A SIMPLIFIED ADAPTIVE NONLINEAR PREDISTORTER FOR HIGH POWER AMPLIFIERS BASED ON THE DIRECT LEARNING ALGORITHM

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ABSTRACT

The adaptive nonlinear predistorter is an effective technique to compensate the nonlinear distortion existing in a digital communication system. In this paper, we first apply the recently developed nonlinear filtered-x LMS and adjoint nonlinear LMS algorithm to design an adaptive Hammerstein nonlinear predistorter for a high power amplifier (HPA) preceded by a linear system. Compared with the adaptive Hammerstein nonlinear predistorter with either direct learning or indirect learning, our developed adaptive nonlinear predistorter is computationally efficient and can be easily implemented via DSP hardware and software. By exploring the robustness of our proposed algorithm and the statistical properties of our virtual filter, we further simplify the adaptive Hammerstein nonlinear predistorter to further reduce the computational complexity and implementation cost. Simulation results confirm the effectiveness of our proposed algorithm.

1. INTRODUCTION

High power amplifiers (HPAs) are known to be the major source of nonlinear distortion in digital communication systems [1]. An adaptive nonlinear predistorter is an effective technique to compensate this type of nonlinear distortion because it varies with time and temperature. However, most available adaptive nonlinear predistorters are based on indirect learning techniques [2,3]. The adaptive nonlinear predistorters based on direct learning techniques [4-6] are computationally expensive and/or complicated in structure. In [7], we introduced an efficient adaptive nonlinear predistorter with a simple structure based on the direct learning algorithm, which can greatly reduce the computational complexity and memory requirements of these algorithms. Simulation results in [7] indicated an improvement of 5-10 dB in mean square error (MSE) compared with an indirect learning algorithm.

However, that algorithm is based on a general polynomial nonlinear model, which may not be suitable (or efficient) for modeling a high power amplifier in digital communication systems like OFDM and CDMA. This is because HPAs usually demonstrate memoryless nonlinear distortion. As a result, people often use a block oriented model that models the HPAs connected with a linear filter to reduce the number of coefficients and thus the computational complexity [8]. Recent research results show that HPAs exhibit some memory effects for a wide-bandwidth input signal [9]. This memory effect can be absorbed into the linear filter model [3], [10].

As a result, we are going to use a Wiener nonlinear model to model our HPA system in this paper. This is because the HPAs in digital communication systems such as an OFDM system are usually preceded by a linear pulse shaping filter, and the Wiener system can also model the HPA with memory. We are going to apply the recently developed nonlinear filtered-x LMS and adjoint nonlinear LMS algorithm [7] to design an adaptive Hammerstein nonlinear predistorter for a Wiener model HPA system. Compared to the adaptive Hammerstein nonlinear predistorter with direct learning and indirect learning, our developed adaptive nonlinear predistorter is computationally efficient and can be easily implemented by DSP hardware and software. Then, by exploring the robustness of that proposed algorithm along with its statistical properties, we propose a simplified adaptive Hammerstein nonlinear predistorter that further reduces the computational complexity and implementation cost. The same method introduced in this paper can be extended to compensate the Hammerstein nonlinear model or a linear-nonlinear-linear (LNL) block oriented model.

We arrange this paper as follows. The adaptive nonlinear predistorter based on direct learning is briefly reviewed in section 2. We then develop an adaptive Hammerstein nonlinear predistorter in section 3. Further simplification of the adaptive Hammerstein nonlinear predistorter is proposed and discussed in section 4. Simulation results are given in section 5. We draw our conclusion in section 6.

