NEURAL NETWORK BASED ADAPTIVE PREDISTORTION FOR THE LINEARIZATION OF NONLINEAR RF AMPLIFIERS

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ABSTRACT

The good spectral efficiency of linear modulation techniques makes them attractive for use in high data rate digital radio systems. Unfortunately, the fluctuating envelopes of such systems combined with the nonlinear nature of the high power RF amplifiers commonly used gives rise to spectral spreading, adjacent channel interference, I-Q crosstalk, and degraded bit error rates.

A possible solution to these problems is the linearization of the transmitter system by predistortion of the baseband digital signal using a nonlinear filter which is the inverse of the amplifier response. In this work, we realize the inverse filter using a backpropagation neural network. A coupler and demodulator provide a feedback path which provides the input to the neural network while the desired signal is the original waveform. The shaped waveform is passed through the network which adaptively corrects for the changing response of the high power RF amplifier. This technique allows us to correct for quite general nonlinearities, significantly reduces spectral spreading, and improves the bit error rate.

1. INTRODUCTION

Simple, constant envelope modulation schemes like unfiltered BPSK and QPSK allow the operation of nonlinear class C and class AB High Power RF Amplifiers (HPA) near saturation with only small degradations in system BER performance. However, increasing demand for larger channel capacity in crowded spectrums necessitates the use of band limiting techniques and more bandwidth efficient modulation schemes such as 8-PSK, 16-PSK, and M-QAM. The BER performance of these systems is extremely sensitive to nonlinearities.

This paper introduces an adaptive predistortion technique to compensate for nonlinearities in HPAs. The technique allows bandwidth efficient modulation schemes to be used with nonlinear HPAs with only minimal degradation in the system BER performance. In addition, the technique adapts to changes in the nonlinearity of the HPA caused by changes to the input power, carrier frequency, aging, temperature, or component replacement.

Several other techniques have been applied to this problem, the most obvious being to use a linear class A HPA, or to operate a nonlinear HPA sufficiently far from saturation to obtain near linear performance. These techniques tend to require larger, more expensive, heavier, and less efficient HPAs than necessary. Other predistortion techniques include analog feedback [1], analog feed-forward [2], and digital table lookup mapping [3]. The analog techniques have been limited by narrow operating bandwidths, extreme sensitivity to HPA variations, instabilities, and in some techniques the requirement for additional RF amplifiers. The digital techniques have been limited by the massive amount of storage required for a sufficiently accurate mapping to be stored. Postdistortion techniques can be implemented in the receiver, but cannot correct for the adjacent channel interference caused by out-of-band emissions from HPA nonlinearities. Clearly, it is desirable to do any corrections for the HPA nonlinearity in the transmitter, where the desired transmit symbol and spectrum are available.

In this paper, we present a preliminary implementation of a data predistortion system using a multilayer perceptron neural network which forms an adaptive nonlinear filter whose response approximates the inverse function of the HPA nonlinearity. We attempt to design a predistorter which is adaptive, robust, and requires only a moderate amount of storage and computational resources by taking advantage of a neural network's ability to estimate a nonlinear function.

The organization of the paper is as follows. In Section 2, we present the signal and amplifier model uti-

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lized. Section 3 discusses the details of the neural network predistorter. Section 4 presents some simulation results, and finally, conclusions are drawn in Section 5.

2. SIGNAL AND AMPLIFIER MODEL

The input RF signal to the HPA can be written as

$$x'(t) = r(t)\cos[\omega_0 t + \psi(t)] = Re[x(t)e^{j\omega_0 t}] \quad (1)$$

where w_0 is the carrier frequency, $r(t)$ and $\psi(t)$ are the modulated envelope and phase, and

$$x(t) = r(t)\cos[\psi(t)] + jr(t)\sin[\psi(t)] \quad (2)$$

is the complex baseband representation of the input signal $x'(t)$. If we assume that the HPA output can be written as

$$y'(t) = A[r(t)]\cos\{\omega_0 t + \psi(t) + \Phi[r(t)]\} = Re[y(t)e^{j\omega_0 t}] \quad (3)$$

where A represents the AM-to-AM distortion and Φ represents the AM-to-PM distortion. Then we can write the complex baseband HPA output as

$$\begin{aligned} y(t) &= A[r(t)]\cos[\psi(t)]\cos\{\Phi[r(t)]\} \\ &+ jA[r(t)]\sin[\psi(t)]\sin\{\Phi[r(t)]\} \end{aligned} \quad (4)$$

Figure 1 illustrates the effect of nonlinearities in the HPA on the signal symbol vector. The magnitude and phase of the HPA output symbol vector are modified based on the magnitude of the input signal vector, $r(t)$. This paper will consider a memoryless nonlinear HPA model described by [4]

$$A(r) = \frac{\alpha_a r}{1 + \beta_a r^2} \quad (5)$$

$$\Phi(r) = \frac{\alpha_\Phi r^2}{1 + \beta_\Phi r^2}. \quad (6)$$

Future work will consider other nonlinear HPA models.

