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Wavelet network based predistortion method for wideband RF power amplifiers exhibiting memory effects*

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Abstract: RF power amplifiers (PAs) are usually considered as memoryless devices in most existing predistortion techniques. Nevertheless, in wideband communication systems, PA memory effects can no longer be ignored and memoryless predistortion cannot linearize PAs effectively. After analyzing PA memory effects, a novel predistortion method based on wavelet networks (WNs) is proposed to linearize wideband RF power amplifiers. A complex wavelet network with tapped delay lines is applied to construct the predistorter and then a complex backpropagation algorithm is developed to train the predistorter parameters. The simulation results show that compared with the previously published feed-forward neural network predistortion method, the proposed method provides faster convergence rate and better performance in reducing out-of-band spectral regrowth.

Key words: Power amplifiers, Predistortion, Memory effects, Wavelet networks
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INTRODUCTION

Scarcity of radio spectrum resources motivates modern wireless communication systems to adopt linear modulation schemes, such as QPSK and QAM. Although these modulation schemes make efficient use of bandwidth, they pose serious problems on RF PAs due to their non-constant envelopes. To increase efficiency, RF power amplifiers are often operated in compression region, where nonlinear distortion is severe. When used with such signals, nonlinear PAs generate significant inter-modulation distortion (IMD) leading to adjacent channel interference and increase in bit-error rate (Lin *et al*., 2006). PA linearization techniques are necessary to compensate for these nonlinear effects.

Digital predistortion is one of the most promising techniques due to its simplicity, flexibility, bandwidth capability, and adaptation to variable conditions. It inserts a digital predistorter in the baseband to create nonlinearities that are complementary to the characteristics of the PA. Thus the cascade of the predistorter and the RF PA would give a linear gain to the original input. In most existing predistortion techniques, RF PAs are usually considered as memoryless devices. Nevertheless, in wideband communication systems, such as WCDMA, CDMA 2000 and OFDM, the memory effects introduced by wideband signals are significant and the performance of the traditional memoryless predistortion is seriously degraded (Ding *et al*., 2004).

Neural networks (NNs) have been successfully utilized to model PAs and design predistorters due to their capability to approximate any nonlinear function with arbitrary accuracy (Liu *et al*., 2004; Isaksson *et al*., 2005; Lee and Gardner, 2006). The feed-forward NN is one of the most commonly used NNs, in which every unit feeds only the units in the next layer. Wavelet networks (WNs) were introduced

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as an alternative to feed-forward NNs in 1992. It has been reported that WNs outperform feed-forward NNs in terms of learning and representing dynamic system behavior. Therefore it is a natural thought that WN-based predistortion scheme may bring better linearization performance than previously published feed-forward NN predistortion. To process complex signals directly, a complex WN with complex inputs, outputs and network parameters was developed in (Li *et al*., 2003). In this study, we present a complex WN-based predistortion method for the linearization of wideband RF PAs exhibiting memory effects.

MEMORY EFFECTS OF WIDEBAND PAS

For wideband applications, PA memory effects cannot be neglected as memoryless predistortion has insufficient linearization performance. This is especially true for high power amplifiers used in wireless base stations, since several carriers are amplified by one RF PA.

Memory effects mean that the current output of the PA depends on not only the current input, but also the past input signals. For a PA with memory effects, the PA response depends on not only the input envelope amplitude, but also its frequency. In the frequency domain, memory effects are defined as changes in the amplitude and phase distortion components caused by changes in modulation frequency (Vuolevi *et al*., 2001). Memory effects can arise from multiple sources, including bias circuit effects, self-heating, and trapping effects.

PAs are traditionally modelled by a memoryless polynomial, which can be written as

$$y(n)=\sum_{k=0}^{K}c_k x^k(n), \tag{1}$$

where $x(n)$ and $y(n)$ represent the complex envelope of the input and output signals respectively and c_k is the complex coefficient. The two-tone input signal can be described as

$$x(t)=A\cos(\omega_c-\omega_m)t+A\cos(\omega_c+\omega_m)t, \tag{2}$$

where A is the magnitude, ω_c is the carrier center frequency, and the tone spacing is $2\omega_m$. Only considering the first four terms in Eq.(1), the amplitude of the third-order IMD in both lower and upper sidebands is $3c_3A^3/4$, which is not a function of tone spacing. However, for wideband applications, PAs do not behave like this. Asymmetries in lower and upper sidebands and IMD magnitude variation depending on modulation frequency (tone spacing) are often observed, as shown in Fig.1. As the input signal bandwidth widens, the gain curves of PAs exhibit dynamic characteristics (Liu *et al*., 2005), as shown in Fig.2. This means that the gains of PAs are not static, but change according to the history of past input levels.

