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Digital predistorter based on Volterra series for nonlinear power amplifier applied to OFDM systems using adaptive algorithms

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Abstract

In this paper, different numerical methods to calculate the optimum coefficients in the Volterra Series are introduced to analyze the performance of a Digital Predistorter (DPD) for Power Amplifier (PA) with memory. The adaptive algorithms used are Least Mean Square (LMS), Normalized LMS (NLMS), Variable Step Size (VSS), and the VSS modified. The parameters in the Volterra Model are typically calculated based on the mean square error criteria, then in this paper we compare alternatives to reduce the complexity, number of operations, and the time in the linearization of PA through DPD measured with the OFDM signal. The simulation results show that the VSS algorithm is faster and effective to calculate the parameters in the Volterra model.

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Keywords: Adaptive Algorithms, Digital Predistorter, Nonlinear Power Amplifier, OFDM, Volterra Series.

1. Introduction

In modern wireless communications systems, nonconstant envelope modulation techniques, that sometimes introduced high peak to average power ratio (PAPR), are used. Example of this is the modulation based on orthogonal frequency division multiplexing (OFDM) [1]. With this kind of modulation, a spectral efficiency for radio frequency (RF) power amplifier is achieved at the cost of operating close to saturation, which produces severe distortion caused by the PA nonlinearities but a high efficiency is obtained.

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Digital Predistortion techniques are used to reduce the nonlinearities and compensate the spectral distortion caused by the PA [2]. Some authors proposed several ways to linearize the PA and reduce the memory effects: e.g., Memory Polynomial Model [3], Envelope Memory Polynomial Model [4], Wiener Model [5], Hammerstein Model [5] [6], Augmented Hammerstein Model [6], Augmented Wiener Model [7], Twin Two-Box Nonlinear Models [8] and, more recently, Open-loop DPD compensation for static distortion and memory effects [9]. All these proposals need a stage for parameter extraction, which increases the implementation complexity and cost of the system. In this paper, we focus our attention on the recently proposed DPD cited in [9], using *dynamic deviation reduction-based Volterra Series* but giving full attention to the parameters extraction through different adaptive algorithms, in order to help us build the DPD in real-time without inverting an input matrix.

This paper is organized as follows. In Section II we introduce the DPD model for this work. Section III presents an overview about the adaptive algorithms to compare. Simulation results are given in Section IV and finally the conclusion is presented in Section V.

2. Digital Predistorter

The Digital Predistorter (DPD) is a device with a nonlinear predistortion function that is the inverse of the distortion function exhibited by the amplifier. This nonlinear predistortion function is built up adapting the characteristics of the PA [10]. Figure 1 shows this predistortion system.

To describe the relationship between the input and output of a nonlinear PA with memory, in this work we use the following Volterra pruned series, called *dynamic deviation reduction* originally proposed in [11] and enhanced in [9]:

$$\tilde{u}(n) = \sum_{l=0}^{\frac{P-1}{2}} \sum_{i=0}^M \tilde{k}_{2l+1,1}(i) |\tilde{x}(n)|^{2l} \tilde{x}(n-i) + \sum_{l=1}^{\frac{P-1}{2}} \sum_{i=1}^M \tilde{k}_{2l+1,2}(i) |\tilde{x}(n)|^{2(l-1)} \tilde{x}^2(n) \tilde{x}^*(n-i) \quad (1)$$

where $\tilde{x}(n)$ and $\tilde{u}(n)$ are the original input and output of the DPD, respectively, and $\tilde{k}_{2l+1,j}$, with $j = \{1, 2\}$, is the complex Volterra series kernel of the system, $(\cdot)^*$ represents the complex conjugate operation and $|\cdot|$ returns the magnitude. P and M are nonlinearity order and memory effect respectively. The parameters extraction is used for determining the values for the complex Volterra kernel, that is:

$$\tilde{k} = (Y^H Y)^{-1} Y^H U \quad (2)$$

where $(\cdot)^H$ represents the Hermitian transpose. This model needs to capture and save the observations performed (received samples) Y , and the desired response (transmitted symbols) U . This equation represents the theoretical solution (TS) and is not possible to implement in a real environment since it would try to invert a matrix with too large dimensions.

