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A review of channel equalization: A survey

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Abstract
This paper shows a comprehensive review on evolution of channel equalization. Apart from that it also shows the performance related parameters for the improvement of channel equalization by using different techniques such as Neural Networks, Subspace Method, Multilayer Perceptron and Sub Carrier allocation techniques. Lastly it also shows the direction of further research work.

Keywords: neural network, equalization technique, MLP.

Introduction

From the initiation of equalization systems, endeavors were made to enhance its execution and dependability on transmitting high information rate. In prior stage Zero Forcing Equalizers are used. At First, in the year of 1960, the performance of equalization system was found by using adaptive equalizer in Multipath radio channel by Widrow *et al*. This method may be popular so that in 1965 Lucky used Least Mean Square Algorithm in Adaptive equalizer. The design of this filter is so popular but it has some limitation that it cannot provide better performance in both Highly Dispersive Channel and Time Varying Channel without any training data. This is due to the fact that linear equalizers show equalization as an inverse filtering problem whereas equalization can be treated as a pattern classification problem. This may take further research with beginning of MLSE and Viterbi implementation. Better result than the conventional one. In the mean while it has been observed that controlled equalization technique outperformed diversity in combating interference.

Quershi *et al* proposed generalization of Adaptive Equalization system analyzed its performance in a fading channel in 1982.The steady-state performance both Linear and nonlinear receiver structures are presented. It is shown that a fractionally spaced equalizer can serve as the optimum receive filter for any receiver. Decision-feedback equalization, decision-aided ISI cancellation, and adaptive filtering for maximum-likelihood sequence estimation are presented in a common framework.

Zhang *et al* [1990] proposed a design process for Adaptive Equalization using Back Propagation Technique. adaptive channel equalizer is presented based on the back propagation algorithm applied to an associative network. Simulations are made for linear and nonlinear channels. The performance is shown to be good and much better than with the LMS algorithm for the nonlinear channel

In the year 1993, in order to achieve higher performance Hush *et al* proposed channel equalization scheme based on Artificial Neural Networks (ANN). Here, the symbol-by-symbol equalizer has been development in associated with Viterbi algorithm and poor performance of conventional equalizers.

Ling *et al* [1995] analyzed the performance of Decision Feedback Equalizer (DFE) and different FIR realization structures for time varying multipath channels. It is shown that when DFE is realized with lattice structure maximum performance is obtained

Further Bang *et al* [1996] attempted to detect the signal in the receiver side using Novel Neural Network circuitry and proved the detection is much robust. Abed-Maraim *et al* [1997], introduced the concept of Subspace Methods in 1997 to perform channel equalization. The proposed method used for blind system identification of MIMO systems which uses Minimum Noise Subspace technique (MNS). It is shown that MNS can be obtained in a parallel structure from a set of tuples of system outputs that form a properly connected sequence (PCS).

In the literature, equalizers are divided into two categories, supervised and blind. However, this paper discussed a third category "Intelligent equalizers" separately. Use of soft and evolutionary computing in equalization is put into this category.

Supervised Equalization

During the transmission of signals some noise is added in the channel which may distorts the signal. Such distortion is removed by using a sequence of pilot signals. At the receiver end the exact replica of signal is present for updation. Fig-1 shows the block diagram of supervised Equalization.

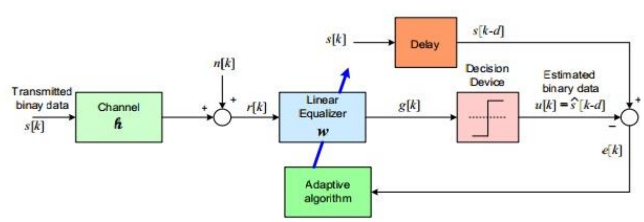

Fig 1: Supervised Equalization

Supervised equalization techniques are up two types. (1) symbol-by-symbol estimation (2) sequence estimation

Symbol-by-symbol estimation also known as finite memory equalizer identify the input signals using a fixed number of

Samples. Here Bayes's theory provides a decision function that is optimum for these equalizes hence this equalizer is also named as Bayesian equalizers.

Sequence estimation commonly known as infinite memory equalizers identify the input sequence using the past -received samples sequence and were implemented with the use of Viterbi Algorithm

This equalization technique apparently takes more band width, hence treated as inefficient or even not properly working in multi user environment.

