Behavioral Modeling of RF Power Amplifiers Using Adaptive Recursive Polynomial Functions

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Abstract — **In this paper a novel adaptive approach is used to model the behavior of a nonlinear RF power amplifier with memory. The recursive input to the model enables a reduction of the number of coefficients required to model the system. Furthermore the equation-error approach used does not suffer from the convergence problems experienced using other recursive adaptive techniques. Validation of the approach was achieved using separate training and validation signals from various nonlinear power amplifiers. The improved performance of the proposed approach was measured using goodness of fit statistics and compared against existing methods.**

Index Terms — **Adaptive, memory effect, delay filters, power amplifiers.**

I. Introduction

As communication systems grow in complexity, there is a need for behavioral models to be developed further to predict system performance more efficiently and accurately than before. Behavioral models aim to predict system level performance more efficiently than circuit level techniques through their ability to describe the input-output signal mapping for large sections of the system, using fewer mathematical expressions. However, many of these models are not suitable for wideband system modeling, as they are based on the assumption that the system behaves as a quasi-memoryless nonlinearity [1].

The power amplifier (PA) plays a key role in the transmitted signal quality in most communication systems, as a result of its operating regimes and nonlinear impairments [2]. Therefore, in order to perform a complete behavioral level simulation of a communication system, an accurate model is required to describe the nonlinearity and memory-effect influences on the signal due to the PA. The PA can be first isolated from the rest of the system, and a behavioral model of the PA can then be extracted separately from its input/output signals from/to the rest of the system.

In recent years, the effort has been directed at developing models to better characterize nonlinear systems with memory. Methods based on truncated Volterra series [3], adaptive neural network structures [4] and other reduced forms of polynomial filters with memory have been investigated [5]. These methods all report improvement over classical quasi-memoryless models. However, the computational effort required to extract the model (and in some cases, even to calculate the output signal estimate) can mitigate the benefits of using the behavioral model if the number of coefficients is too large.

In this paper we present a novel structure to provide a behavioral model of the PA which can characterize the nonlinearity and memory effects. It is shown to give good accuracy and efficient computation using a relatively small coefficient vector. The model has a similar form to an infinite impulse response (IIR) filter, which inherently includes a delayed output signal feedback path to the input. Employing the equation-error formulation, the model can be trained using adaptive algorithms, similar to those used to train finite impulse response (FIR) adaptive filters. The equation-error formulation has only a global minimum and the adaptive algorithms for this method of training generally have fast convergence [6].

Section II presents the model structure used. Section III details the method used to calculate the model coefficients and indicates the benefits of training the model in the proposed way. Section IV describes the procedure and goodness-of-fit statistics used to validate the model.

II. Model Overview

In this section a recursive filter structure is considered to model the nonlinear and memory effects contributed by an RF power amplifier in system level simulations. We begin with a linear IIR filter, for which the estimated output signal $\hat{d}(n)$ of Fig.1 can be written in difference equation form as

$$\hat{d}(n)=\sum_{m=1}^{N-1} a_m \hat{d}(n-m) + \sum_{m=0}^{M-1} b_m x(n-m) \qquad (1)$$

$\{a_1,...,a_{N-1},b_0,...,b_{M-1}\}$ is the set of coefficients which must be calculated, $N-1$ and M are the number of coefficients in the feedback and forward paths, respectively. The delayed samples of the estimated signal $\hat{d}(n)$ and the input signal $x(n)$ are multiplied by the coefficients to calculate the current output sample. Using delay-operator notation, where q^{-1} represents a unit delay, (1) can be written as follows:

$$\hat{d}(n)=A(q)\hat{d}(n)+B(q)x(n) \qquad (2)$$

where

$$A(q)=\sum_{m=1}^{N-1} a_m q^{-m} \text{ and } B(q)=\sum_{m=0}^{M-1} b_m q^{-m} \qquad (3)$$

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$A(q)$ and $B(q)$ are polynomials in q. The delay-operator equation of a recursive filter is shown in (2). For it to be IIR, at least one of the "a" terms must be non zero and the number of zeros should be less than the number of poles [7].