In this work the k parameters (kernel) are determined by an adaptive algorithm. In this way it is not necessary to compute the matrix inverse in equation (2). At the beginning, the DPD is bypassed while the adaptive algorithm calculates the optimum kernel for Volterra series and the DPD is done. After this stage the DPD is connected and the compensation is completed.

3. Adaptive Algorithms

Usually, an adaptive algorithm unit consists of a transfer filter to process the input signal, and an algorithm to update the coefficients. The general form of the adaptive filter is illustrated in Figure 2. There exist several proposals to do the coefficients adaptation: Least Mean Square or LMS algorithm [12] updates the coefficients according to

$$W(n+1) = W(n) + \mu e(n) X(n), \quad (3)$$

$X(n)$ is the input signal and W is the filter coefficients vector and is given by

$$W(n) = [w_0, w_1, w_2 \dots w_l] \tag{4}$$

and the $e(n)$ is the error for the n^{th} sample expressed in the following equation

$$e(n) = d(n) - X^T(n)W(n), \tag{5}$$

here $d(n)$ is the desired output and $X^T(n)W(n)$ is the signal estimation denoted by $y(n)$ in Figure 2. Finally, μ is the parameter that controls the step size and stability. The parameter μ must be within the following bounds to ensure convergence [13]:

$$0 < \mu < \frac{1}{\lambda_{max}} \tag{6}$$

where λ_{max} is computed as the maximum eigenvalue of the autocorrelation matrix of the input signal. To eliminate this dependence on the input signal, there is a normalized version of the LMS algorithm called NLMS (Normalized-LMS) algorithm explained in [14]. For the normalized one, the update coefficients are estimated by

$$W(n + 1) = W(n) + \beta e(n)X(n) \tag{7}$$

where the parameter β is

$$\beta = \frac{\alpha}{X^T(n)X(n)}. \tag{8}$$

In this case, α is a constant whose value may be set independently of the input signal characteristics. In these two algorithms with fixed step, when the step size increases, the speed of convergence also increases, but with a bigger error. On the other hand, with a small step size, the algorithm needs more iterations and takes longer to adapt the coefficients. In order to remove this dependence and decrease the error and the convergence time, the Variable Step Size (VSS) algorithm was proposed in [15], where the adjustment for the new step is

$$\hat{\mu}(n) = \alpha\mu(n - 1) + \gamma e^2(n - 1), \tag{9}$$

and the parameter α works as a memory factor of the previous step, while the parameter γ is the memory factor of the previous iteration. The step is bounded by

$$\mu(n + 1) = \begin{cases} \mu_{max} & \text{if } \hat{\mu}(n) > \mu_{max}, \\ \mu_{min} & \text{if } \hat{\mu}(n) < \mu_{min}, \\ \hat{\mu}(n) & \text{otherwise.} \end{cases} \tag{10}$$

The coefficients vector is computed with the equation (3).

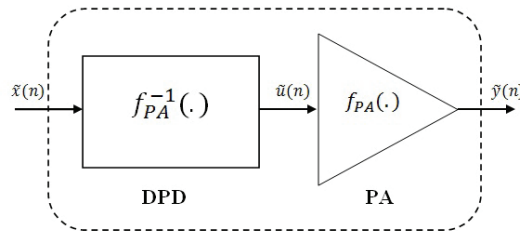


Fig. 1. Predistortion system. The predistortion function in the DPD is the inverse of the PA distortion function. The complete cascade of the DPD followed by the PA gives a linear system.

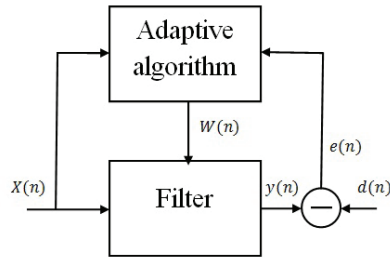


Fig. 2. A general adaptive algorithm unit.

