand\times(x_j^{max}-x_j^{min})\ldots\ldots(1)$$

where rand represents a uniformly distributed random variable within the range (0, 1), xmin j and xmaxj represent the minimum and maximum value for jth parameter. The parameters of ith learner for the generation g are given by

$$X^{g}_{(i)}=\left[x^{g}_{(i,1)},x^{g}_{(i,2)},\ldots\ldots\ldots,x^{g}_{(i,j)}\ldots\ldots,x^{g}_{(i,D)},\right]\ldots\ldots\ldots(2)$$

III.1 Teacher phase

The mean parameter Mg of each subject of the learners in the class at generation g is given as

$$M^{g}=\left[m^{g}_{1},m^{g}_{2},\ldots\ldots m^{g}_{j},\ldots\ldots m^{g}_{D}\right]\ldots\ldots\ldots(3)$$

The learner with the minimum objective function value is considered as the teacher Xg Teacher for respective iteration. The Teacher phase makes the algorithm proceed by shifting the mean of the learners towards its teacher. To obtain a new set of improved learners a random weighted differential vector is formed from the current mean and the desired mean parameters and added to the existing population of learners.

$$Xnew^{g}_{(i)}=X^{g}_{(i)}+rand\times\left(X^{g}_{Teacher}-TFM^{g}\right)\ldots\ldots(4)$$

TF is the teaching factor which decides the value of mean to be changed. Value of TF can be either 1 or 2. The value of TF is decided randomly with equal probability as,

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$$T_{F=round\ [1+rand\ (o,1)\{2--1\}]} \cdots\cdots\cdots\cdots\cdots\cdots.(5)$$

Where TF is not a parameter of the TLBO algorithm. The value of TF is not given as an input to the algorithm and its value is randomly decided by the algorithm using Eq. (5). After conducting a number of experiments on many benchmark functions it is concluded that the algorithm performs better if the value of TF is between 1 and 2. However, the algorithm is found to perform much better if the value of TF is either 1 or 2 and hence to simplify the algorithm, the teaching factor is suggested to take either 1 or 2 depending on the rounding up criteria given by Eq. (5). If Xnew is found to be a superior learner than Xg in generation g , than it replaces inferior learner Xg in the matrix.

III.2 Learner phase

In this phase the interaction of learners with one another takes place. The process of mutual interaction tends to increase the knowledge of the learner. The random interaction among learners improves his or her knowledge. For a given learner Xg , another learner Xg is randomly selected (i ≠ r). The ith parameter of the matrix Xnew in the learner phase is given as

$$Xnew^{g}{}_{(i)=\{x_i^g+rand\times(X_i^g-X_r^g)\ if\ f(X_i^g)<f(X_r^g)} \atop {X_i^g+rand\times(X_r^g-X_i^g)\ otherwise\ \ldots\ldots\ldots\ldots(6)}$$

III.3 Algorithm termination

The algorithm is terminated after MAXIT iterations are completed.

III.4 MPNN Filter

The proposed equalizer in this paper shown in Figure 1 and consists of two basic components, one MPNN filter and one TLBO. The purpose of filter is to receive the distorted output from the channel and will form two separate and independent patterns, one for {+1} and next for {-1}. The purpose of the TLBO is to optimize the cost function and thereby minimizing the error.

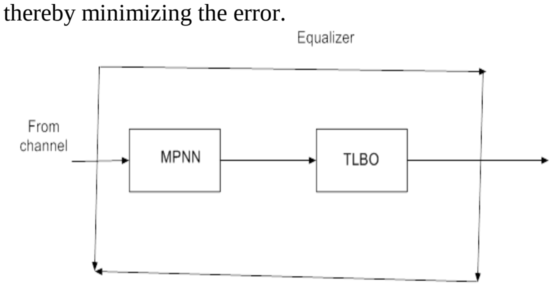

Figure 1 Proposed equalizer structure

The MP neural network architecture is a four-neuron layers network model as shown in Fig. 2. These four layers include the input unit, the pattern unit, the summation unit and the output unit. The input unit contains a number of input image data and the pattern unit node number equal the number of training data, the output unit represents the classification results.

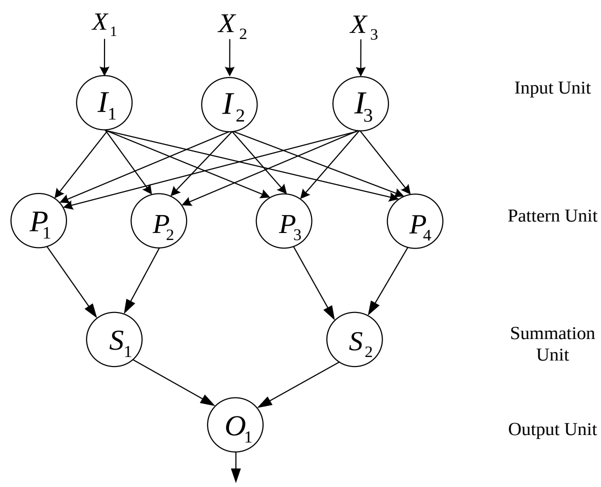

Figure 2 the MP neural network architecture

The raw data are divided into *k* classes, which represent the *k* situations to be explained. Each class has *m*-dimensional observations, i.e. $X=[X_1, X_2, \cdots X_m]$. The following Bayes decision rule is used to classify the raw data into *k* classes:[12]

$$h_i c_i f_i(X) > h_j c_j f_j(X) \quad \forall \quad j \neq i,$$

Where h_k is the prior MP of class *k*; C_k is the representative center that belongs to the class *k*, but the loss function has been a miscarriage of justice; and f_k is the MP density function of class *k*

The MP density function for each class can be expressed as follow:

$$f_i(x) = \frac{1}{(2\pi)^{\frac{d}{2}}\sigma^d}\frac{1}{N_i}\sum_{j=1}^{N_i}\exp\left[\frac{-(x-x_{ij})^t(x-x_{ij})}{2\sigma^2}\right]$$

where $f_i(x)$ denotes the dimension of training vector, σ is the smoothing parameter and d is the dimension of training vector. N_{ij} denotes the total number of training vector in category i, and x_{ij} is the neruon vector and χ is test vector.