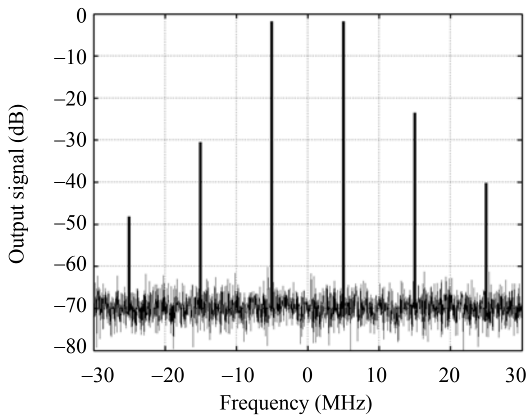

Fig.1 Output spectrum of two-tone test

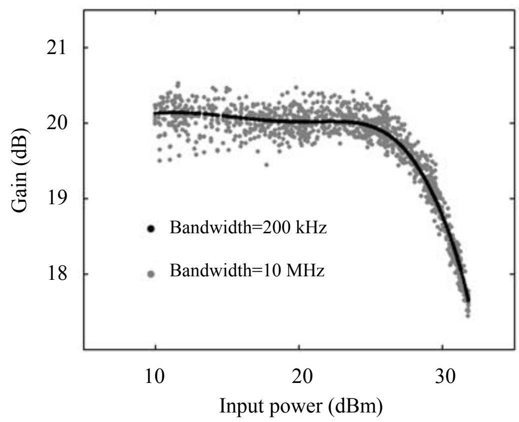

Fig.2 Gain curves of the power amplifier

WN-BASED PREDISTORTION METHOD

Predistorter model

WNs can be considered as a special case of feed-forward basis function NNs. Many topologies of NNs have been reported in the literature for the modelling of different kinds of circuits exhibiting different types of nonlinear behaviors. Here, a complex WN, which has complex inputs, outputs, weights, dilation and translation parameters, is adopted to construct the predistorter. Therefore it is unnecessary to convert the complex signals into a rectangular representation or polar one and much simpler network architecture can be achieved. The configuration of the proposed predistorter is shown in Fig.3.

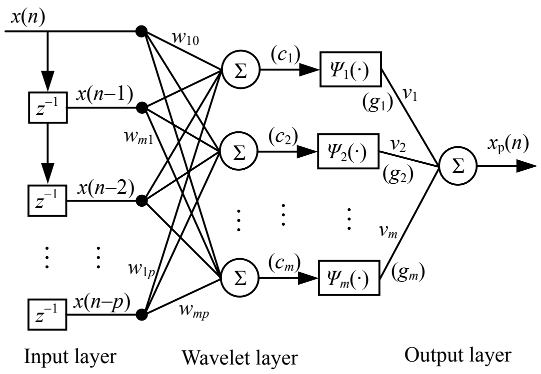

Fig.3 Configuration of the wavelet network based predistorter

Memory effects are introduced into the predistorter by tapped delay lines, which make the predistorted signal be a function not only of the instantaneous input, but also of previous time samples. The notations used in the figure are as follows. $x(n)$: input signal at instant n; p: memory length; w_{ik}: connection weight from the kth input to the ith wavelet neuron; c_i: input of the ith wavelet neuron; g_i: output of the ith wavelet neuron; m: number of nodes in the wavelet layer; v_i: connection weight from the ith wavelet neuron to the predistorter output; $x_{\rm p}(n)$: predistorted signal at instant n.