Figure 2 plots these functions for a typical amplifier ($\alpha_a = 1.96$, $\beta_a = 0.99$, $\alpha_\Phi = 2.53$, $\beta_\Phi = 2.82$). Figure 3 shows an example of the distortion to a 64 QAM symbol constellation upon application of the nonlinearity depicted in Figure 2. The effect of the HPA is a nonlinear mapping of the complex signal plane. If a nonlinear filter could be found with a response that is complementary to that of the HPA, the undesirable effects of the HPA nonlinearity could be reduced or eliminated by placing this filter before the HPA.

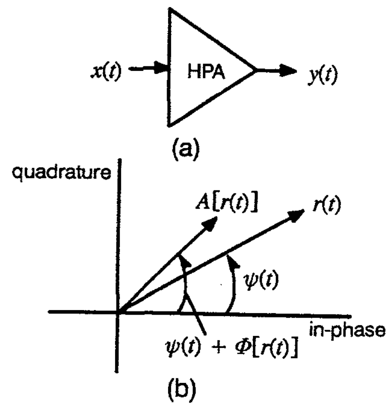

Figure 1. Effect of HPA Nonlinearity

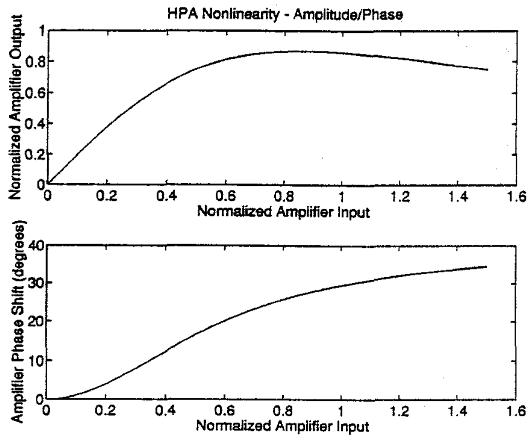

Figure 2. Nonlinear HPA Response

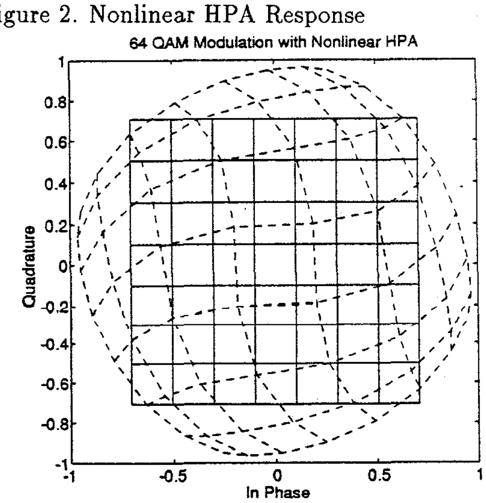

Figure 3. QAM 64 Symbol Constellation (solid line - original symbols, dashed line - after application of nonlinearity)

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3. NEURAL NETWORK PREDISTORTER

Neural networks have been shown to provide an efficient and versatile tool to implement nonlinear mappings. In fact, it was been shown in [5] that certain types of neural networks are universal approximators for an arbitrary continuous function with support on the unit hypercube. Since the nonlinear response of the HPA is a continuous function, it is a natural choice to apply a neural network. In this case, the neural network performs as a nonlinear adaptive filter which will be trained to approximate the inverse of the nonlinear response of the HPA.

The neural network utilized in this work is a multilayer perceptron using the backpropagation learning algorithm[6]. The model used for each individual artificial neuron is presented in Figure 4. The overall network structure is depicted in Figure 5. The activation level for an individual neuron is

$$y_k^{(l)} = \varphi^{(l)}[\sum_{j=0}^{p} w_{kj}^{(l)} x_j^{(l)}] \quad (7)$$

where φ is the activation function (possibly nonlinear), w_{kj} are the synaptic weights, x_j are the inputs to the neuron and the superscript denotes the layer. In this application, the network is comprised of three layers: an input layer (layer 0), a hidden layer (layer 1), and an output layer (layer 2). The output of the network may be expressed as

$$o_n = \varphi^{(2)}[\sum_k w_{nk}^{(2)} \varphi^{(1)}[\sum_j w_{kj}^{(1)} \varphi^{(0)}[\sum_i w_{ji}^{(0)} x_i^{(0)}]]] \quad (8)$$

