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A novel joint-processing adaptive nonlinear equalizer using a modular recurrent neural network for chaotic communication systems[☆]

Haiquan Zhao[a,b,*], Xiangping Zeng[b,c], Jiashu Zhang[b], Yangguang Liu[d], Xiaomin Wang[b], Tianrui Li[b]

[a] School of Electrical Engineering, Southwest Jiaotong University, Chengdu, 610031, China
[b] School of Information Science & Technology, Southwest Jiaotong University, Chengdu, 610031, China
[c] Center of Electronic Lab, Chengdu University of Information Technology, Chengdu, 610255, China
[d] Ningbo Institute of Technology, Zhejiang University, Ningbo, 315100, China

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ABSTRACT

To eliminate nonlinear channel distortion in chaotic communication systems, a novel joint-processing adaptive nonlinear equalizer based on a pipelined recurrent neural network (JPRNN) is proposed, using a modified real-time recurrent learning (RTRL) algorithm. Furthermore, an adaptive amplitude RTRL algorithm is adopted to overcome the deteriorating effect introduced by the nesting process. Computer simulations illustrate that the proposed equalizer outperforms the pipelined recurrent neural network (PRNN) and recurrent neural network (RNN) equalizers.

1. Introduction

In recent years, most proposals for chaos-based communication systems have been based on the assumption of a rather idealized communication environment, in which signals are transmitted without distortion and with only a moderate added noise (Feng & Tse, 2001; Gencay & Liu, 1997; Leung, 1998). However, in actual communication environments, the signals at the receiver end can be seriously impaired by non-ideal channel characteristics and noise, especially nonlinear distortion introduced by the modulation/demodulation process (Feng & Lu, 2002). To compensate for the distortion, several approaches have been proposed in chaos-based communication systems, such as the radial basis function (RBF)-based equalizer (Feng & Tse, 2001; Xie & Leung, 2003, 2005), recurrent neural network (RNN)-based equalizer (Feng & Lu, 2002; Feng, Tse, & Lau, 2003), etc. The RNN can yield smaller structures than nonrecursive neural networks in the same way that infinite impulse response (IIR) filters can replace longer finite impulse response (FIR) filters. Therefore, the local/global recurrence and internal/external feedback of RNNs enable them to acquire a state representation, which makes them suitable for application to adaptive equalization of communication channels (Kechriotis, Zervas, & Manolakos, 1994a). Though the RNN equalizer has shown better performance than a linear equalizer, the major disadvantage of heavy computational loads limits its applications. To reduce the computational complexity of the RNN, Haykin and Li proposed the pipelined recurrent neural network (PRNN), which is an extension of the conventional RNN, in 1995 (Haykin & Li, 1995). The design is based on the principle of divide-and-conquer. In other words, a complex RNN with a large number of neurons can be divided into a number of simpler small-scale RNN modules with low computational load. Recently, two novel adaptive nonlinear filters with a modular architecture were proposed to reduce the computational complexity of the Volterra filter (Zhang & Zhao, 2010; Zhao & Zhang, 2009). Consequently, with this in mind, a novel joint-processing adaptive nonlinear equalizer based on the pipelined recurrent neural network, the JPRNN, is proposed in this paper. This equalizer inherits the merits of the PRNN but has better performance in chaos-based communication systems and less computational complexity.

2. Low complexity JPRNN equalizer

In this paper, a JPRNN equalizer for a nonlinear channel in chaotic communication systems is designed, as shown in Fig. 1.

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* Corresponding author at: School of Electrical Engineering, Southwest Jiaotong University, Chengdu, 610031, China. Tel.: +86 28 87601756.
E-mail addresses: hqzhao0815@yahoo.com.cn (H. Zhao), jszhang@yahoo.cn (J. Zhang).

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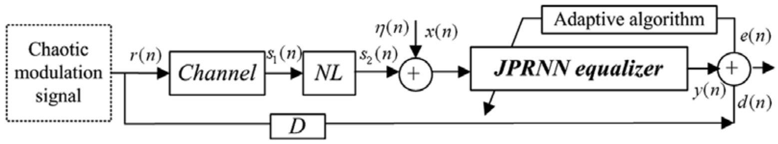

Fig. 1. A digital transmission system with the JPRNN equalizer.