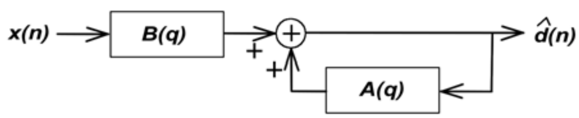

Fig. 1. Recursive Filter

Compared with FIR filters, IIR filters can achieve a given filtering characteristic using less memory and calculations than an FIR filter with a similar number of coefficients. It can also be shown that the IIR filter structure can be used to model a system with infinite duration impulse response [8]. However it is also known that care must be taken to address stability issues in this kind of structure. In this paper we seek to extend the representation of Fig. 1 to that of a nonlinear system with memory by augmenting the feedforward branch to that of a truncated discrete Volterra filter. The extension of the filter structure to deal with orders of nonlinearity, enables the new recursive structure to characterize the nonlinearity of the PA and has an effective filter memory length greater than the length of the coefficient vector. The difference equation for the new model is

$$\hat{d}(n)=\sum_{m=1}^{N-1} a_m \hat{d}(n-m) + \sum_{m=0}^{M-1} b_m x(n-m) + \sum_{i=0}^{M-1}\sum_{j=0}^{M-1} b_{ij} x(n-i)x(n-j)+\cdots+err(n) \tag{4}$$

where $err(n)$ is the truncation error.

Consider $x(t)=Re[\tilde{x}(t)e^{j\omega_c t}]$ and $y(t)=Re[\tilde{y}(t)e^{j\omega_c t}]$ as the input and output signals of a power amplifier, where ω_c is the carrier frequency and $\tilde{x}(t)$ and $\tilde{y}(t)$ represent the complex valued envelopes of the input and output signals, respectively [9]. Using the difference equation introduced above, the new complex valued recursive polynomial model of the PA is expressed as:

$$\hat{y}_{EST}(n)=\sum_{m=1}^{N-1} a_m \hat{y}_{EST}(n-m) + \sum_{m=0}^{M-1} b_m \tilde{x}(n-m) + \sum_{i=0}^{M-1}\sum_{j=0}^{M-1} b_{ij}\tilde{x}(n-i)\tilde{x}^*(n-j) +\cdots+err(n) \tag{5}$$

where $\hat{y}_{EST}(n)$ is the estimated output from the model. It may be noted that, unlike the case of the discrete truncated Volterra series, the memory effect modeling capability is here not strictly limited to the number of delayed samples selected. Note also that the feedback signal provides the model with information about the previous output signal samples from the PA, thus allowing it to track the dynamics of this signal itself and its resultant effect on the output. This in turn contributes to the improved memory performance using the new model over classical PA models. The structure of the model developed can also be used in adaptive predistortion of the complex valued input signal by a simple transfer of coefficient values [10].

III. Model Training

Here we introduce the novel approach used to extract the values for the PA model coefficients. In using this method to extract the behavioral model, it is assumed that the input and desired output signals are known from measurement or simulation. Therefore, given the desired response signal $\tilde{y}$ and input signal $\tilde{x}$, we can use the equation-error adaptive training method to calculate the estimate $\hat{y}_{EST}$ of the desired signal. As shown in the difference equation below

$$\hat{y}_{EST}(n)=\sum_{m=1}^{N-1} a_m^{(n)}\tilde{y}(n-m) + \sum_{m=0}^{M-1} b_m^{(n)}\tilde{x}(n-m) + \sum_{i=0}^{M-1}\sum_{j=0}^{M-1} b_{ij}^{(n)}\tilde{x}(n-i)\tilde{x}^*(n-j) +\cdots+err(n) \tag{6}$$

where $^{(n)}$ denotes the coefficient estimate at time sample n.

Again in delay-operator notation the output estimate equation during training can be written as

$$\hat{y}_{EST}(n)=A(n,q)\,\tilde{y}(n)+B(n,q)\,\tilde{x}(n) \tag{7}$$

where $A(n,q)$ is equivalent to a linear FIR filter, and $B(n,q)$ describes a truncated Volterra filter.

The main difference between this approach and other adaptive estimation approaches is that the equation-error method forms the estimate using samples of the input and desired response signals directly.