The predistorted signal $x_{\rm p}(n)$ is represented by the following equation:

$$\begin{aligned} x_{\rm p}(n) &= f\left[x(n), x(n-1), ..., x(n-p)\right] \\ &= \sum_{i=1}^{m} v_i \Psi_i(c_i) = \sum_{i=1}^{m} v_i \Psi[(c_i - b_i)/a_i], \end{aligned} \quad (3)$$

where $c_i = \sum_{k=0}^{p} w_{ik} x(n-k)$, b_i is the translation parameter, and a_i is the dilation parameter. The complex wavelet function $\Psi(\cdot)$ is defined as (Benvenuto and Piazza, 1992)

$$\Psi(s) = \psi(s_{\rm R}) + {\rm j}\psi(s_{\rm I}), \quad (4)$$

where s is a complex variable, the subscripts R and I denote the real part and imaginary part of the signals respectively, and $\psi(\cdot)$ is the conventional real-valued wavelet function. Here we choose the Mexico-hat wavelet

$$\psi(x) = (1 - x^2)\exp(-x^2/2) \quad (5)$$

as the mother wavelet.

Predistortion scheme

There are mainly two types of approaches to implement the predistortion scheme. One is to model the PA first and then identify the inverse of the PA model. However, identifying the inverse of a nonlinear system with memory is generally not easy (Ding *et al.*, 2006). The other is to design the predistorter directly. Since the nonlinear behavior of the amplifier is unknown, a feedback path is added to obtain the predistorter parameters directly, which is called indirect learning architecture (Eun and Powers, 1997).

The block diagram of the proposed system is shown in Fig.4. An indirect learning architecture is adopted to identify the predistorter parameters. The PA output signal $y_{\rm RF}$ is attenuated and fed to the predistorter training block after demodulation and A/D conversion. The predistorter training block, whose output is $\hat{x}_{\rm p}(n)$, has the same architecture as the predistorter. Ideally, when the error term $e(n)$=0, $y(n)$=$Gx(n)$, where G is the desired gain of the PA. Once the identification algorithm converges, the training block is temporarily removed, until changes of PA characteristics require a predistorter parameter update. The benefit of such a predistortion scheme is that we can design the predistorter directly without identifying the inverse of the PA model.

Training algorithm

In this subsection, a training algorithm for adjusting the predistorter parameters is developed. The parameters to be estimated are as follows:

$$q = \{w_{ik}, v_i, a_i, b_i\},\ i=1,2,...,m;\ k=0,1,...,p. \quad (6)$$

We note that all these parameters are complex

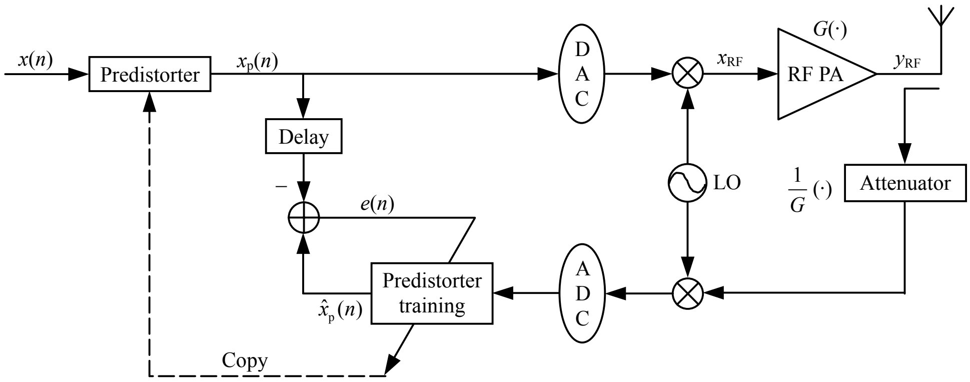

Fig.4 Block diagram of the predistortion scheme

variables. The instantaneous error signal $e(n)$ can be written as

$$e(n)=\hat{x}_{\mathrm{p}}(n)-x_{\mathrm{p}}(n). \tag{7}$$

The real-valued cost function is defined as

$$E(n)=\frac{1}{2}|e(n)|^2=\frac{1}{2}e(n)e^*(n), \tag{8}$$

where the superscript * denotes the complex conjugate. We utilize the complex backpropagation algorithm to train the established WN. The algorithm minimizes the cost function $E(n)$ by recursively altering the parameters based on the gradient search technique (Benvenuto and Piazza, 1992). The adaptation rule is

$$q(n+1)=q(n)-\eta\left(\frac{\partial E(n)}{\partial q_{\mathrm{R}}(n)}+\mathrm{j}\frac{\partial E(n)}{\partial q_{\mathrm{I}}(n)}\right), \tag{9}$$

where η is the learning rate, a real positive constant. Thus, finding the gradient vector of $E(n)$ is the main idea of deriving the training algorithm.

