Digital Predistortion without Lookup Tables

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Abstract Digital Pre-Distortion (DPD) algorithms are critical for lowering out-of-band interference in broadband base stations yet their cost-effective implementation is compromised by excessive approximations. We present a high-performance nonlinear moving-average power amplifier linearization technique that uses pure signal processing and needs no lookup table (LUT). Simulation results show that our algorithm provides better performance than LUT-based DPD methods and leads to smaller silicon implementations by reducing hardware complexity.

Key words Digital Pre-Distortion, power amplifier linearization, non-linear moving average

1. Introduction

RF power amplifiers (PA) are well-known for their nonlinearity. The input-output characteristic curve of a typical RF PA has been shown in Figure 1. As shown in Figure 1, the output power reaches a saturation level as the input power P_{in} is increased. Near the saturation level, the output power P_{out} is less than the expected power P_{Linear} were a linear gain maintained. The nonlinearities present in PA cause amplitude and phase distortions of the PA output signal. These cause both in-band and out-of-band signal distortions. The simplest method for preventing such distortions is to increase PA back-off (BO). That is, lowering the operating point of the PA such that the output stays in the linear region for the useful range of the input signal. This however is not the preferred method for achieving linearity as it leads to dramatic reductions in the efficiency of the PA. There are many techniques which act on the input and/or output of a PA in order to compensate PA nonlinearities [1]. The most popular method for linearizing PA output is the digital pre-distorter (DPD). The block diagram of a PA with DPD is shown in Figure 2. Here, the DPD distorts its input signal with the inverse of the PA characteristics similar to the one shown in Figure 1. Thus the combination of DPD and PA would result in an extended linear output range.

For the design of DPD, it is essential to characterize the PA nonlinearity. PA nonlinearity has been traditionally

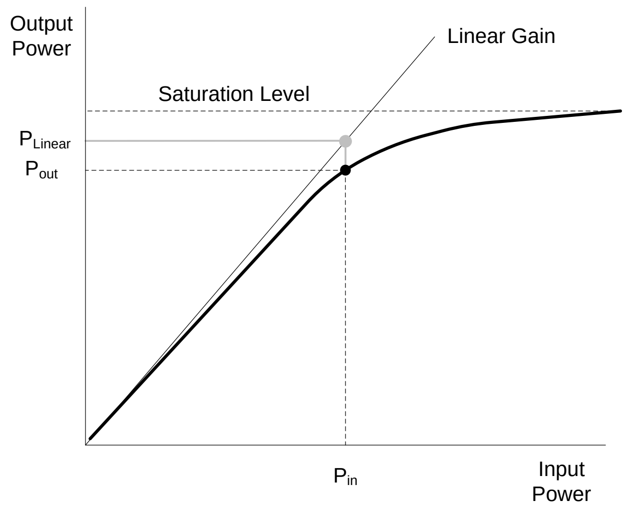

Figure 1. The input-output characteristic curve of a typical RF PA.

characterized by its output amplitude and phase distortions. These are modeled by the so-called AM/AM and AM/PM curves [2], respectively. However, these do not take into account the PA memory effect [3]. The memory effect is negligible for RF bandwidths in the order of a few hundreds of kHz. But, for signal bandwidths used in modern communication systems like the UMTS, WiMAX, and 3G LTE, the PA memory effect cannot be ignored. As such, more complicated mathematical models based on the Volterra series [4,5], the Wiener [6], or Hammerstein polynomials [7] and the like have been applied for PA modeling. A major disadvantage of these models is their excessive computational requirements leading to increased chip area and/or excessive power consumption.

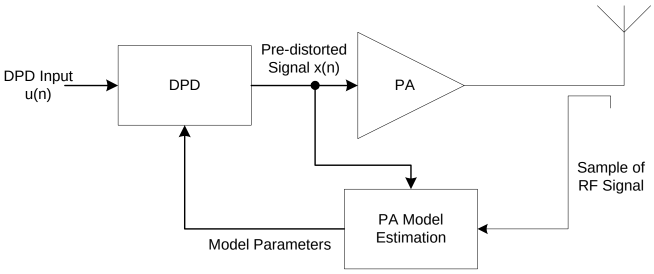

Figure 2. The conceptual block diagram of a PA with digital predistortion.