2. ADAPTIVE NONLINEAR PREDISTORTER BASED ON DIRECT LEARNING METHOD

The LMS adaptive nonlinear predistorter introduced in [7] is based on a general nonlinear polynomial model

$$y(n) = X'(n)W(n) \tag{1}$$

where

$$X(n) = [\phi_1(\bar{x}(n)) \quad \phi_2(\bar{x}(n)) \quad \cdots \quad \phi_Q(\bar{x}(n))]' \tag{2}$$

$$W(n) = [w_1 \quad w_2 \quad \cdots \quad w_Q]' \tag{3}$$

$X(n)$ and $W(n)$ are the state and the coefficient vectors of the nonlinear system. $\bar{x}(n)$ represents the input sequence to a nonlinear device (i.e. $x(n)$ and its delays), $y(n)$ is the output, $w_i(n)$ is the i^{th} complex coefficient at time n, Q is the total number of terms, and $\phi_i(\bar{x}(n))$ is the one term in the polynomial that is a function of $\bar{x}(n)$ and differentiable with $\bar{x}(n)$ everywhere except at a limited number of points. Consequently, the general polynomial nonlinear model is linear with regard to $w_i(n)$.

Using the general nonlinear polynomial model, we developed an adaptive nonlinear predistorter based on the direct learning algorithm. We called it the nonlinear filtered-x LMS algorithm, and its block diagram is given in figure 1. In the figure, $W(n)$ and $\hat{H}(n)$ are the coefficient vectors of the adaptive nonlinear predistorter and identification filter, respectively. The block $H(n)$ represents a nonlinear device. The adaptive nonlinear predistorter input is $u(n)$ and its output, denoted by $y(n)$, is fed into the nonlinear device $H(n)$. We want the output of the nonlinear device, denoted by $\hat{d}(n)$, to be as close as possible to $d(n)$, which is a delayed and amplified version of the input $u(n)$. The update function of the adaptive nonlinear predistorter $W(n)$ is

$$W(n) = W(n-1) + ue^*(n)U_f(n) \tag{4}$$

where

$$U_f(n) = \sum_{r=0}^{M-1} g(r,n)U(n-r) = U(n) * \tilde{H}(n) \tag{5}$$

$$\tilde{H}(n) = \left[g(0,n) \quad g(1,n) \quad \cdots \quad g(M-1,n) \right] \tag{6}$$

$$g(r,n) = \frac{\partial \hat{d}(n)}{\partial y(n-r)} \tag{7}$$

The combiner generates every nonlinear state $U(n)$. $\tilde{H}(n)$ is called the virtual filter of $H(n)$. This algorithm is exactly the same as the nonlinear filtered-x LMS introduced in [4], except that by introducing the virtual filter, we have achieved a new structure that is more easily implemented.

However, the developed algorithm remains computationally expensive. One reason is that every state in $U(n)$ must be filtered by the virtual filter. We further introduced the adjoint LMS algorithm, whose update function is

$$W(n+1) = W(n) + ue_f^*(n)U(n-M+1) \tag{8}$$

with

$$e_f^*(n) = e^*(n) * \tilde{H}^*(n) \tag{9}$$

$$\tilde{H}^*(n) = [g(M-1,n) \quad g(M-2,n-1) \quad \cdots \quad g(0,n-M+1)] \tag{10}$$

M is the memory of $H(n)$. From this perspective, we find that we are only required to filter the error signal with an adjoint virtual filter $\tilde{H}^*(n)$ (given in (10)) and adding some delays to the nonlinear state. This algorithm requires far fewer computations and memory. Our simulation results indicate that this efficient predistorter retains the good performance of the more complex nonlinear filtered-x LMS.