We first find the partial derivative of $E(n)$ with respect to the complex connection weight v_i on the output layer, and then extend to other parameters. Since $E(n)$ is not analytic, we need to derive the partial derivative of $E(n)$ with respect to the real and imaginary part of v_i separately. For simplicity, n is omitted in the following derivation. For example, $v_{i\mathrm{R}}$ is a short notation for $v_{i\mathrm{R}}(n)$. The gradient of $E(n)$ with respect to the real part and imaginary part of v_i can be respectively described as

$$\frac{\partial E}{\partial v_{i\mathrm{R}}}=\frac{\partial E}{\partial x_{\mathrm{pR}}}\frac{\partial x_{\mathrm{pR}}}{\partial v_{i\mathrm{R}}}+\frac{\partial E}{\partial x_{\mathrm{pI}}}\frac{\partial x_{\mathrm{pI}}}{\partial v_{i\mathrm{R}}}, \tag{10}$$

$$\frac{\partial E}{\partial v_{i\mathrm{I}}}=\frac{\partial E}{\partial x_{\mathrm{pR}}}\frac{\partial x_{\mathrm{pR}}}{\partial v_{i\mathrm{I}}}+\frac{\partial E}{\partial x_{\mathrm{pI}}}\frac{\partial x_{\mathrm{pI}}}{\partial v_{i\mathrm{I}}}. \tag{11}$$

We note the following partial derivatives:

$$\frac{\partial x_{\mathrm{pR}}}{\partial v_{i\mathrm{R}}}=g_{i\mathrm{R}},\ \frac{\partial x_{\mathrm{pR}}}{\partial v_{i\mathrm{I}}}=-g_{i\mathrm{I}},\ \frac{\partial x_{\mathrm{pI}}}{\partial v_{i\mathrm{R}}}=g_{i\mathrm{I}},\ \frac{\partial x_{\mathrm{pI}}}{\partial v_{i\mathrm{I}}}=g_{i\mathrm{R}}. \tag{12}$$

By substituting Eq.(12) into Eqs.(10) and (11), the gradient of $E(n)$ with respect to v_i can be compactly written as

$$\partial E/\partial v_i=-eg_i^*. \tag{13}$$

Therefore, v_i is updated according to

$$v_i(n+1)=v_i(n)+\eta e(n)g_i^*(n). \tag{14}$$

We now apply the chain rule to the translation parameter b_i. The gradient of $E(n)$ with respect to the real part of b_i can be expressed as

$$\begin{aligned}\frac{\partial E}{\partial b_{i\mathrm{R}}}&=\frac{\partial E}{\partial x_{\mathrm{pR}}}\left(\frac{\partial x_{\mathrm{pR}}}{\partial g_{i\mathrm{R}}}\frac{\partial g_{i\mathrm{R}}}{\partial z_{i\mathrm{R}}}\frac{\partial z_{i\mathrm{R}}}{\partial b_{i\mathrm{R}}}+\frac{\partial x_{\mathrm{pR}}}{\partial g_{i\mathrm{I}}}\frac{\partial g_{i\mathrm{I}}}{\partial z_{i\mathrm{I}}}\frac{\partial z_{i\mathrm{I}}}{\partial b_{i\mathrm{R}}}\right)\\&\quad+\frac{\partial E}{\partial x_{\mathrm{pI}}}\left(\frac{\partial x_{\mathrm{pI}}}{\partial g_{i\mathrm{R}}}\frac{\partial g_{i\mathrm{R}}}{\partial z_{i\mathrm{R}}}\frac{\partial z_{i\mathrm{R}}}{\partial b_{i\mathrm{R}}}+\frac{\partial x_{\mathrm{pI}}}{\partial g_{i\mathrm{I}}}\frac{\partial g_{i\mathrm{I}}}{\partial z_{i\mathrm{I}}}\frac{\partial z_{i\mathrm{I}}}{\partial b_{i\mathrm{R}}}\right)\\&=\frac{1}{a_i a_i^*}\big[e_{\mathrm{R}}v_{i\mathrm{R}}\psi'(z_{i\mathrm{R}})a_{i\mathrm{R}}+e_{\mathrm{R}}v_{i\mathrm{I}}\psi'(z_{i\mathrm{I}})a_{i\mathrm{I}}\\&\quad+e_{\mathrm{I}}v_{i\mathrm{I}}\psi'(z_{i\mathrm{R}})a_{i\mathrm{R}}-e_{\mathrm{I}}v_{i\mathrm{R}}\psi'(z_{i\mathrm{I}})a_{i\mathrm{I}}\big],\end{aligned} \tag{15}$$

