Compensation of Distortions in OFDM System by Recurrent Neural Networks

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Abstract　High power amplifier often brings a nonlinear distortion for the orthogonal frequency division multiplexing system in the transmitter. Diagonal Recurrent Neural Network (DRNN) is a modified model of the fully connected recurrent neural network with the advantage in capturing the dynamic behavior of a system. In this paper. DRNN is introduced to compensate transmitted signal before the signal passes the high power amplifier. The algorithm of gradient descent method is developed to train the DRNN, which requires a low amount of Random Access Memory (RAM) and is with much faster convergence speed from a blind start. The simulation shows that the network owns a rapid convergence and a low amount of RAM is required if this recurrent neural network is applied as predistorter.

Key words　nonlinear distortion;　orthogonal frequency division multiplexing;　recurrent neural network

基于循环神经网络的OFDM系统的失真补偿

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【摘要】在OFDM系统的发射机部分高功率放大器常常引起发射信号的非线性失真。对角循环神经网络是一类经过修正的全连接循环神经网络，在系统动态行为的俘获方面具有明显的优势。该文引入了这类对角循环神经网络，对发射信号在高功率放大之前进行前置补偿，对网络的训练提出了梯度下降算法。该算法具有更少的RAM需求和以盲起点为初始值的更快的网络收敛速度的特点。仿真显示以该神经网络作为前置补偿，系统具有更快的收敛速度和更少的RAM。

关　键　词　非线性失真;　正交频分多路复用;　循环神经网络

中图分类号　TN929.1　　　**文献标识码**　A

Multicarrier modulation realized by Orthogonal Frequency Division Multiplexing (OFDM) shows its advantage in reliable and high-rate data transmission over a wireless channel. OFDM owns the potential ability of combating the Inter Symbol Interference (ISI) introduced by time dispersive nature of the wireless channel. So it is proposed for the next generation communication system, which is expected to provide users with the information rates over 2 Mbs. Now, OFDM has also been chosen for several new standards, such as terrestrial digital audio broadcasting and digital video broadcasting in Europe, and broadband wireless local area network standards.

It is well known that OFDM systems are significantly sensitive to nonlinear distortions, which are introduced by the High Power Amplifier (HPA) and the channels. Usually an adaptive nonlinear equalizer is applied at the receiver to minimize signal distortions. However, this does not seem to be effective sometimes, when distortion is mainly introduced from the HPA. So a predistorter placed in front of the HPA is suggested for efficient compensation of nonlinear distortion[1]. A

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Biography：LI Ming-qi was born in 1970. He is currently an associate professor and his research interests include digital signal processing and dynamic system.
作者简介：李明奇(1970－)，男，在职博士生，副教授，主要从事数字信号处理和动力系统方面的研究.

well-designed predistorter will be helpful to achieve the transmitted signal we need by twice distortion.

There are several kinds of predistorter to compensate nonlinear distortions. The first one is linearization of the power amplifier by predistortion, such as an analog cubic predistortion[1]. The second one applies a lookup table[2], which is updated in real time. The lookup table is used as the coefficient to multiply the signal before feeding it to the HPA. However, a large amount of RAM is needed in the adaptive predistorter in an OFDM system, and the parametric in the adaptive predistorter can be updated slowly for convergence speed of the predistorter.

Recently, the neural network is applied as a predistorter[2-3] in the wireless communication system, and is proposed as an adaptive predistortion technique for satellite communication channel[4]. The Diagonal Recurrent Neural Network (DRNN) is one of the selections as an adaptive predistorter. DRNN is a modified model of the fully connected recurrent neural network with one hidden layer, and the hidden layer comprises self-recurrent neurons[5]. Due to the recurrence, the DRNN can capture the dynamic behavior of a system. It can not only handle dynamic nonlinear problem easily, but also possess many advantages such as simple structure and easily formed training arithmetic. So the diagonal recurrent neural network has been applied widely. This paper focuses on the application of the DRNN as a predistorter in the OFDM communication system. A generalized gradient descent method is developed to train the DRNN, so that the DRNN requires a low amount of RAM and has much faster convergence speed from a blind start. The simulation shows it is a better way to compensate the nonlinearity at the transmitter before the transmitted signals are sent out.