which simplifies to

$$o_n = \sum_k w_{nk}^{(2)} \varphi^{(1)}[\sum_j w_{kj}^{(1)} x_j^{(0)}] \quad (9)$$

for linear activation functions at the input and output layer. A desired output signal, $\mathbf{d}(n)$, is provided to the neural network,which allows us to form an error signal

$$e_j(n) = d_j(n) - o_j(n) \quad (10)$$

The local gradients, $\delta_j^{(l)}(n)$, are computed for the output layer (where the error signal is directly available),

$$\delta_k^{(2)}(n) = e_k^{(2)}(n) o_k(n)[1 - o_k(n)] \quad (11)$$

and for the hidden layer (where the error signal is propagated back from the output layer),

$$\delta_j^{(1)}(n) = y_j^{(1)}(n)[1 - y_j^{(1)}(n)] \sum_k \delta_k^{(2)}(n) w_{kj}^{(2)}(n). \quad (12)$$

The synaptic weights are adjusted using

$$w_{ji}^l(n+1) = w_{ji}^l(n) + \alpha[w_{ji}^l(n) - w_{ji}^l(n-1)] + \eta \delta_j^l(n) y_i^{l-1}(n) \quad (13)$$

where α is the momentum constant, and η is the learning rate parameter.

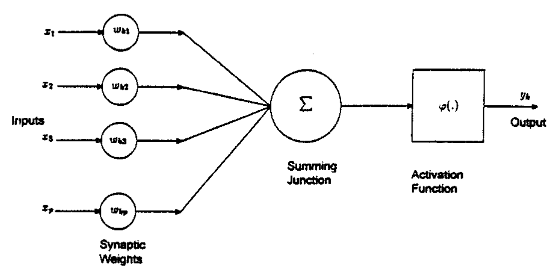

Figure 4. Artificial Neuron Model

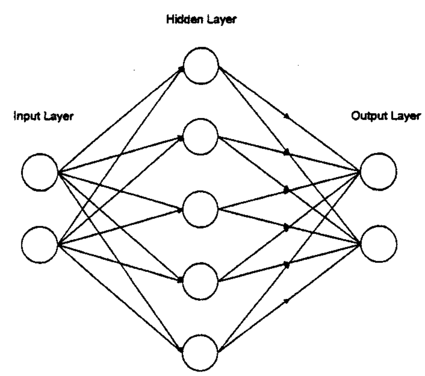

Figure 5. Neural Network Architecture

The neural network predistorter is implemented as in Figure 6. There are two identical neural networks used, one performing the predistortion function, while the other is trained using samples of the actual amplifier output. An RF coupler and demodulator are used to provide a sample of the transmitted symbol from the HPA to the training neural network. This functions as

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the input, while the desired output signal is provided by the output of the predistorter neural network. As the training neural network converges, it approximates a nonlinear mapping which is the inverse of the HPA.

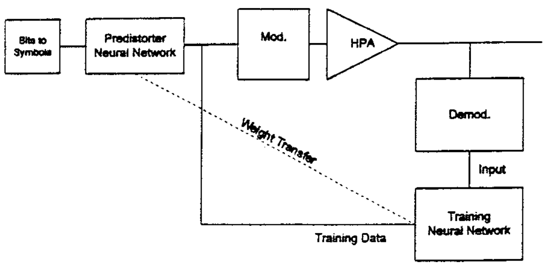

Figure 6. Neural Network Predistorter System

The inputs to the predistorter neural network are the in-phase and quadrature portions of the symbol to be transmitted, and the outputs are the predistorted version of the symbol components.The synaptic weights of the predisorter neural network are fixed, while the synaptic weights of the training neural network are updated continuously. Periodically, the weights from the training network are transferred to the predistorter neural network to allow the predistorter to adapt to any changes in the characteristics of the HPA.

This architecture also has the advantage of allowing the two neural networks to operate at different rates. Updating the training neural network requires many more computations than are required to estimate the inverse HPA function in the predistorter neural network. Thus we can achieve a substantially higher overall data rate by operating the predistorter neural network at the symbol rate, while the training neural network can be run at a slower rate.

4. SIMULATION RESULTS

All components were modeled in software at baseband at the symbol rate as described in section 2. The effects of pulse shaping will be considered in future work. The predistorter neural network was initialized with synaptic weights which provided an approximation of the identity function. This prevented the large distortion that would result if an untrained network was placed in the signal path. The training neural network was initialized with random synaptic weights. Its convergence is depicted in Figure 7. The data presented to the system was organized in epochs, each of which consisted of the entire symbol constellation with additive white noise at an SNR of 30 dB.