where $z_i=(c_i-b_i)/a_i$. Similarly,

$$\begin{aligned}\frac{\partial E}{\partial b_{i\mathrm{I}}}&=\frac{1}{a_i a_i^*}\big[e_{\mathrm{R}}v_{i\mathrm{R}}\psi'(z_{i\mathrm{R}})a_{i\mathrm{I}}-e_{\mathrm{R}}v_{i\mathrm{I}}\psi'(z_{i\mathrm{I}})a_{i\mathrm{R}}\\&\quad+e_{\mathrm{I}}v_{i\mathrm{I}}\psi'(z_{i\mathrm{R}})a_{i\mathrm{I}}+e_{\mathrm{I}}v_{i\mathrm{R}}\psi'(z_{i\mathrm{I}})a_{i\mathrm{R}}\big].\end{aligned} \tag{16}$$

Combining Eqs.(15) and (16) into complex form, the partial derivative of $E(n)$ with respect to b_i is

$$\frac{\partial E}{\partial b_i}=\frac{1}{a_i^*}\left[\mathrm{Re}(ev_i^*)\psi'(z_{i\mathrm{R}})+\mathrm{j\,Im}(ev_i^*)\psi'(z_{i\mathrm{I}})\right]. \quad (17)$$

Hence, the translation parameter b_i is updated according to

$$\begin{aligned} b_i(n+1)=b_i(n)-\frac{\eta}{a_i^*(n)}\{&\mathrm{Re}[e(n)v_i^*(n)]\psi'(z_{i\mathrm{R}}(n)) \\ &+\mathrm{j\,Im}[e(n)v_i^*(n)]\psi'(z_{i\mathrm{I}}(n))\}. \end{aligned} \quad (18)$$

Since the procedures of deriving the training formula for the dilation parameter a_i and connection weight w_{ik} are quite similar, we do not present them here.

Training of the WN predistorter is done in a similar manner as that for the usual feed-forward NN. First, the output error is calculated (forward pass). Then the error is backpropagated to every node in the network and the parameters are adjusted accordingly (backward pass). When the error is acceptably small, the training process is discontinued.

VALIDATION RESULTS

Computer simulations were performed to validate the proposed predistortion method. An equivalent circuit model of an LDMOS transistor based RF PA was implemented in the Agilent Advanced Design System (ADS) simulator. The amplifier, whose output power is about 40 W, is suitable for cellular base stations. The PA input is a two-carrier WCDMA signal with 10-MHz bandwidth and carrier frequency of 2.14 GHz. The training process was carried out in Matlab.

To evaluate the performance of the proposed predistortion method, a feed-forward NN predistortion system with similar architecture was also implemented for comparison. To make the comparison as fair as possible, the number of hidden layer nodes was selected in such a way that the resulting numbers of adjustable parameters in NN and WN predistorter were approximately equal.