1 Modeling of OFDM Transmitter and Neural Predistorter

Fig.1 is the block diagram of the OFDM transmitter. In the transmitter, the transmitted random data is firstly converted from serial to parallel, and then fed into OFDM modulator. The transmitted data on each parallel subcarrier can be QAM modulated. In this paper, we consider a quadrature modulated data sequence to simplify our discussion. So each transmitted symbol $d_n(k)$ can be described as

$$d_n(k) = d_{\mathrm{In}}(k) + \mathrm{j}d_{\mathrm{Qn}}(k) \tag{1}$$

where $(d_{\mathrm{In}}(k),\ d_{\mathrm{Qn}}(k))$ are equal to $\{\pm 1,\ \pm 3\}$ and denote in-phase and quadrature data symbols, respectively. These data symbols are fed into an Inverse Fast Fourier Transform (IFFT) block to form the OFDM signal. Then the transmitted signal from output of the OFDM modulator is given by

$$s(t) = \sum_{k \in Z} \sum_{i=0}^{N-1} d_i(k) \exp(\mathrm{j}2\pi f_i (t - kT_s)) f(t - kT_s) \tag{2}$$

where T_s is the symbol duration of the OFDM signal, N is the number of subcarriers, and f_i is the frequency of the i-th subcarrier. Then the OFDM signal is fed into a bandpass filter, which limits the bandwidth of the OFDM signal. The output from the bandpass filter amplifier enters the block C/P, where the signal is transformed from Cartesian form to polar one. Then polar signal is predistorted in the Neural Predistorter. Finally, the signal is fed into the nonlinear amplifier (HPA), which is modeled as memoryless nonlinear circuit. The attenuator applied in the feedback loop adjusts the signal sampled at the HPA output to the level we needed by the adaptation of the predistorter.

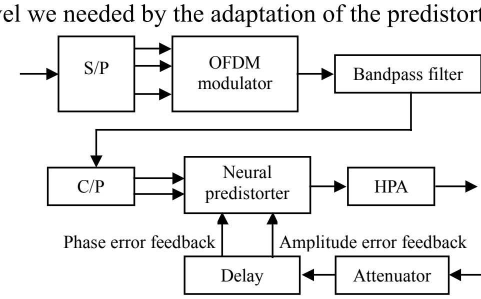

Fig.1 The block diagram of the OFDM transmitter

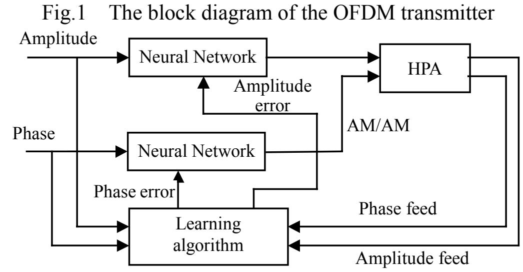

Fig.2 The neural predistorter

The input power and output power of HPA is often described in AM/AM, which is a conversion of the signal amplitude presenting on the input and the output. Another description on the nonlinear relationship between the input signal and the output signal is a conversion from amplitude of the input signal to phase of the output signal. This conversion is often denoted as AM/PM. These conversions may be modeled in the form of polar [6-7]. That is

$$A(r)=\alpha_1\frac{r}{1+\beta_1 r^2},\quad \Phi(r)=\alpha_2\frac{r^2}{1+\beta_2 r^2} \tag{3}$$

where α_1, β_1, α_2, and β_2 are constants and r is the envelope of the input signal. Nonlinear distortion can be reduced, by backing off the power amplifier from saturation. To achieve a desirable high power transmitted signal, we cannot reduce the amount of backing off required. So some forms of nonlinear compensation is introduced. To mitigate nonlinear distortion, a simple DRNN [8-9] is adopted to perform the function of the HPA predistorter of the OFDM signals. The block diagram of the proposed neural predistorter is shown in Fig.2.

