

# Chapter VIII

## Complex-Valued Neural Networks for Equalization of Communication Channels

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### ABSTRACT

*The equalization of digital communication channel is an important task in high speed data transmission techniques. The multipath channels cause the transmitted symbols to spread and overlap over successive time intervals. The distortion caused by this problem is called inter-symbol interference (ISI) and is required to be removed for reliable communication of data over communication channels. In this task of ISI removal, the signals are complex-valued and processing has to be done in a complex multidimensional space. The growing interest in complex-valued neural networks has spurred the development of many new algorithms for equalization of communication channels in the recent past. This chapter illustrates the application of various types of complex-valued neural networks such as radial basis function networks (RBFN), multilayer feedforward networks and recurrent neural networks for training sequence-based as well as blind equalization of communication channels. The structures and algorithms for these equalizers are presented and performances based on simulation studies are analyzed highlighting their advantages and the important issues involved.*

### INTRODUCTION

The complex-valued neural networks have attracted a great deal of interest in recent years. The growing interest could be attributed to superior learning ability of complex-valued neural networks in comparison with the real valued counterparts. A number of new low complexity and fast learning algorithms have also been proposed by the researchers for complex-valued neural networks, facilitating their use in various applications (Nitta, 1997; Leung & Haykin, 1991). The applications of complex-valued neural networks have emerged in the areas of seismic, sonar and radar signal processing, speech and image processing, environmental science and wireless communications where signals are typically complex valued (Haykin, 1994a; Mandic & Chambers, 2001).

Digital communication through multipath channels is subject to intersymbol interference and its cancellation using adaptive equalizers has been studied for several years by the signal processing community. Also, in order to maximize efficiency of digital radio links, the transmitter high-power amplifiers are often required to operate near saturation, introducing nonlinearities which in turn cause degradation of the received signal. The nonlinearity may affect both amplitude and phase of the signal. It is well known that the signals like QAM are very sensitive to nonlinear distortion which causes spectral spreading, inter-symbol interference (ISI) and constellation warping. The classical approaches to equalization rely on the existence of a training sequence in the transmitted signal to identify the channel (Proakis, 1995).

In adaptive equalization, when the channel is varying, even slowly, the training sequence has to be sent periodically to update the equalizer. Since the inclusion of reference training signals in conventional equalizers sacrifices valuable channel capacity, adaptation without using the training signals i.e. blind equalization is preferred (Godard, 1980; Haykin, 1994b).

With the development of complex-valued versions of training algorithms, the nonlinear adaptive filters can be realized as neural networks for both conventional as well as blind equalization as they are well suited to deal with the complex-valued communication signals. Although, the real valued and complex-valued networks have been both extensively studied for equalization of communication channels, the advantages of using complex-valued neural networks instead of a real valued counterpart fed with a pair of real values is well established. Among neural network equalizers, the application of radial basis function networks (RBFN) has been extensively covered in the literature. The studies of Chen, Mulgrew and, Grant (1993), Cha and Kassam (1995), Jianping, Sundararajan, and, Saratchandran (2002) and Li, Huang, Saratchandran and, Sundararajan (2006) are some of the examples. The technique proposed by Chen et al. (1993) is based on the clustering of data and uses a real valued network. Cha and Kassam (1995) have proposed an adaptive complex-valued RBFN for equalization. In their approach, the inputs and outputs of the network are both complex-valued while the radial basis functions are real valued. Jianping et al. (2002) and Li et al. (2006) have considered RBFN- based equalization of channels, where growing and pruning strategy is used for selection of nodes. All these approaches show a remarkable improvement in the performance of the equalizers in comparison with conventional equalizers.

Uncini, Vecchi, Campolucci, and Piazza (1999) have presented a study on the use of complex-valued neural networks with adaptive activation functions. An intelligent use of activation function has been shown to reduce the number of synaptic interconnections while preserving the universal approximation and regularization properties of the network, resulting in efficient implementation of nonlinear filters.

For blind equalization of communication channels, the neural network approaches are, generally, based on higher order statistics (HOS) where the minimization of a cost function is required. You and Hong (1998) have argued that these cost functions are non-convex and nonlinear functions of tap weights, when implemented using linear FIR filter structures. A linear FIR filter, however, has a convex decision region, and hence, is not adequate to optimize such cost functions. Therefore, a blind equalization scheme with a nonlinear structure that can form nonconvex decision regions, is desirable. Some blind equalization schemes based on complex-valued neural networks with higher level complex-valued signal constellations such as M-ary phase shift keying (PSK) and quadrature amplitude modulation (QAM) are proposed in (Pandey, 2001).

Most of the communication channels are non-stationary and the performance of the equalizers in nonstationary environment is governed by its training algorithm. Therefore, the development of suitable models and algorithms for equalization in nonstationary environment is important. Gan, Saratchandran, Sundararajan, and Subramanian (1999) and Wolfgang, Chen, and Hanzo (2004) have studied the use of RBFNs for equalization of time-varying channels. For blind equalization, a scheme with adaptive activation function is considered by Pandey (2004) to improve the performance of blind equalizers.

The feedforward neural equalizers usually require a large amount of storage and computation. Therefore, to reduce the burden of the feedforward neural equalizers, recurrent neural networks (RNN) for the equalization have been used. Parisi, Elio Claudio, Orlandi, and Rao (1997) consider a least squares approach with RNN for equalization with higher convergence rate, whereas Kechriotis, Zervas, and Manolakos (1994) have applied RNN for linear and nonlinear equalization with 4-PAM and 4-QAM symbol constellations. Another study on RNN as infinite impulse response (IIR) filter can be found in (Ong, You, Choi, & Hong, 1997). The application of complex-valued RNN for blind equalization with higher order constellations is shown in (Pandey, 2005a).

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