Table 1. Parameters for fixed-step Algorithms

Algorithm	Step
LMS	$\mu = 4 \times 10^{-1}$
NLMS	$\alpha = 6 \times 10^{-1}$

Several proposed modifications of the VSS algorithm can be found in the literature [16]-[18] but in all of them the step size iterative equation can be written as the equation (9). We tested the VS-LMS with general modifications, particularly with those proposed in [18] where the γ parameter is compensated with the constant β as follows

$$\gamma(n+1) = \begin{cases} \beta\gamma(n) & \text{if } \hat{\mu}(n) > \mu_{max}, \\ \gamma(n) & \text{otherwise.} \end{cases} \quad (11)$$

We omit the other algorithms because they increase the number of parameters to update the step, and this results in a higher complexity for a real implementation.

4. Simulation Results

To evaluate the performance of the proposed algorithms described above, we take the AM/AM curve to observe the linearization of the PA. Real PA's work close to the nonlinear region, which results in a compression of the output signal. The DPD tries to compensate this compression in order to restore the original signal. The signal used for stimulate the adaptation algorithms is an OFDM signal defined and described in *IEEE802.11a* standard [1] for WiFi wireless networks. We can observe the Power Spectral Density (PSD) of this system and how the nonlinear response from the PA causes an unwanted spread of the spectrum. And finally, we show the convergence towards optimal values of the kernel of the Volterra series.

In order to evaluate the proposal, we tested all adaptive algorithms with the specific parameters presented in the Table 1 for the LMS and NLMS algorithms (fixed-step type), and Table 2, for the VSS and VS-LMS algorithms (variable-step type). The values presented here, are the same as those reported in the original papers, except μ_{max} and μ_{min} proposed here equal in both algorithms for comparison. The Volterra series presented in equation (1) were estimated with polynomial order 5 and a memory length 2 ($P = 5$ and $M = 2$). With these parameters we then have a kernel of size $\tilde{k} : 13 \times 1$.

Figure 3 shows the AM/AM curve with and without DPD. The simulated PA is compressed respect to the ideal response, however the DPD makes a very good compensation for this compression introduced by the nonlinear PA. We can observe the linearization using DPD with the LMS algorithm. Other algorithms reach similar linearization performance, except that some require more iterations to reach the same result, this is because the linearization itself is not outcome of the adaptive algorithm, but it is made by Volterra series which is responsible for DPD creation. What we show here is the good performance of DPD as a result of pruned Volterra Series. Equivalently, in Figure 4 we present the Power Spectral Density results

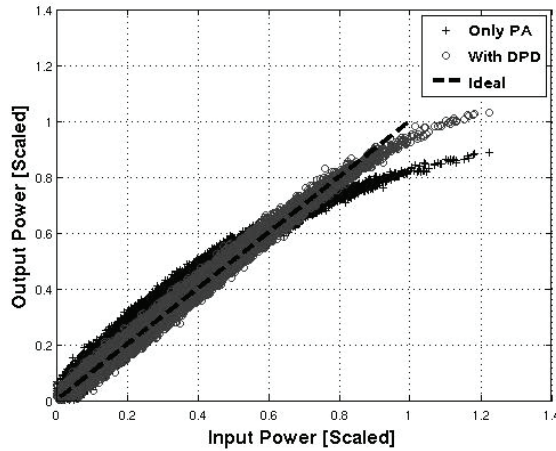


Fig. 3. AM/AM response simulated with an OFDM signal and DPD calculated by LMS algorithm.

of the four adaptive algorithms plotted in the same graph. Figure 4 illustrates, as expected, that the performance is maintained in restoring original spectra with any algorithm, because the compensation is mainly performed by the DPD from the Volterra series. It is observed in the dotted zoom area, that the offsets are very similar for all algorithms, which is not true for the number of iterations required to reach this PDS. The LMS algorithm required around 6×10^4 iterations, the NLMS algorithm 120×10^4 , and the algorithms VSS and VS-LMS, 4×10^4 iterations.

The results for the convergence of the Volterra series kernel, obtained through simulations, are presented in Figures 5 and 6. Dotted lines are the optimal solution (TS) and lines of convergence of each algorithm to this solution. The step size for the fixed-step algorithms, μ and α , and the bounded, μ_{max} and μ_{min} , for the variable-step algorithms is elected so that the convergence presents the minimum standard deviation. Here, any algorithm are faster than the often used for parameters extraction represented in equation (2), and also very expensive in practical implementation.