2 DRNN

Diagonal recurrent neural network has three layers: input layer, hidden layer, and output layer. Neurons in the hidden layer are dynamic neurons in which the output of each hidden neuron is fed back to its input through a delay unit. These local feedback paths introduce dynamic behaviors into the network. Hidden neurons use the sigmoid activation function[9-10], while the output layer neurons use a linear activation function. The structure of a DRNN is illustrated in Fig.3.

Let p, q, and r be the numbers of input neurons, hidden neurons, and output neurons, respectively. Then the dynamic model for the DRNN can be modeled as

$$\begin{cases} O_j(k)=\sum_{i=1}^{q}\boldsymbol{W}_{ji}^{\mathrm{O}}X_i(k) \\ X_j(k)=f(S_j(k)) \\ S_j(k)=\boldsymbol{W}_j^{\mathrm{D}}X_j(k-1)+\sum_{i=1}^{p}\boldsymbol{W}_{ji}^{\mathrm{I}}I_j(k) \end{cases} \tag{4}$$

where for each sampling time k, $I_j(k)$ is the jth input to the DRNN, $S_j(k)$ is the sum of input to the jth recurrent neuron, $X_j(k)$ is the output of the jth recurrent neuron, and $O_j(k)$ is the output of the ith output neuron, W^{I} is the weight matrix ($p\times q$) connecting the ith input to the jth hidden neuron, W^{D} is the feedback weight matrix ($q\times 1$) of the jth hidden neuron, W^{O} is the output layer weight matrix ($r\times q$) connecting the jth hidden neuron and the output neuron. The function $f(x)$ is the activate function of the hidden layer. The input neurons represent the raw information that is fed into the neural network. Hidden units are determined by the activities of the input units and weights on the connections between the input and the hidden units. Behaviour of the output neurons depends on the activity of the hidden neurons and the weights between the hidden and output neurons.

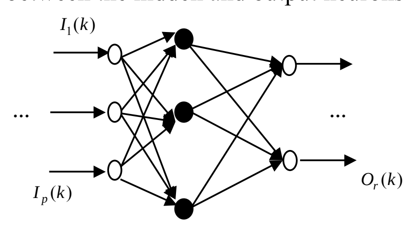

Fig.3 Diagonal recurrent neural network structure

Modifying the knowledge stored in the network as function of experience implies a learning rule for changing the values of the weights.

3 Algorithms and Simulation

If $\tilde{O}_j(k)$ is the desired network output, and $O_j(k)$ is the actual network output, then the objective of the network training is to choose a proper iterative learning algorithm to minimize the error function:

$$E(k)=\frac{1}{2}\sum_{j=1}^{r}\left|O_j(k)-\tilde{O}_j(k)\right|^2 \tag{5}$$

The error function $E(k)$ is a function with parametric: the input weight matrix W^{I}, the output layer weight matrix W^{O} and the feedback weight vector W^{D}. If W is one of the weight vector, the grads of it is described by

$$\frac{\partial E(k)}{\partial W}=\sum_{j=1}^{r}\left[\left(O_j(k)-\tilde{O}_j(k)\right)\frac{\partial O_j(k)}{\partial W}\right] \tag{6}$$

According to the gradient descent method, the weight of this network upgrades by the iterative equation

$$\boldsymbol{W}(k+1)=W(k)+\eta\frac{\partial E(k)}{\partial W} \tag{7}$$

where η is the training rate of weight vector. So the input weights is

$$W^{\mathrm{I}}(k+1)=W^{\mathrm{I}}(k)+\eta_{\mathrm{I}}\frac{\partial E(k)}{\partial W^{\mathrm{I}}} \tag{8}$$

The input weights is

$$W^{\mathrm{O}}(k+1)=W^{\mathrm{O}}(k)+\eta_{\mathrm{O}}\frac{\partial E(k)}{\partial W^{\mathrm{O}}} \tag{9}$$

The hidden weights is

$$W^{\mathrm{D}}(k+1)=W^{\mathrm{D}}(k)+\eta_{\mathrm{D}}\frac{\partial E(k)}{\partial W^{\mathrm{D}}} \tag{10}$$

To evaluate the performance of the predistorter and effectiveness of the algorithm, we set the number of subcarriers N=128. The input parallel signal of OFDM modulator is in form of 16-QAM. The HPA we adopt is with the parameters $\alpha_1=\beta_1=\beta_2=1,\ \alpha_2=\pi/3$.