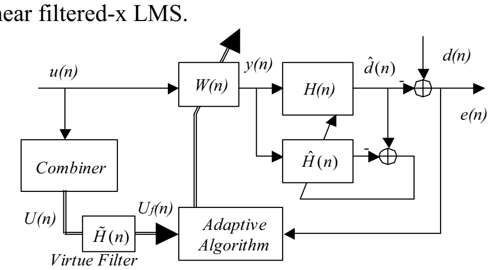

Figure 1. Adaptive nonlinear predistorter based on the nonlinear filtered-x LMS

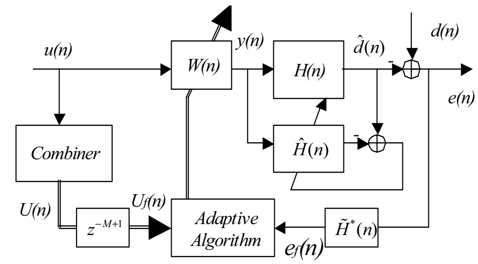

Figure 2. Adaptive nonlinear predistorter based on adjoint nonlinear LMS

3. ADAPTIVE HAMMERSTEIN NONLINEAR PREDISTORTER

As discussed in the introduction, we model the HPA preceded with linear filter via a block oriented model – the Wiener nonlinear model. This is a memoryless nonlinear system N preceded by a linear filter $L(n)$. The Wiener nonlinear model can be linearized by an adaptive Hammerstein nonlinear predistorter as in figure 3. This predistorter is the cascade of a memoryless adaptive nonlinear filter $P(n)$ and an adaptive linear filter $W(n)$. Using the method of section 2, we need to first find the virtual and adjoint virtual filters for the path from the adaptive filter output to the point of summation.

From figure 3, this path is the Wiener nonlinear filter. So, we can find the virtual filter as

$$\begin{aligned}
\tilde{V}_1(n) &= [\frac{\partial \hat{d}(n)}{\partial y(n)}, \frac{\partial \hat{d}(n)}{\partial y(n-1)}, \cdots, \frac{\partial \hat{d}(n)}{\partial y(n-r)}, \cdots \frac{\partial \hat{d}(n)}{\partial y(n-N+1)}] \\
&= \frac{\partial d(n)}{\partial z(n)} [\frac{\partial z(n)}{\partial y(n)}, \frac{\partial z(n)}{\partial y(n-1)}, \cdots, \cdots, \frac{\partial z(n)}{\partial y(n-N+1)}] \\
&= \frac{\partial d(n)}{\partial z(n)} L(n) = N'\Big|_{z(n)} L(n)
\end{aligned} \tag{11}$$

$N'|z(n)$ is the differentiation of a memoryless nonlinear function with respect to its input $z(n)$ and estimated at that input. The block diagram of the virtual filter $V(n)$ is shown in figure 4(a). In figures 4-6, the box is a linear filter and the triangle is a gain. The adjoint virtual filter can be obtained from equation (10)

$$\begin{aligned}
\tilde{V}_1^*(n) = [&L(N-1)N'\Big|_{z(n)}, L(N-2)N'\Big|_{z(n-1)}, \\
&\cdots, L(N-r)N'\Big|_{z(n-r+1)}, \cdots, L(0)N'\Big|_{z(n-N+1)}]
\end{aligned} \tag{12}$$

This is shown in figure 4(b). Note that the time-varying gain must be before the linear FIR Filter. The path from the output of the adaptive filter $P(n)$ to the summation point is also a Wiener filter. Thus, we have the virtual filter

$$\tilde{V}_2(n) = N'\Big|_{z(n)} [W(n) * L(n)] \tag{13}$$

The * denotes linear convolution. The corresponding adjoint virtual filter may be obtained as before.

Based on this virtual filter and update function (4), we derive the update function for the adaptive filters in the Hammerstein predistorter

$$W(n) = W(n-1) + ue^*(n)S_f(n) \tag{14}$$

$$P(n) = P(n-1) + ue^*(n)U_f(n) \tag{15}$$

The block diagram is given in figure 5. Inspecting these functions and the updating functions in [5], we see that eq. (14) and (15) are the same as those introduced in [5]. However, using our virtual filter, we find that our configuration has a much simpler structure that is easy to implement. Here, *S(n)*, which is generated by the combiner 2 in figure 5, represents *[s(n) s(n-1) ... s(n-M+1)]*. Due to the time-varying nature of the virtual filter $\tilde{V}_1(n)$, all states in *S(n)* must be filtered by $\tilde{V}_1(n)$.

With the adjoint virtual filters and update function (8), we have the updates for the adjoint nonlinear LMS algorithm (and shown in figure 6)

$$W(n) = W(n-1) + ue^*_{f1}(n)S(n) \tag{16}$$

$$P(n) = P(n-1) + ue^*_{f2}(n)U(n) \tag{17}$$

Note that the predistorter using the nonlinear adjoint LMS algorithm has a much simpler structure, and requires less computation, than the one based on the nonlinear filtered-x LMS. Table 1 gives out the number of multiplications for each algorithm per iteration.