When a new input image X is added, the pattern unit will be calculated with the individual weight vector W^{ip} of the product to make a nonlinear transformation to Z_i :

$$Z_i = X \cdot W^{ip}.$$

The MP of neural network with back propagation networks can approximate any continuous nonlinear function. In this paper, we use the Gaussian function as the activation function:

$$P(Z_i) = \exp\left[(\frac{Z_i - 1}{\sigma^2}) \right]$$

With the above equation, X and W^{ip} have been normalized with their unit length:

$$P_i(X) = \exp\left[-\frac{(X - W^{ip})^t (X - W^{ip})}{2\sigma^2} \right]$$

The summation unit will be calculated from the pattern unit by summarizing and averaging the output of N_i neurons to generate an output MP vector, i.e.

$$S_i(X) = \frac{1}{N_i} \sum_{p=1}^{N_i} \exp\left[\frac{(X - W^{ip})^t (X - W^{ip})}{2\sigma^2} \right]$$

Finally, one or many larger values are chosen as the output unit that indicates these data points are in the same class via a competition transfer function from the output of summation unit [7], i.e.

$$O(X) = \arg\max(S_i(X)), \quad i = 1, 2, \cdots, m$$

IV simulation Result

To test the effectiveness of the proposed equalizer, a real symmetric channel impulse response with an impulse response considered as: H(z)=0.2887+0.9129z^1+0.288z^{-2}.[13]Transmitted signal constellation was set to {± 1} keep-ing the transmitted power unity. Co-channel Interference was treated as noise. For simulation the training data consisted of 8 random values of p , and 25 random values of (including n=0, and n=256). For the simulations, optimization parameters chosen as:N=40,D=256 and iteration=100. in the simulation result we consider the different size of code block according our population size and trained pattern.

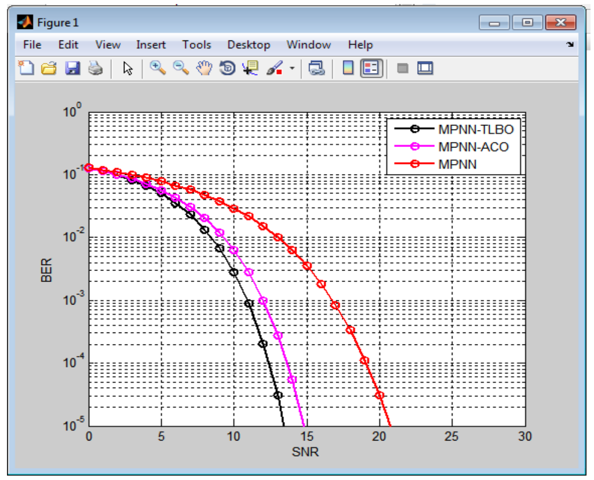

Figure 3 shows that bit error rate Vs signal to noise Ratio in MPNN filter with two optimization algorithms in case of 20 size of leaner and 50 iteration

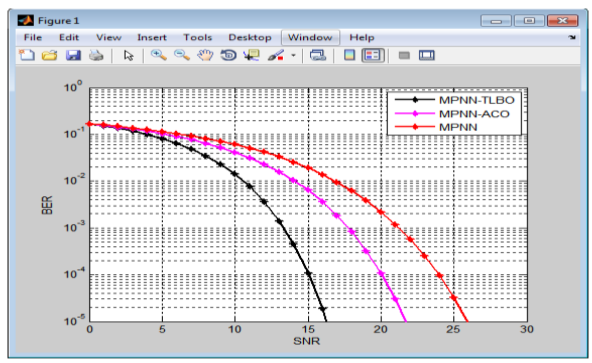

Figure 4 shows that bit error rate Vs signal to noise Ratio in MPNN filter with two optimization algorithms in case of 30 size of leaner and 75iteration

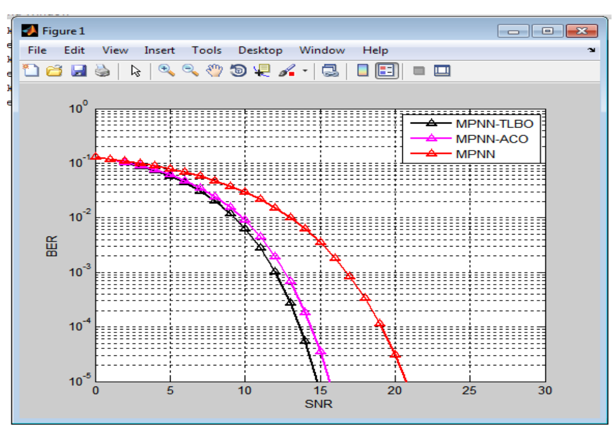

Figure 5 shows that bit error rate Vs signal to noise Ratio in MPNN filter with two optimization algorithms in case of 40 size of leaner and 100 iteration

V Conclusion and Future work

In this paper proposed a novel equalizer where a hybrid structure of four multi-layer neural networks acts as a classifier to classify the detected signal pattern. The neurons were embedded with teacher learning optimization algorithms. Simulation results prove the superior performance of the proposed equalizer. Works reported in this paper can also be extended to other optimization algorithms like orthogonal teacher learning based algorithm, also can be tested with hybrid algorithms developed using GA, ACO, hill clamming etc.

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