For the performance of each algorithm in terms of adaptation speed for updating the Volterra series kernel, we show (Figure 5) that the NLMS algorithm is the slowest because it requires above 7×10^4 iterations (120×10^4 to that shown in Figure 4), but it makes a convergence smoother than any other; the standard deviation is small compared with that of the other algorithms. The LMS algorithm, with about 6×10^4 iteration, already shows a good approximation to the theoretical solution. The LMS algorithm is almost twice as fast that the NLMS algorithm although NLMS algorithm presents more benefits in terms of convergence and stability [14].

Both the VSS and LS-VSS algorithms have almost the same performance. This can be seen in Figure 6, where around iteration number 4×10^4 presents already a good approximation to the optimal solution. This algorithm required 2×10^4 , resulting in the best behavior with respect to values for LMS.

Table 2. Parameters for variable-step Algorithms

Algorithm	Update step	Bounded
VSS	$\alpha = 0.9995$ $\gamma = 4.8 \times 10^{-4}$	$\mu_{max} = 75 \times 10^{-2}$ $\mu_{min} = 65 \times 10^{-2}$
VS-LMS	$\alpha = 2 \times 10^{-1}$ $\beta = 7 \times 10^{-1}$ $\gamma = 7 \times 10^{-4}$	$\mu_{max} = 75 \times 10^{-2}$ $\mu_{min} = 65 \times 10^{-2}$

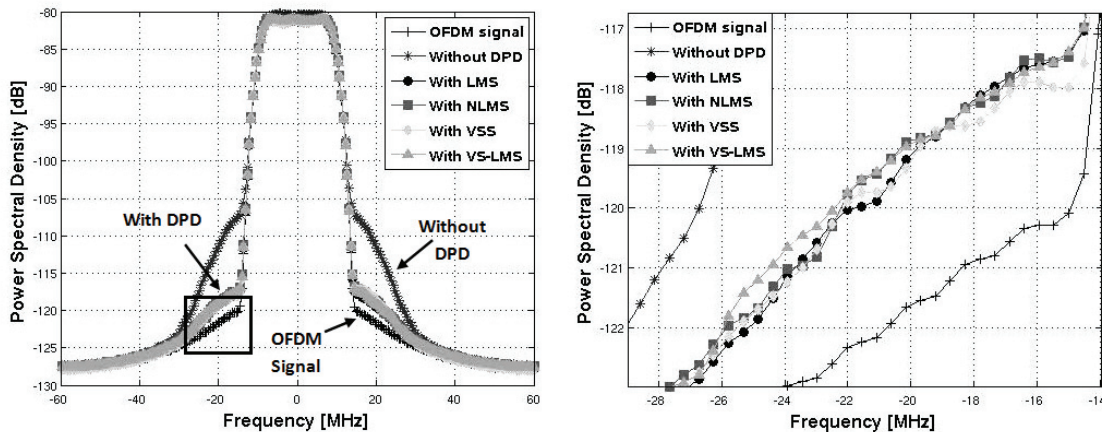


Fig. 4. Spectral plots of the system with DPD Volterra series kernel adapted by LMS, NLMS, VSS and VS LMS and a zoom for them.

5. Conclusions

The distortions, the nonlinear response and unwanted spread spectrum of the power amplifier, are properly compensated by DPD with Volterra Pruned series. We tested four adaptive algorithms and compare with the TS to obtain the kernel in the Volterra series and we evaluated: a) the correct performance in the linearization and spectral compensation, and b) the speed of parameters extraction for the kernel. We have shown that any of the algorithms proposed is better than the TS, particularly the VSS algorithm has better performance without introducing many operations and parameters, in comparison with the VS-LMS. The LMS and NLMS algorithms have good adaptation speed and reasonable number of iterations, just a little behind the VSS. For the other algorithms, not shown here and referred in Section II, the number of operations and parameters for the update step size increases drastically which makes its real implementation very difficult.