Blind Equalization

In order to avoid the drawback of supervised equalization this techniques are used. Here transmitted symbol statistics is used at the equalizer. In this method by using Finite Impulse Filter method the channel can be modeled. A simple method of equalization via zero forcing algorithms (ZFA) for minimum phase channel. But for non-minimum phase channels this algorithm is not more stable.

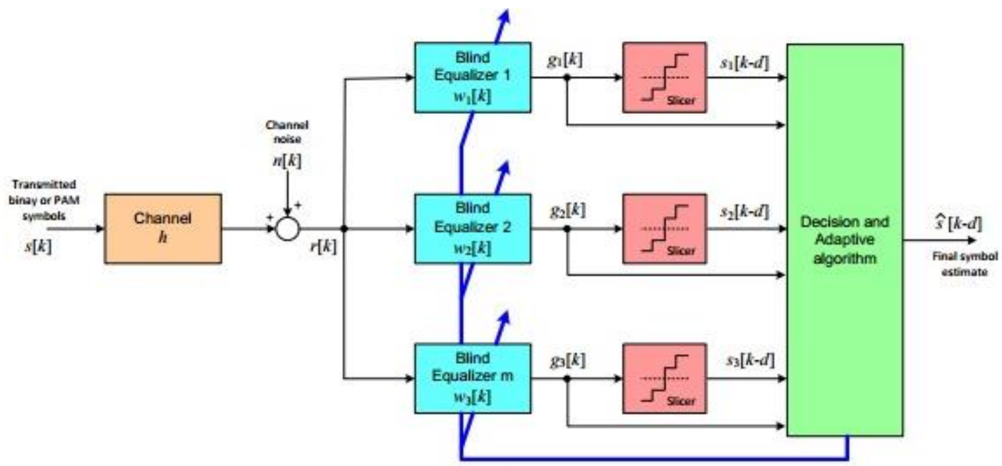

Fig 2: Blind Channel Equalization

This approach divides in to two classes. 1. Based on higher order statistics (HOS) 2. Based on second order statistics (SOS) of the transmitted symbols. In particular fractionally spaced Equalization (FSE) the higher order statistics is not working because for HOS the computationally cost is high.

Intelligent equalizers

Earlier equalizers have been taken over by the neural network based equalizers. NN based equalizers can provide significant improvement in performance for a large number of channels. Objective of this section is to review NN based channel equalization that includes real and complex-valued networks and RBF networks, recurrent neural networks, cellular networks, polynomial perceptions, self-organizing maps, information geometry-based approaches, etc. A variety of realvalued NN based adaptive equalizers can be found in the literature on equalization [34-37]. These equalizers using various kinds of ANN structures like RBFNNs, multi-layer perceptions and modular networks, successfully equalize the nonlinear channels and outperform traditional linear equalizers.

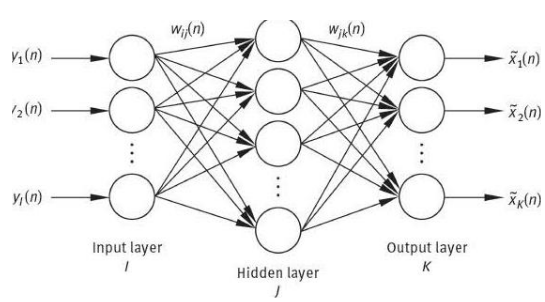

Fig 3

This can be proved from following examples, in [38] Chen *et al*. proved that MLP based equalizers can generate separation curves those are complex and also nonlinear and hence can equalize channels with high degree of nonlinearity. Authors in [39] present a programmable VLSI ANN processor for equalization that is very powerful and can be implemented through a chip configured as a four-layer perceptron. Research in [39] Introduces a functional-link ANN based decision DFE to overcome ISI, CCI and additive noise. The said structure proved to provide superior performance in terms of BER as compared to the conventional DFE, RBF equalizers, linear transversal equalizer (LTE) and MLP equalizers. An analytical study on the performance for MLP-based receivers was proposed by De viciana and Zakhor in [40]. In their study they have shown that for large SNR values, it can be predicted to find the noise variance ratio between the output and the input. They have shown it to depend on the product of weights of neurons at the input and output layers, the number of saturated nodes and the temperature parameter of the nonlinearity. Chen *et al*. introduced complex-RBFNN in [41, 42] revealing that the structure can generate complex non-linear decision surface and also can approximate any arbitrary non-linear function of complex multi-dimensional space. This was then applied for equalization of 4-QAM digital communication channel. It found structural equivalence between the complex RBFNN and optimal Bayesian equalizer. This provoked the research to develop fast training algorithms for implementation of Bayesian RBF equalizers. Gram-Schmidt orthogonal decomposition idea generated application of lattice polynomial perceptron (LPP) to equalization of 64-QAM channels, frequency-selective slow fading channel with ACI in [43] and found to outperform conventional equalizers like DFE. The performance of cellular neural network [44] has been proposed for MLSE of signals in the presence of noise and ISI and applied with improved performance for equalization in [45]. They have addressed the hardware structure, model of the network and neuron in terms of BER performance, and found to be very efficient in realizing the MLSE receiver. Other kinds of hardware realization issues can be found from [46].