2. Augmented Moving Average for PA Modeling

The Moving Average (MA) model and its nonlinear variant NMA are powerful and elegant tools for characterizing systems with nonlinearlity [8]. The NMA has a modest computational complexity compared with its counterparts such as the Volterra series or the Wiener-Hammerstein polynomials. However, it lacks the accuracy of these models. The accuracy of the NMA is largely improved by introducing additional polynomial terms into the NMA model [6]. This socalled augmented NMA, or for short ANMA, is given as follows,

$$x(n) = \underbrace{\sum_{l=0}^{L}\sum_{k=0}^{K} a_{lk}\left|u(n-l)\right|^{k} u(n-l)}_{NMA} + \underbrace{\sum_{m=1}^{M}\sum_{w=1}^{W} b_{mw}\left|u(n-m)\right|^{w} u(n)}_{Cross-product\ terms} \qquad (1)$$

Here, $x(n)$ is the complex-valued output sample of the PA. The first double-summation represents the NMA, involving nonlinear functions of the complex-valued undistorted signal samples $u(n-l)$ for lag l; l=0,1, …, L. The second double-summation contains cross-product terms of the current signal sample $u(n)$ with the past samples $u(n-m)$. It is important to note from (1) that ANMA does not contain cross-product terms between $u(n-m)$ and any other lag other than zero, i.e. $u(n)$. This significantly reduces the number of the coefficients b_{mw} thus the complexity of representing the PA nonlinearity according to (1). The block diagram of ANMA is shown in Figure 3. The functional block MCD (Manhattan-Chebychv Distance) calculates magnitude of its input, $|u(n)|$, very efficiently as reported in detail in [9]. By using MCD we avoid square-root computations associated with calculation of the magnitude of the complex-valued input signal $u(n)$.

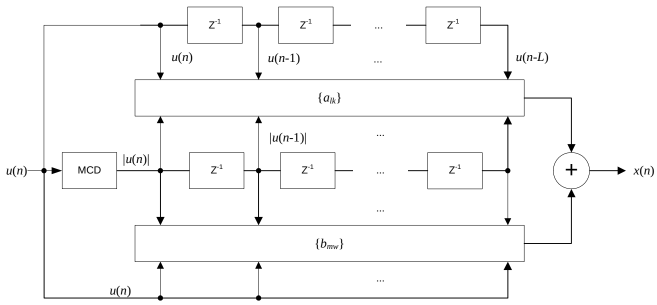

Figure 3. The functional block diagram of ANMA DPD.

3. PA Model Parameter Estimation

Characterization of the PA using (1) involves estimation of the ANMA coefficients $\{a_{lk}\}$ and $\{b_{mw}\}$. Determination of the above coefficients is a model identification problem and can be solved by, for example, the Least Squares (LS) or Least Mean Squares (LMS) algorithms during a socalled DPD training interval.

DPD training requires significant numbers of input and output samples from the PA, especially when the number of coefficients to be estimated is large. For training not to interfere with PA operation, it is advisable to train the DPD during the initial startup of the base-station.

During the training interval, the coefficients of the model are calculated. Here, we calculate these coefficients by the RLS algorithm because of its accuracy and fast speed of convergence. Before giving the RLS algorithm for DPD coefficients, we rewrite (1) in matrix form as follow:

$$x(n) = \mathbf{C}(n) \cdot \mathbf{U}(n) \qquad (2)$$

where,

$$\mathbf{C}(n) = \begin{bmatrix} \mathbf{A}_0 & \mathbf{A}_1 & \cdots & \mathbf{A}_L & \mathbf{B}_0 & \mathbf{B}_1 & \cdots & \mathbf{B}_M \end{bmatrix} \tag{3}$$

and,

$$\mathbf{U}(n) = \begin{bmatrix} \mathbf{u}_0^{(a)} & \mathbf{u}_1^{(a)} & \cdots & \mathbf{u}_L^{(a)} & \mathbf{u}_0^{(b)} & \mathbf{u}_1^{(b)} & \cdots & \mathbf{u}_M^{(b)} \end{bmatrix}^T \tag{4}$$

In addition,

$\mathbf{A}_l = \begin{bmatrix} a_{l0} & a_{l1} & \cdots & a_{lK} \end{bmatrix}$ for l=0,1, …, L;