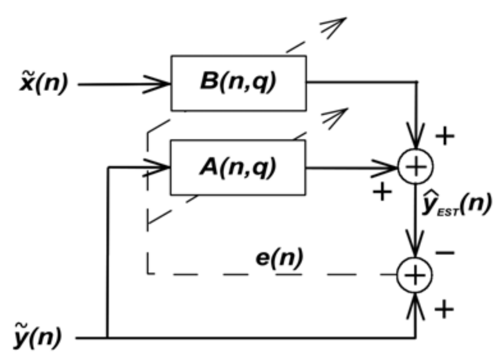

Fig. 2. Equation-Error Training of Adaptive Recursive Filter

In this way the filter acts as a two input single output FIR filter during training. As shown in Fig. 2, at each time sample n, the output signal estimate is compared with the desired output signal, and the coefficients of the two adaptive blocks are updated so as to minimize the equation-error $e(n)$. By using the input and desired response signals, and not the output samples from the filter itself, the filter does not have feedback during training and the output is a linear function of the coefficients. As a result, similarities between the adaptive FIR and equation-error adaptive IIR filter exist in the methods used to learn the coefficient values and the performance of the learning algorithms. Equation (6) can be written in more compact form as

$$\hat{y}_{EST}(n) = \theta(n)\Phi(n) \tag{8}$$

where θ is the coefficient vector and Φ, the signal vector.

$$\theta(n) = [a_1^{(n)}, \dots, a_{N-1}^{(n)}, b_0^{(n)}, \dots, b_{M-1M-1}^{(n)}] \tag{9}$$

$$\Phi(n) = [\tilde{y}(n-1), \dots, \tilde{y}(n-N+1), \tilde{x}(n), \dots, \tilde{x}(n-M+1).\tilde{x}^*(n-M+1)]^T \tag{10}$$

Equation (8) has the form of a linear regression, where θ corresponds to the estimated parameters and Φ is the regression vector, containing the data. The regressor is independent of the coefficients, as shown in (6). Therefore many linear adaptive techniques can be used to find the optimal set of parameters. In this paper the recursive least-square (RLS) algorithm was chosen to update the coefficient values because of its very good convergence characteristics. The exponentially weighted RLS algorithm aims to minimize, at each time sample, the cost function defined by

$$J(n) = \sum_{k=0}^{n} \lambda^{n-k} \left(\tilde{y}(k) - \hat{y}_{EST}^{(n)}(k)\right)^2 \tag{11}$$

where $\hat{y}_{EST}^{(n)}(k)$ is defined in (6), and the forgetting factor, λ is a constant value which controls the speed of convergence of the coefficient weights, $0 < \lambda < 1$. Typically, the value of λ is close to 1. Having performed the training, the equation-error adaptive recursive polynomial filter can operate as a pole-zero model, by copying the weights of $A(n,q)$, while an adaptive FIR filter is strictly an all-zero model. A necessary condition for the calculated coefficients of the recursive filter to work, is that the inverse of $1 - A(n,q)$ must be stable. If it is not stable, then the roots can be projected inside the unit circle using existing methods [7].

IV. VALIDATION

In this paper the model extraction and validation is performed first using a circuit level PA model stimulated with a wideband multi-tone signal and secondly, using measurement data from a PA that is stimulated with a wideband digitally modulated input signal.

First the model is used to characterize an existing circuit level description of a PA. The true frequency response for the input and output signals are calculated from an in-house convolution based transient solver simulation of the device model. The output signal is filtered and shifted in frequency to calculate the complex valued envelopes of the multi-tone signals centered at the carrier frequency. Two different sets of signals are used for the training and validation. The model is first trained using a wideband signal containing 20 tones about a 2GHz carrier frequency. In order to validate the model, a second multi-tone input signal containing 14 tones is used, and the resulting outputs from the circuit level simulation and new PA model are compared.

The average normalized mean square error (NMSE) is calculated for a discrete classical Volterra model truncated after third order with memory length of 10 samples and the new model. The truncated Volterra filter has 285 coefficients and the recursive model uses 69. The results for the NMSE are compared in Table 1. The validation signals are shown in Fig. 3 and Fig. 4 in the time and frequency domains.