The convergence curves of two types of predistorters are shown in Fig.5 showing that compared with the feed-forward NN predistortion, the proposed method with similar network size provides faster convergence rate and improved normalized mean square error. Fig.6 and Fig.7 show AM-AM and AM-PM characteristics of the PA respectively. From the significant dispersion of the curves without predistortion, it can be concluded that the PA exhibits important memory effects (Liu *et al*., 2005). With WN-based predistortion, the nonlinearities and memory effects of the PA are compensated simultaneously. The spectral correction achieved by different predistortion methods is shown in Fig.8. The performance of memoryless predistortion, which works well in narrowband applications, is severely degraded in wideband applications. Compared with the feed-forward NN predistortion, the proposed method achieves further about 8 dB improvement in suppressing spectral regrowth.

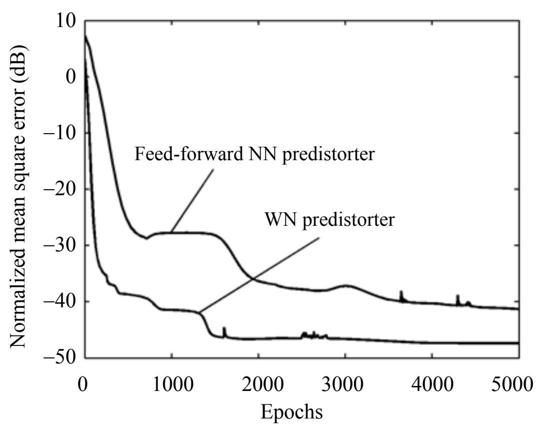

Fig.5 Convergence curves of the training process

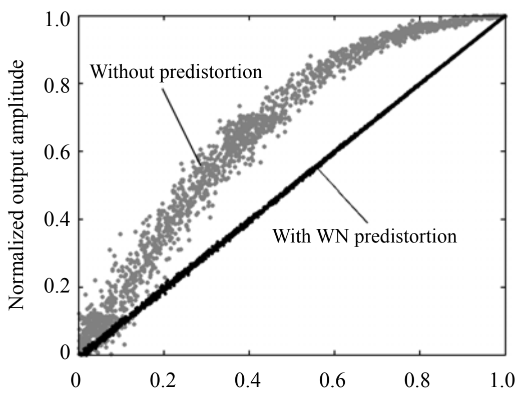

Fig.6 AM-AM characteristics

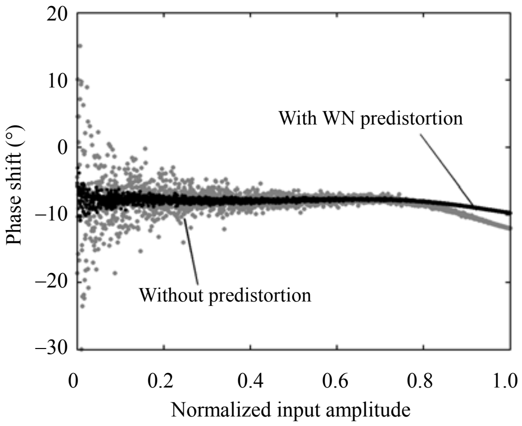

Fig.7 AM-PM characteristics

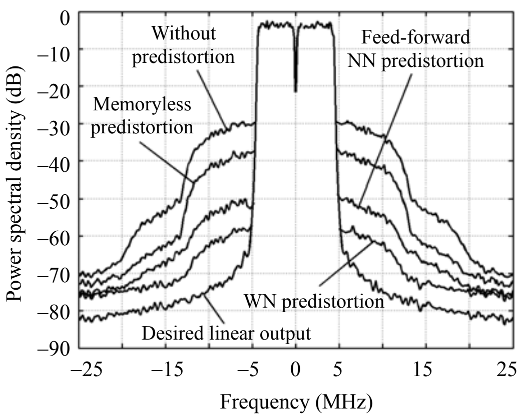

Fig.8 Performance of different predistortion methods

CONCLUSION

In this paper, a WN-based predistortion method has been proposed for the linearization of wideband RF PAs exhibiting memory effects. A complex WN with tapped delay lines is applied to construct the predistorter. Since the predistorter can process complex signals directly, much simpler network architecture is achieved. Moreover, to identify the predistorter parameters, a complex backpropagation algorithm has been developed. Validation results showed that the proposed predistortion method outperforms the previously published feed-forward NN schemes in convergence rate and reducing out-of-band spectral regrowth.

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