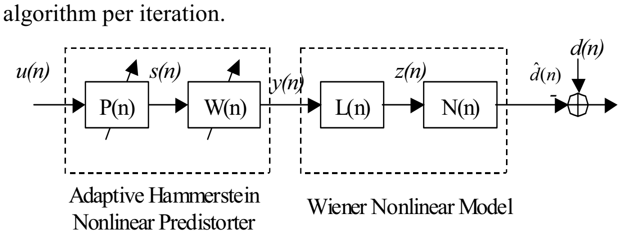

Figure 3. the Hammerstein nonlinear predistorter AND the Weiner nonlinear model of HPA system

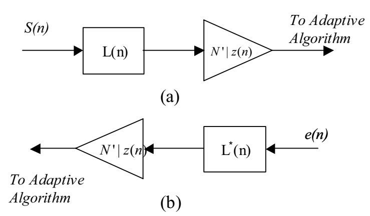

Figure 4. Block diagram of virtual filter (a) and adjoint virtual filter (b) for the Wiener nonlinear model

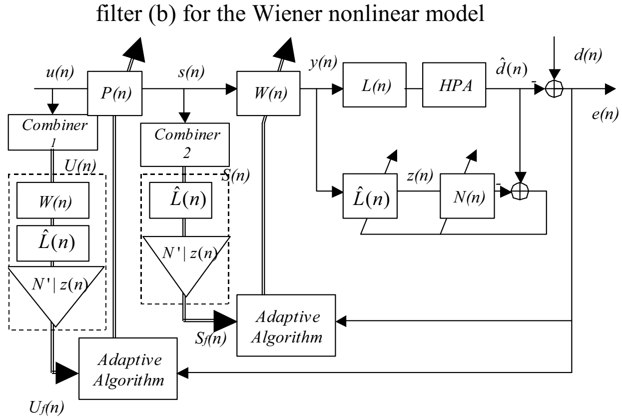

Figure 5. Adaptive Hammerstein Nonlinear Predistorter Based on nonlinear filtered-x LMS

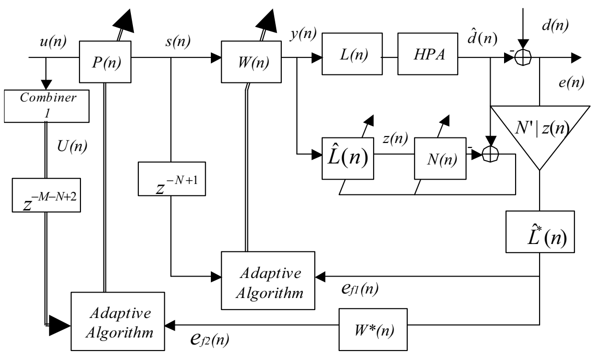

Figure 6. Adaptive Hammerstein Nonlinear Predistorter Based on nonlinear adjoint LMS

4. SIMPLIFICATION USING PHASE ROBUSTNESS

The nonlinear filtered-x LMS and adjoint LMS algorithm case can be regarded as an extension (or as a generalization) of the linear filtered-x LMS and adjoint LMS. The main idea behind nonlinear filtered-x LMS and nonlinear adjoint LMS is common to its linear counterparts – to keep the reference signal and error signal aligned in time. The virtual filter and adjoint virtual filter in the two algorithms serve this purpose. However, to keep the two signals aligned, we are only required to filter using a filter with nearly the same phase response as the virtual filter or adjoint virtual filter in the nonlinear filtered-x LMS algorithm and nonlinear adjoint LMS algorithm. With this proviso, the adaptive filter should still converge for a sufficiently small step size. According to [11], we only need a filter with the phase frequency response within $\pm 90^o$ of the actual phases response. As a result, we can say the nonlinear filtered-x LMS algorithm and nonlinear adjoint LMS algorithm are robust, and can tolerate some estimation errors.