Five memory cells of the delay line are adopted in the amplitude and phase branches before the phase error feedback and amplitude error feedback are inputted into the predistorters. In the DRNN, there are two neurons in the input layer, 5 neurons in the hidden layer and two neurons in the output layer. That is $p=2,\ q=5,\ r=2$ in the model of DRNN Equ. (4).

Fig.4 shows the convergence of the neural network trained with the algorithm of gradient descent method, where the curve shows the Mean Square Error (MSE) changes with the number of training symbols. We find the MSE is close to zero, when the number of training symbols reaches 20. So we need less time and energy to achieve the stable network we need[5]. That shows the effectiveness of the DRNN to combat the predistortion from the HPA, when the gradient descent learning algorithm is applied.

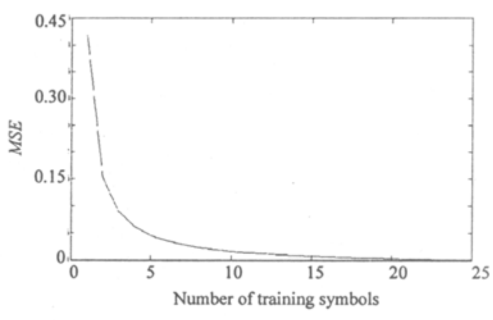

Fig.4 Convergence of the neural network trained with the gradient algorithm

4 Conclusions

An diagonal recurrent neural network predistorter is proposed in this paper. It can adaptively compensate the nonlinear distortion from the HPA in the transmitter. Meanwhile, the algorithm of gradient descent method is applied in the predistorter to lead a fast convergence speed. Simulations demonstrate that the efficiency of the DRNN when an OFDM system suffers from nonlinear distortions.

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References

[1] BENEDETTO M D, MANDARINI P. A new analog predistortion criterion with application to high efficiency digital radio links[J]. IEEE Trans. on Comm., 1995, 43(12): 2966-2974.

[2] KARAM G, SARI H. A data predistortion technique with memory for QAM radio systems[J]. IEEE Trans. on Comm., 1991, 39(2): 336-344.

[3] BENVENUTO N, PIAZZA F, UNCINI A. A neural network approach to data predistortion with memory in digital radio systems[C]//1993 International Comm. Conf. Geneva, Switzerland: [s.n.], 1993: 232-236.

[4] IBNKAHLA M. Adaptive predistortion techniques for satellite channel equalization[C]//IEEE ICASSP. Istanbul, Turkey: [s.n.], 2000.

[5] KANG H W, CHO Y S, YOUN D H. On compensating nonlinear distortion of an OFDM system using an efficient adaptive predistorter[J]. IEEE Trans. on Comm., 1999, 47(4): 522-526.

[6] SALEH A A M. Adaptive linearization of power amplifiers in digital radio systems[J]. The Bell Sys. Tech. J., 1983: 1019-1033.

[7] KENINGTON P B. High-linearity RF amplifier design[M]. London, Boston: Artech House Inc., 2000.

[8] TANG W S, WANG J. A recurrent neural network for minimum infinity-norm kinematic control of redundant manipulators with an improved problem formulation and reduced architecture complexity[J]. IEEE Trans. on Sys., Man, and Cyber. Part B, 2001, 31(1): 98-105.

[9] KU C-C, LEE K Y. Diagonal recurrent neural networks for dynamic systems control[J]. IEEE Trans. on Neural Network, 1995, 6(1): 146-155.

[10] KWAN C, LEWIS F L. Robust backstepping control of nonlinear systems using neural networks[J]. IEEE Trans. on Systems, Man, and Cybernetics, 2000, 30(6): 753-766.

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