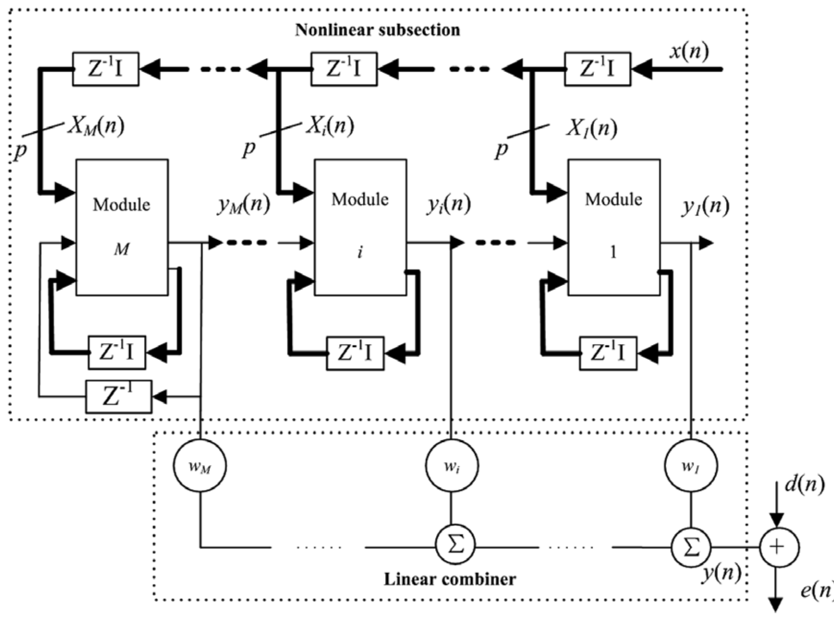

Fig. 2. A JPRNN with M modules.

The transmitted signal produced by the chaotic modulator is denoted by $r(n)$. The combined effect of the transmitter filter, the transmission medium and other components are included in the '*Channel*', whose output at time instant n may be written as

$$s_1(n) = \sum_{i=0}^{N_f} h(i)r(n-i) \tag{1}$$

where $h(i)$ is the channel tap value and N_f is the length of the FIR channel model. The '*NL*' block represents the nonlinear distortion of the symbols in the channel, and its output may be written as follows

$$s_2(n) = \psi(s_1(n)) \tag{2}$$

where $\psi(\cdot)$ is a nonlinear function generated by the '*NL*' block. The output $s_2(n)$ of the channel is subjected to additive white Gaussian noise $\eta(n)$ (AWGN) with zero mean and variance σ^2. Then this corrupted signal is received at the receiver end, and is given by $x(n) = s_2(n) + \eta(n)$. The desired signal $d(n)$ is defined by $d(n) = r(n-D)$, where '*D*' denotes the transmission delay associated with the physical channel. To reconstruct $r(n)$ from $x(n)$, our scheme is based on Taken's embedding theory using the JPRNN, described as follows.

Fig. 2 shows the structure of the JPRNN equalizer with M models, which includes the nonlinear subsection and a linear combiner. The cascaded RNN of the nonlinear subsection provides pre-processing for the linear combiner. Moreover, each RNN of the nonlinear subsection can provide a local interpolation for M sample points, the final linear combiner presents a global interpolation with good localization properties. In Fig. 2, each module is designed as a RNN with q neurons; it has $q-1$ neuron outputs as feedback to its input and the remaining neuron output (the first neuron output) is applied directly to the next module. In the case of the nonlinear section in the JPRNN equalizer, module M is a fully connected RNN, and a one-unit delayed signal of module M's output is assumed to be fed back to the input. Information flowing into and out of the modules proceeds in a synchronized fashion. Therefore, all the modules of the equalizer operate similarly in that they all have exactly the same number of external inputs and feedback signals, which are properly timed. Moreover, all the modules are designed to have exactly the same $(p+q+1)$-by-q synaptic weight matrix $H(n)$. An element $h_{k,l}(n)$ of this matrix represents the weight of the connection to the lth neuron from the kth input node. Therefore, the weight matrix $H(n)$ may be written as:

$$H(n) = [h_1(n), \dots, h_k(n), \dots, h_q(n)]^T \tag{3}$$

where the superscript T denotes transposition, and $h_k(n)$ is a $(p+q+1)$-by-1 vector defined by

$$h_k(n) = [h_{1,k}(n), h_{2,k}(n), \dots, h_{p+q+1,k}(n)]^T, \quad 1 \le k \le q. \tag{4}$$

In addition, the sequential use of a nonlinear subsection and linear combiner forms an efficient combination that is capable of extracting both the linear and nonlinear relationships underlying the source signal to overcome nonlinear distortion.

The detailed structure of module i with q neurons and p external inputs is illustrated in Fig. 3. For the ith module, the external input signal described by the p-by-1 vector $X_i(n)$ at the nth time is defined by

$$X_i(n) = [x(n-i), x(n-(i+1)), \dots, x(n-(i+p-1))]^T \tag{5}$$

and is delayed by $Z^{-i}I$ at the input of the module i, where Z^{-i} denotes the delay operator by i time units, I is the $(p \times p)$-dimensional identity matrix, and p is the order of the adaptive nonlinear equalizer. The other input vector $r_i(n)$ applied to module i is the q-by-1 feedback vector

$$r_i(n) = [y_{i+1,1}(n), \hat{r}_i(n)]^T, \quad i = 1, 2, \dots, (M-1) \tag{6}$$

where $y_{i+1,1}(n)$ is the first neuron output of the previous module $i+1$.