From this notion, we closely examine the virtual filter of the Wiener model. First, consider that the expected value of $N'|z(n)$ is a constant. So the pure gain $N'|z(n)$ will not introduce phase delay and hence we can disregard it. Thus, we can further simplify the adaptive filter, which has the similar structure as in figure 6, but without the pure gain $N'|z(n)$. However, we must exercise some caution with the step size in this case. Consider that the update function of (16) becomes

$$W(n) = W(n-1) + \mu' err^*_{f1}(n)S(n) \tag{18}$$

where the err^*_{f1} is corresponding to e^*_{f1} in figure 6 but without pass thought the gain $N'|z(n)$. If we take $\mu' = \mu E[N'|z(n)]$, then they are the same. The simplification will affect the step size bound of the adaptive algorithm. If $E[N'|z(n)] \ll 1$ is a small value, then μ' should take a value much less than μ for convergence. This simplification can reduce the computational count and simplify the structure in the update of the adaptive nonlinear predistorter. Even more importantly, in the identification procedure, we find that we need only identify the linear part of the Wiener model because the filtering does not cause a shift of more than $\pm 90^o$.

The number of multiplications of the above-discussed algorithms per iteration is given in table 1. This number ignores the nonlinear system identification procedure that is required by all algorithms. In the table, M and N represent the order of the $W(n)$ and $L(n)$ respectively. Q_1 and Q_2 represent the order of nonlinearity in $P(n)$ and $N(n)$ respectively. From this table, we see that our proposed methods can greatly reduce the computational complexity.

Hammerstein Predistorter	Number of Multiplications
Nonlinear Filtered-x LMS	$(Q_1+3+N)M+(N+2)Q_1+Q_2-1$
Nonlinear Adjoint LMS	$3M+3Q_1+N+Q_2$
Further Simplification	$3M+3Q_1+N+1$

Table 1. The number of multiplications for the different algorithms per iteration

5. SIMULATION

In the following simulations, we use the Wiener nonlinear HPA model from [6] and assume an ideal channel without fading and noise. A 16-QAM constellation signal is modulated and transmitted through the predistorter, linear filter, and HPA. From figure 7, we see that the proposed methods can successfully compensate most of the distortion. The relation between OBO and remaining mean square error (MSE) based on different algorithm are also given in figure 8, which shows our proposed methods have remaining MSE figures similar to the method introduced in [6], but are much more efficient in structure and computational requirements.

6. CONCLUSION

In this paper, we successfully applied our recently developed adaptive nonlinear predistorter based on direct learning technique to design an adaptive Hammerstein nonlinear distorter for a Wiener model HPA system. Compared with the same model nonlinear predistorter, ours has better performance, a simpler structure and lower computational efficiency. By examining the robustness and statistical properties of the developed algorithm, we are able to propose a simplified adaptive nonlinear predistorter that further reduces the computational complexity and implementation cost. Similar methods can be applied to other block oriented nonlinear models such as the Hammerstein and the linear-nonlinear-linear (LNL) models. Simulation results confirm the effectiveness of our proposed method.

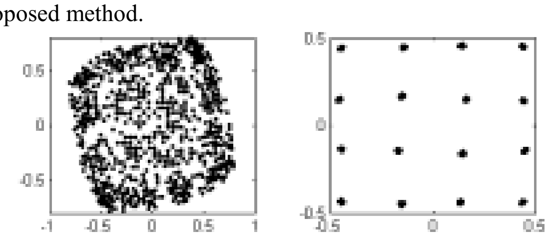

Figure 7. Received 16-QAM constellation signal without (left) and with (right) our proposed predistorters

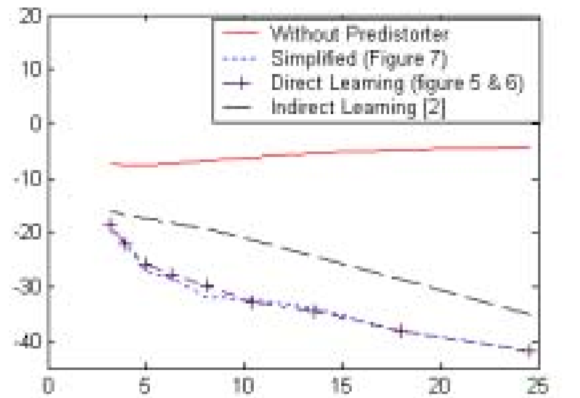

Figure 8. OBO versus MSE for proposed different nonlinear predistorter

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