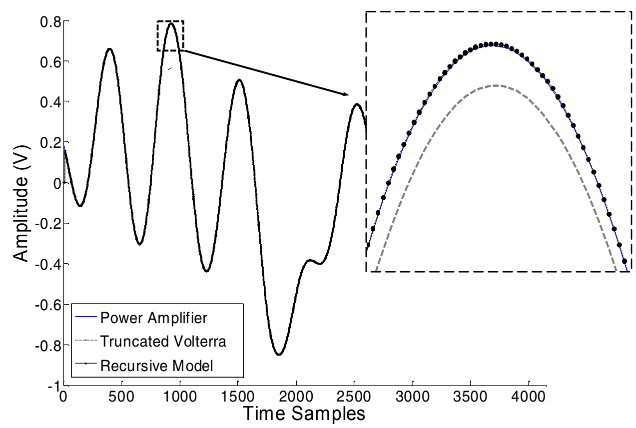

Fig. 3. Real Part Time Domain Validation

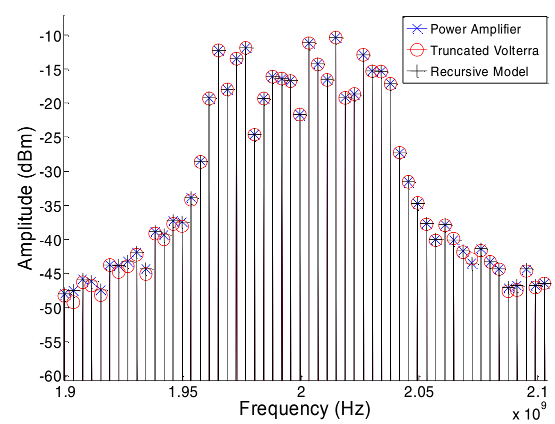

Fig. 4. Frequency Spectra of Output Estimates

Table 1. Measured and Modeled NMSE Comparison

	NMSE (dB)
Truncated Volterra Filter Order = 3, Memory = 10	- 53.12
Recursive Filter Order = 2,1, M = 10, N=5	-72.26

As a second test, the complex envelopes of the input and output signals for a general purpose HBT medium power amplifier are measured using the ADS-ESG-VSA connected solution from Agilent technologies [11]. The signal used was centered at 2.14GHz and modulated by a 3GPP W-CDMA signal of 3.84Mcps chip rate. As shown in Fig. 3 the baseband complex envelope signal is generated in Agilent ADS software and downloaded to an Agilent E4438C ESG vector signal generator. The signal is then input to the PA and the resulting complex envelope of the output signal measured on the E4406A VSA and read into the ADS software using the Agilent 89601A VSA software. Again, independent measurements are taken to extract separate signal sets for training and validation of the new PA model. Having measured the complex envelope signals and stored them on the PC, the model can be extracted, implemented and validated in Matlab. The validation NMSE values are displayed in Table 2, and time domain plot presented in Fig. 5.

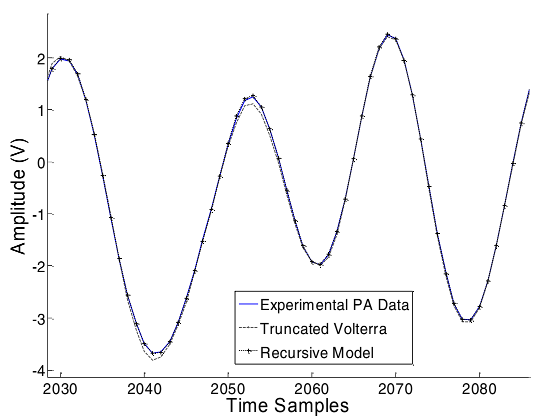

Fig. 5. Real Part Time Domain Validation Signals

Table 2. Experimental and Modeled NMSE Comparison

	NMSE (dB)
Truncated Volterra Filter Order = 3, Memory = 10	-27.63
Recursive Filter Order = 2,1, M = 10, N=5	-42.64

V. Conclusion

In this paper a novel behavioral model has been presented for use in microwave PA modeling. We used a recursive filter structure to model the PA and circumvented the problems involved in training recursive structures by employing the equation-error approach to adaptively update the coefficient values.

The advantage of using this model over classical methods is that it provides a more accurate approximation of the PA response. The improvement in accuracy does not come at the cost of an increased coefficient vector size or need for complicated training procedures.

The extraction of the model can be performed using time-domain complex envelope input and output signals. These can be generated either from existing circuit simulation results or calibrated time-domain measurements. The model can also be easily incorporated in most commercial CAD tools.

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