$\mathbf{B}_m = \begin{bmatrix} b_{m1} & b_{m2} & \cdots & b_{mW} \end{bmatrix}$ for m=1,2, …, M;

$$\mathbf{u}_l^{(a)} = \begin{bmatrix} u(n-l) & |u(n-l)|u(n-l) & \cdots & |u(n-l)|^K u(n-l) \end{bmatrix}$$

for l=0,1, …, L;

$$\mathbf{u}_m^{(b)} = \begin{bmatrix} |u(n-m)|u(n) & |u(n-m)|^2 u(n) & \cdots & |u(n-m)|^W u(n) \end{bmatrix}$$

for m=1,2, …, M;

Now, the RLS algorithm for the estimation of the DPD coefficients $\mathbf{C}(n)$ is given as follows.

RLS algorithm for estimation of the model coefficients

Initialize:

$\mathbf{C}(0) = \mathbf{0}$

$\mathbf{Q}_{inv}(0) = \delta\mathbf{I}$

For n=1,2,.. compute:

$\boldsymbol{\pi}(n) = \mathbf{Q}_{inv}(n-1)\mathbf{U}(n)$

$\mathbf{k}(n) = \dfrac{\boldsymbol{\pi}(n)}{\lambda + \mathbf{U}^H(n)\boldsymbol{\pi}(n)}$

$\xi(n) = x(n) - \mathbf{C}^H(n-1)\mathbf{U}(n)$

$\mathbf{C}(n) = \mathbf{C}(n-1) + \mathbf{k}(n)\xi^*(n)$

$\mathbf{Q}_{inv}(n) = \lambda^{-1}\mathbf{Q}_{inv}(n-1) - \lambda^{-1}\mathbf{k}(n)\mathbf{U}^H(n)\mathbf{Q}_{inv}(n-1)$

End

Here, $0<\lambda<1$ is the forgetting factor of the algorithm, and δ is a large positive constant. $(.)^H$ represent the Hermitian of matrix, and $(.)^*$ is the complex conjugation. Also, $\mathbf{I}$ is the identity matrix of size $(K{\cdot}L{\cdot}M{\cdot}W)$.

The PA nonlinearity and thus its model coefficients are subject to variations because of temperature and input power of the PA. Therefore, it would be necessary to track these variations with time once the initial model identification has been carried out. The PA temperature changes smoothly. But the PA input power can change sharply because of power control or changes arising from addition or omission of services in a multiservice case. The positive number λ in the RLS algorithm controls the algorithm rate of convergence. A large λ slows down the rate of change of the coefficients by reducing the significance of new inputs, whereas a small λ increases the algorithm's responsiveness to the new inputs.

Changes due to temperature can be tracked effectively even with a large λ as the changes are slow. But the adaptation of the coefficients needs consider the input power of the PA too. When the input power is small, the PA characteristic is linear and thus the DPD coefficients should not be adapted aggressively as that would deteriorate the quality of the coefficients. On the other hand, when the input power is large such that the PA operates near saturation, DPD coefficients should be adapted more rapidly to capture any changes in the model nonlinearity. Based on these observations the forgetting factor λ can be adjusted according to

$$\lambda = 1 - \frac{\gamma P_u}{P_{u,\max}} \tag{5}$$

where, P_u is the input power to the DPD and $P_{u,max}$ is the maximum input power that DPD is designed to operate at. The positive constant γ is chosen in the range of]0,1[to control the influence of P_u on λ.

4. Results

Computer simulations were performed to measure the effectiveness of NMA and ANMA with a Class B power amplifier. We used the Error Vector Magnitude (EVM) as the performance metric. This can be calculated as:

$$EVM \doteq \frac{\sqrt{\frac{1}{N}\sum_n \left(\Delta I_n + \Delta Q_n\right)^2}}{S_{\max}} \tag{6}$$

Where $S_{\max} = \sqrt{\frac{18}{10}}$ is peak-to-average power ratio of the 16-QAM constellation.

Fig. 4 shows the measured output of the Class B power amplifier as a distorted QAM constellation with no DPD. The EVM amounts to 11.3%, which may violate the requirements for certain standards.

Fig. 5 shows the reduction in distortion that can resut from using a NMA DPD. In this case, the amplifier output constellation is visibly less distorted with an EVM of 3%.

