Chapter IX
Learning Algorithms for Complex-Valued Neural Networks in Communication Signal Processing and Adaptive Equalization as its Application

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ABSTRACT

In this chapter, the complex Backpropagation (BP) algorithm for the complex backpropagation neural networks (BPN) consisting of the suitable node activation functions having multi-saturated output regions is presented and analyzed by the benchmark testing. And then the complex BPN is utilized as nonlinear adaptive equalizers that can deal with both quadrature amplitude modulation (QAM) and phase shift key (PSK) signals of any constellation sizes. In addition, four nonlinear blind equalization schemes using complex BPN for M-ary QAM signals are described and their learning algorithms are presented. The presented complex BP equalizer (CBPE) gives, compared with conventional linear complex equalizers, an outstanding improvement with respect to bit error rate (BER) when channel distortions are nonlinear.

INTRODUCTION

Intersymbol interference (ISI) of the digital communication channel becomes a main drawback to efficient use of frequency bandwidth efficiency and performance improvement. So, it is necessary to use adaptive equalizers to restore the digital signal distorted by ISI. For equalization, many powerful adaptive algorithms have been

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developed such as the least mean squares (LMS) algorithm, the recursive least squares (RLS) algorithm and so on. But, the linear adaptive algorithms were not successful occasionally when channel distortion is nonlinear because of the assumption that the equalizer output is a linear function of the inputs. On this account, nonlinear adaptive equalization techniques have been required and developed. Among these nonlinear adaptive equalization algorithms, the backpropagation (BP) algorithm has occupied an important position because of its ease of implementation and nontrivial mapping capabilities (Arai, 1989, June).

On the other hand, in conventional equalizers, we assume that the receiver has knowledge of the transmitted information sequence in forming of the error signal between the desired symbol and its estimate for initially adjusting the equalizer weights. However, there are some applications, such as multipoint communication networks involving a control unit connected to several data terminal equipments (DTEs) and wireless communication systems using digital technology, where it is desirable for the receiver to adjust the equalizer weights without a known training sequence available. Equalization techniques based on initial adjustment of the weights without a training sequence are said to be *self-recovering* or *blind* (Proakis, 1989; Godard, 1980; Haykin, 1989). Among the useful blind equalization algorithms, stochastic-gradient iterative equalization schemes are based on minimizing a nonconvex and nonlinear cost function. However, as they use a linear FIR filter with a convex decision region, their residual estimation error is high.

In this chapter, the complex BP algorithm is described where the node activation function is composed of two real activation functions for the real and the imaginary net value of the node output. Also, the general characteristics of the required activation function are introduced and some examples are presented. In an example, each real activation function has multi-saturated output region in order to deal with signals of any constellation sizes. Also, a nonlinear adaptive equalizer scheme using the complex BP algorithm is presented. To see whether the complex BP algorithm works or not, the benchmark tests are introduced. In addition, four nonlinear blind equalization schemes employing a complex-valued multilayer perceptron instead of the linear filter are presented and their learning algorithms are derived. After the important properties that a suitable complex-valued activation function must possess are discussed, the suitable complex-valued activation function is introduced to deal with QAM signals of any constellation sizes. It has been proven that by the nonlinear transformation of the activation function, the correlation coefficient between the real and imaginary parts of input data decreases when they are jointly Gaussian random variables. Lastly, the effectiveness of the presented schemes is verified in terms of initial convergence speed and MSE in the steady state.

BACKGROUND

Many authors have studied to solve equalization problems by using BP algorithm (Gibson, Siu, & Cowan, 1989, May) and have acquired the good results. Their applications, however, have been limited to binary {0, 1} or bipolar {-1, 1} valued signals, due to the sigmoid function or the tanh($ax/2$) taken as the nonlinear activation function. The used channels are also the real-valued models. But, as applications of the BP algorithm have progressed in various fields, the BP algorithm for complex-valued channel models and complex-valued signals with bigger signal constellation, which have been used widely in many applications of the digital communications or signal processing, has been requisite. For instance, the modulation techniques such as M-ary QAM (Quadrature Amplitude Modulation) or MPSK (M-ary phase shift key) in digital communications use the signal that has two components, i.e., amplitude and phase. Therefore, algorithms for the complex BP and activation functions for signals with multi-level constellation communication are very important in related fields.

Beginning with the paper by Sato (Sato, 1975) that is focused on PAM signal constellations, several blind equalization algorithms using a stochastic gradient approach have been developed. Sato's original work was generalized to two-dimensional and multidimensional signal constellations in the algorithms devised by Godard (Godard, 1980), Benveniste and Goursat (Benveniste, & Goursat, 1984), and Picchi and Prati (Picchi, & Prati, 1987). Such stochastic-gradient iterative equalization schemes are based on LMS adaptation, and apply a memoryless nonlinearity in the output of a linear finite-duration impulse response (FIR) equalization filter for the purpose of generating the "desired response", as shown in Fig. 1. Thus, the cost functions of these LMS-type blind algorithms are nonconvex and nonlinear functions of the tap weights. However, a linear FIR filter structure

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