High degree of nonlinear dynamic characteristics of RNN [47] showing a rich and complex dynamical behavior [47] found application in channel equalization. The RTRL algorithm [47] was extended to the complex plane by Kechriotis *et al*. [48]. In equalization complex RTRL equalizer and linear TDL equalizers shows comparable performance for linear channels, but it outperforms for the channels with transfer function having spectral nulls or having severe nonlinear distortions. Also, RNNs outperform MLP equalizers for linear and nonlinear channels. The RTRL algorithm has been also applied in blind equalization, and shown to perform better than the CMA in all the channels. As an alternative to gradient-based learning algorithms and also providing higher convergence speed then gradient-based methods, one training approach for RNN proposed in [49] based on the principle of discriminative learning [50] that minimizes an error function which is a direct measure of the error in classification. They used LS methods (most common in the signal processing applications) to fully RNNs and found to perform better than the RTRL algorithm in equalization. A general ANN structure parameterizes the received signal to find conditional probability distribution function (PDF) of the transmitted proposed by Adali *et al*. in [51]. The PDF is estimated by minimizing the accumulated. Provides high complex decision boundaries, and abrupt changes can be tracked in a nonlinear channel response where the MSEbased MLP fails. The self-organizing map (SOM) has been connected either in cascade or in parallel with conventional equalizers such as DFE and LTE [52]. The adaptive decision was defined by M_I vector given that $e(n) = y(n) - M_I(n)$.

ANNs have been applied in equalization of satellite UMTS channels in NEWTEST ACTS European Project [53]. A variety of NN structures and combinations of them has been applied in the project for the real-time trials. They have revealed that ANN approaches outperform classical equalizers for complicated modulation schemes like M-QAM modulations, $M > 4$) are used [54]. In bulky signal processing system, a requirement of easy integration is always there. Because ANNs are more suitable for the requirement, there is abundant number of applications in nonlinear channel equalization. Since ANNs have resemblance with other schemes like coding and modulation techniques, signal processing, etc., ANNs found this multiple scale of applications.

Though ANNs perform well in equalization, but however associated with some of disadvantages like

- The ANN structure becomes bulky because they are in no way related to the problem of equalization.
- High degree of non-linearity in ANN structure makes it difficult for performance analysis and comparison among parameters for adaptation. And also trial and error method is only available to select the parameters for training.
- There is no standard relation between the MLP and the optimal Bayesian equalizer.
- ANN equalizer does not guarantee to converge since it starts with random weights during training.
- The popular BP algorithm takes longer time to train ANN,
- The MLP associated with very large computational complexity.

Summary: Limitations and Future Research Directions

To get rid of the above mentioned disadvantages of BP trained ANN equalizers, we have used evolutionary algorithms to train ANN and RBFNN. The following trend is also an addition to the choices made:

Recently, GA [62] PSO [63] has been used to train ANN. But, these are limited in updating the weights ANN., G. Das, *et.al* used PSO in [64] to get an optimal topology for ANN. Once again, since search by PSO is limited to a finite space and may easily traps to local minima [65]. On the other hand FFA [66] has an improved ability to search. ANN training using FFA for weight updation also carried out in [67]. Works can be carried out on: ANN training using GA/FFA and their variants, RBFNN training using GA/FFA and their variants and also use of these ANN and RBFNN in channel equalization. In summary, this paper has provided a detailed review on channel equalization. This paper also points out the motivation and provides a direction for future research.

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