Fig. 6 shows the ANMA algorithm in action. Now the EVM has reduced to 0.87%, and the amplifier constellation appears close to a perfect 16-QAM constellation.

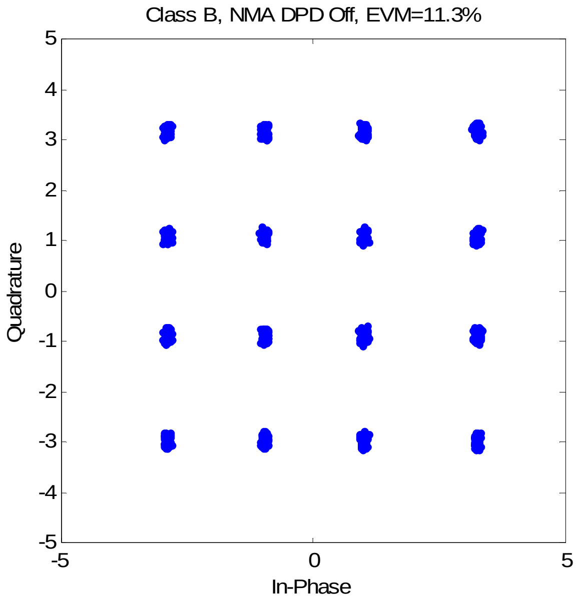

Figure 4. The baseband constellation of Class B power amplifier output with no DPD. An EVM of 11.3% is observable.

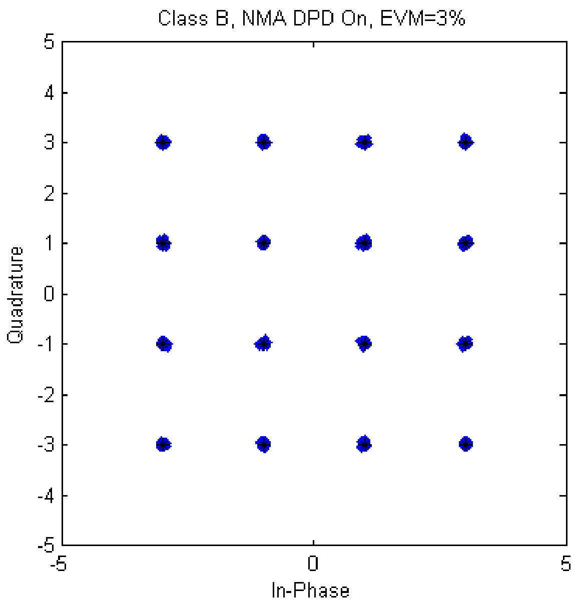

Figure 5. The baseband constellation of Class B power amplifier output with NMA DPD. Now EVM reduces to 3%.

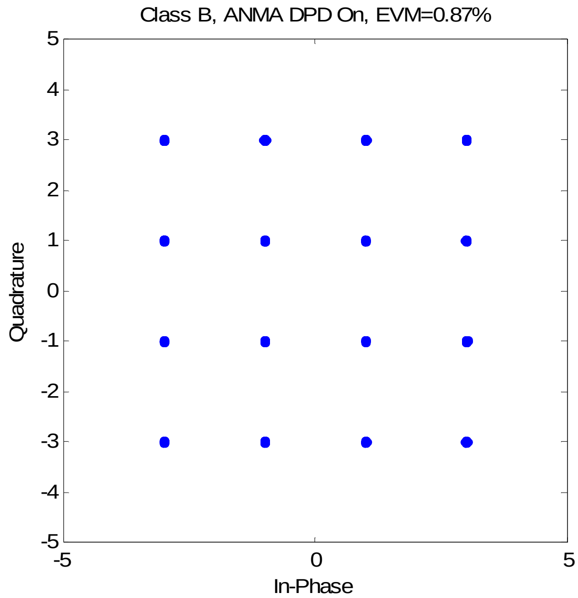

Figure 6. The baseband constellation of Class B power amplifier output with ANMA DPD. Now EVM reduces to 0.87%.

5. Conclusions

The ANMA digital predistortion algorithm outperforms memoryless NMA algorithms by the including cross-correlation filtering terms. The use of MCD as an accurate and efficient approximation for computing the absolute value of the complex baseband signal eliminates the need for lookup techniques. All the necessary predistortion computations can be done by arithmetic units.

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