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Research Article

A SURVEY ON CHANNEL EQUALIZATION

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ABSTRACT

This paper provides a detailed survey on channel equalization. Starting with beginning of the era on equalization, this paper, have given a detailed classification. With the progress and developments in this field, we have given the detailed limitations of neural networks. Finally the paper points out the probable directions for further research.

INTRODUCTION

Digital communication has been already passed through different stages namely first to fifth generations. However, Inter Symbol Interference (ISI), Co-channel Interference (CCI) and Adjacent Channel Interference (ACI) always remains as a problem. These along with noise corrupts the signal inside the channel and hence exact recovery of transmitted signal at the receiver side is always an challenge. The process of nullifying and or diminishing the effects of noise, ISI, CCI and ACI has been carried out with the equalizer set at the receiver. The present paper provides a survey on early equalizers and a study on present day of research on equalization.

Equalization-classification

The study on the equalization of channel started during 1960's but was centered on the zero forcing equalizers, basic theories and structures. Use of adaptive filters in equalization started with development of the LMS algorithm [1]. However, Lucky [1] was the first person to design adaptive channel equalizers using LMS algorithm in 1965. Very soon, adaptive linear filters become popular in the application in channel equalization and efforts were made to eliminate the limitations of LMS and adaptive filters. However, for highly dispersive channels, even best trained linear equalizers fails to provide acceptable performance. This paves the way to the research in other techniques for equalization. In 1970's, the development of the MLSE equalizer [2] and also its viterbi implementation [3] was added to the literature.

The IIR form of the linear adaptive equalizer also developed during the same time. Then, the equalizer started employing feedback [4] and was termed as DFE. Then, the adaptive equalizers of PAM systems were extended to other complex signaling systems as in [5]. Fast convergence and/or computational efficient algorithms also used in equalization during 1970's and 1980's. The Kalman filters [6], recursive least square (RLS) algorithm, fractionally spaced equalizers (FSE) [8] and RLS lattice algorithm [7] are some examples. A detailed review of equalizers up to 1985 can be found in [9]. In the late 1980's there was a beginning for use of artificial neural network (ANN) in equalization [10], discussed separately under intelligent equalizers.

In the literature, equalizers are classified into two categories, supervised and blind. However, this thesis 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, the channel distorts the transmitted signal. This distortions can be eliminated using a training signal, also known as pilot signal, transmitted periodically along with the information transmission. The receiver uses a replica of the training signal that can be made available at the receiver to update its parameters. The corresponding equalizers are termed as supervised equalizers. There are two kinds of supervised equalization:

(1) symbol-by-symbol estimation (also known as finite memory equalizers): detect the transmitted symbol using a fixed number of input samples The MAP criterion based on Bayes's theory [11] provides a decision function that is optimum for these equalizes, and hence also termed as be termed as Bayesian equalizers [12].. and (2) sequence estimation (also known as infinite memory equalizers and MLSE [2]): detect the transmitted symbol using the past-received samples sequence and were implemented with the use of Viterbi Algorithm [3].

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Bayesian equalizer with infinite memory may provide a better performance as compared to MLSE; however its large computational complexity limits this use. Hence, Bayesian equalizer with finite memory is used to provide performance that is comparable with that of the MLSE and also with reduced computational complexity [13]. Further advances on Bayesian equalizers can be found in [14-16].

Blind Equalization

In supervised equalization, use of training samples or sequences consumes bandwidth. To avoid this phase, techniques available are termed as unsupervised or blind equalization. Here, the transmitted symbol statistics is used at the equalizer. The channel here is modeled as a FIR filter. If all the zeroes of channel transfer function lie within unit circle, the channel is termed as minimum phase channel. For minimum phase channels, there is a simple method of equalization via zero forcing algorithms (ZFA). However, non-minimum phase channels are used in this thesis, where ZFA is no more stable. The blind equalization algorithms found in the literature classified into two classes based on statistics used. First category is based on higher order statistics (HOS) and the second based on second order statistics (SOS) of the transmitted symbols. Other types of blind equalization schemes not falling into this two classes are discussed in [17].The HOS schemes also can be divided into two classes based on use of HOS. They are, Explicit HOS (EHOS) and Implicit HOS (IHOS) as follows:

(1) In EHOS [17-19], DFT of HOS termed as polyspectra have been used. Though EHOS schemes can exactly recover the symbols transmitted over non-minimum phase channels but associated with large complexity and slower convergence.

(2) IHOS [20-27] also termed as Busgang type algorithm. Here, HOS is used indirectly. It is Godard [21] gave a class of widely used Constant Modulus Algorithm (CMA) for blind equalization [22]. IHOS schemes also coverge to local minima [26, 27]. Seminal work by Gardener [28] and Tong *et al*. [29, 30] shifted HOS based algorithms to SOS based algorithms [31-33]. Here, the cyclo-stationary property of over sampled signal is used for blind equalization using SOS of symbols. Subspace methods fall into this category which are of two types, deterministic subspace methods (DSM) [31, 33] and statistical subspace methods (SSM) detailed in [33]. The disadvantage of DSM approaches is overestimation of channel order is not possible. Also, these approaches are applicable for only finite samples. The disadvantage of SSM approaches is assumption that the source is a random sequence with known SOS and with zero mean, white with unit variance.

Intelligent equalizers

Traditional 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 perceptrons, self-organizing maps, information geometry-based approaches, etc. A variety of real-valued 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 perceptrons and modular networks, successfully equalize the nonlinear channels and outperform traditional linear equalizers. 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 relative entropy (LRE) of the cost function. LRE equalizer provides high complex decision boundaries, and abrupt changes can be tracked in a nonlinear channel response where the MSE-based 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 vectors of the SOM. Given that $y(n)$ is the output of the DFE, then the error, $e(n) = y(n) - m_i(n)$, controls the adaptation behavior of the DFE. Hence, DFE compensates the dynamic linear distortions. But, SOM adaptively compensates for the nonlinear distortions. While applied to a nonlinear two-path channel, It was seen that the SOM-based equalizer outperforms conventional equalizers for different types of non-linearity and different levels of SNR.

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. Following are some of very interesting finding in the literature.

A RBFNN based blind equalization scheme proposed in [55] makes use of simplex genetic algorithm (GA). A hybrid of GA and simulated annealing (SA) has been used in [56] for equalization. In both of these works, channel states were estimated using Bayesian likelihood cost function. However in two models proposed in [57], CMA cost function has been used for blind equalization using complex-valued feed forward NNs avoiding the necessity of external phase correction. A DFE model classifier using Jordan NN along with delay estimation was proposed in [58].

In [59], A three-layer ANN was used for equalization. gradient algorithm was used for weight up-dation in the second layer followed by Kalman filter to estimate channel coefficients in the third layer. This ANN has improved estimation accuracy and the speed of convergence. In [60], RBFNN based equalizer has been used to estimate MMSE using the relationship between the hidden and output layers. Convergence speed was further improved using FLNNCPAE combining FLNN, MLP and RBF as proposed in [61].

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 up-dation also carried out in [67]. In this thesis we optimize structure of ANN using FFA. Works can be carried out on: ANN training using GA/FFA and their variants, RBFNN training using GA/FFA and their variants and also u/se of these ANN and RBFNN in channel equalization. In summary, this paper has provided a detailed review on channel equalization. /T/his paper also points out the motivation and provides a direction for future research.

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