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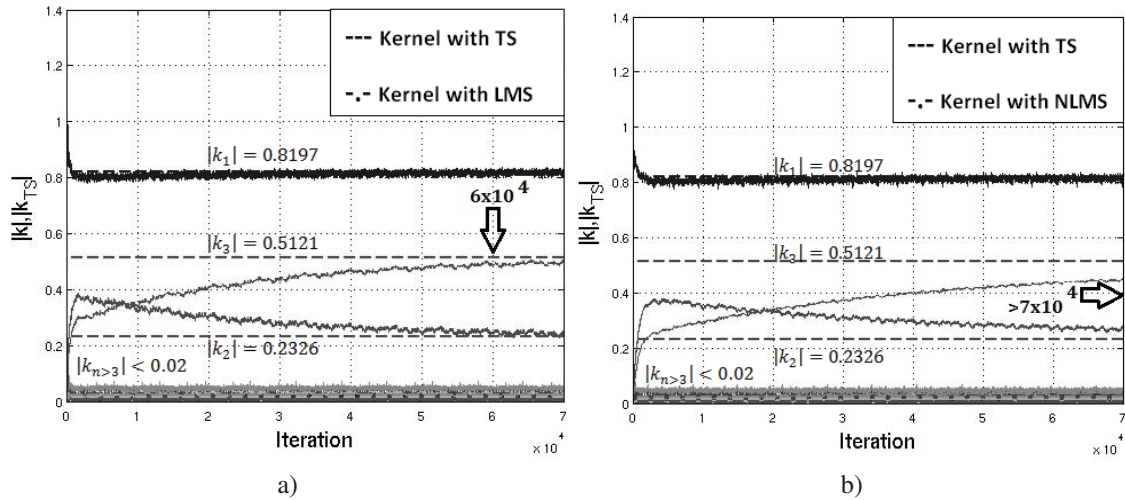


Fig. 5. Fixed-step Algorithms, performance in number of iterations need for updating the Volterra series kernel. a) LMS and b) NLMS. The Volterra series kernel more significant in terms of value are k_1 , k_2 and k_3 , and for values of $k_{n>3}$ the coefficients are small. The arrow indicates a good approximation to the TS.

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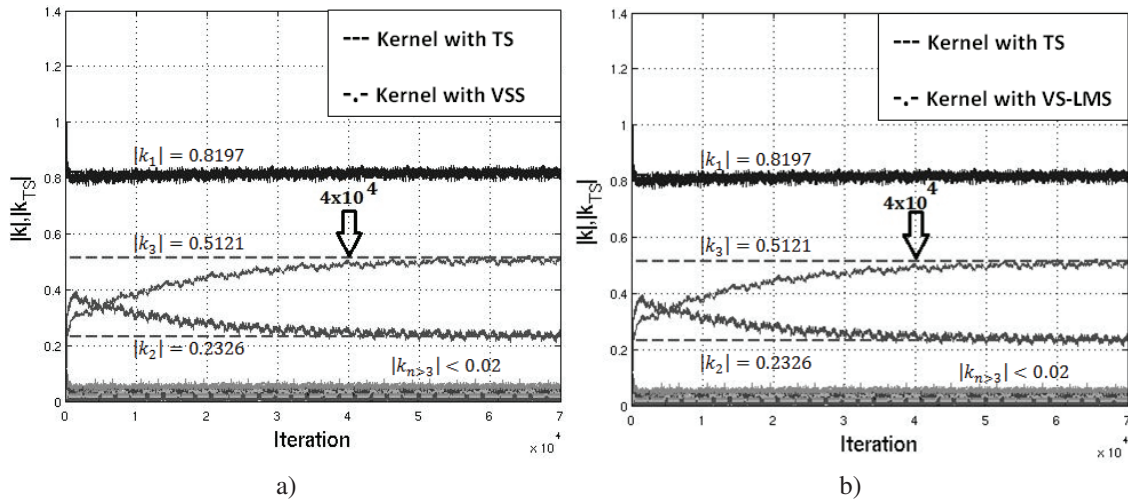


Fig. 6. Variable-step Algorithms, performance in number of iterations need for updating the Volterra series kernel. a) VSS and b) VS-LMS. The Volterra series kernel more significant in terms of value are k_1 , k_2 and k_3 , and for values of $k_{n>3}$ the coefficients are small. The arrow indicates a good approximation to the TS.