The neural network predistorter was applied to a 64 QAM modulated signal using the nonlinearity depicted in Figure 2. The resulting symbol constellation after passing through the predistorter and the HPA is shown in Figure 8. The neural network predistorter is seen to compensate for most of the nonlinearities induced by the HPA. This is illustrated in Figure 9 where the predistorter-HPA combined gain curve approaches that of a linear gain curve. Finally, the BER performance plotted in Figure 10 illustrates the significant improvement obtained by the application of the predistorter.

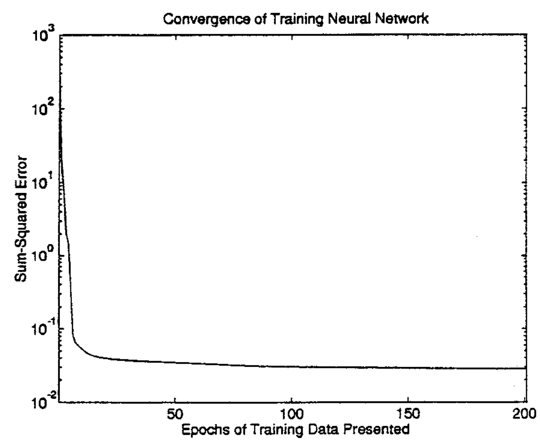

Figure 7. Convergence of Training Neural Network

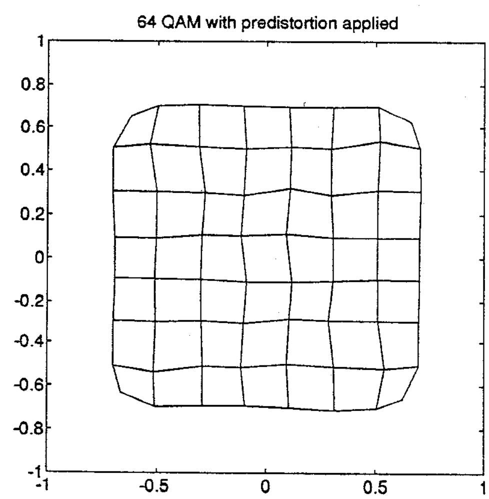

Figure 8. 64 QAM Symbol Constellation after application of Predistortion and HPA Nonlinearity

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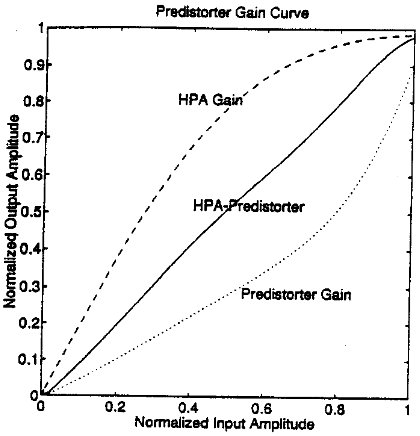

Figure 9. HPA and Predistorter Gain Curves

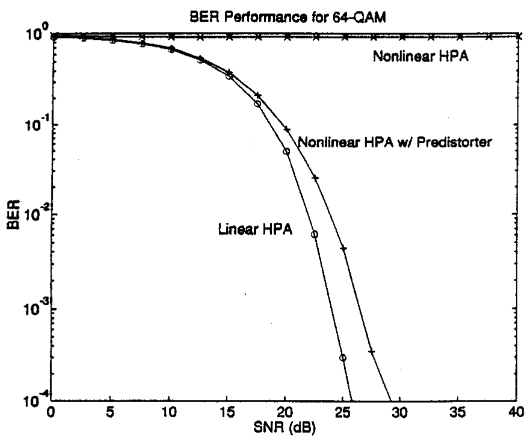

Figure 10. BER Performance Comparison

5. CONCLUSIONS

The preliminary results presented here indicate that neural networks have potential use in the predistortion of nonlinear HPAs. Their nonparametric approach, combined with the fact that the algorithm performs as a universal approximator should allow its successful use in a variety of conditions and amplifier designs. The linearization of the HPA provided by the predistorter may allow the use of nonlinear HPAs with bandwidth efficient modulation schemes.

In order to make the transition to a more practical system, several areas remain to be addressed. Most work on predistortion has centered around the assumption that the nonlinearity of the HPA can be modeled as memoryless. Some recent work indicates that this assumption may not be valid [7]. Thus, a predistorter that can operate on a nonlinearity with memory must be studied. Also the effects on the performance of this technique resulting from the non-ideal nature of the demodulator, ADC, and other equipment used to provide data to the training neural network must be investigated.

6. REFERENCES

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