Composite Adaptive Digital Predistortion with Improved Variable Step Size LMS Algorithm

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Abstract. This paper presents a composite learning (CL) architecture. The CL can make use of the advantages of both direct and indirect learning. By an appropriate threshold, the indirect learning can be switched into direct learning. In order to further improve the performance of direct learning, an improved variable step size LMS algorithm is proposed. The proposed algorithm has the lower normalized mean-square error (NMSE) with low computation complexity. The outstanding performance is confirmed by simulation results.

1 Introduction

The nonlinear behavior of power amplifier (PA) generates in-band and out-of-band distortion of the output signal, resulting in increased bit error rate and the adjacent channel interference in wireless communication system [1]. Numerous researches have been carried out to solve this problem. Among the possible linearization techniques, the adaptive digital predistortion (DPD) is the most potential technique to compensate for the nonlinear distortion of power amplifier [2-5].

The indirect learning and direct learning are widely used in DPD technology. The former has better convergence performance, but worse ability to resist noise. The direct learning results in slow convergence, but better ability to resist noise. In addition, the classic adaptive algorithms, such as least mean square (LMS) and recursive least squares (RLS), may be difficult to achieve satisfactory performance in DPD. Although some improved adaptive algorithms have been proposed in recent years [6-7], these approaches are either with high computational complexity, or difficult for real-time implementation and poor noise performance.

In this paper, we present a composite adaptive digital predistortion with improved variable step size LMS algorithm for linearization of power amplifier. The memory polynomial model of PA is simplified to avoid the complicated identification. A threshold-determinant composite predistortion architecture is proposed, which is combined with the advantages of direct learning and indirect learning. A new variable step size LMS algorithm is proposed for fine estimation and update predistortion parameters. The performance of the input and output amplitude (AM/AM), the input amplitude and output phase (AM/PM), power spectral density, signal constellation, normalized mean square error (NMSE) are investigated by computer simulation, witch confirms the superiority of the proposed scheme.

2 Simplified Memory Polynomial Model

Behavioral modeling is important for the implementation of DPD. Conventional DPD mostly use memoryless model, which suggests that the current output depends only on the current input. However, higher power amplifiers may exhibit memory effects that can no longer be ignored in wideband applications. The earlier memory polynomial (MP) model was proposed in [2]. The digital baseband predistorter was studied using memory polynomials in [3]. The general memory polynomial (GMP) model was proposed in [4], which combines the memory polynomial (MP) model with cross-terms between the signal and lagging/leading exponential envelope terms. In our studies, however, to reduce the model complexity for practical engineering, we merely consider the current input impact by the memory envelope (CIME) and the memory time influence by the current envelope (MICE) items. Then we get the simplified GMP (S-GMP) model as below

$$y_{\text{S-GMP}} = \sum_{k=1}^{N_1}\sum_{m=0}^{M_1} a_{km}\left|x(n-m)\right|\left|x(n-m)\right|^{k-1} + \sum_{k=1}^{N_2}\sum_{m=0}^{M_2} b_{km}\left|x(n)\right|\left|x(n-m)\right|^{k} + \sum_{k=1}^{N_3}\sum_{m=0}^{M_3} c_{km}\left|x(n-m)\right|\left|x(n)\right|^{k} \quad (1)$$

where x and $y_{\text{S-GMP}}$ are the equivalent baseband signals of the input and output of the PA. N_1, M_1 , a_{km}, N_2, M_2 , b_{km} and N_3, M_3 , c_{km} are the MP, CIME , MICE order ,memory depth and coefficients, respectively.

As a signal passes through a nonlinear PA, the produced the third-order intermodulation component is close to the signal spectrum in output and it is difficult to get rid of it by filtering. The higher order intermodulation component is much smaller than the third-order intermodulation, the effect of which can be ignored in engineering. Therefore, in this paper, we only consider the third-order intermodulation of CIME and MICE.

3 Composite Adaptive DPD Scheme

Composite Learning Architecture. The indirect learning can be used with classical adaptive algorithm, which has better convergence performance, but has poor ability to resist noise. However, direct learning can obtain the optimal DPD parameters usually by random search, resulting in slow convergence, but has the ability to resist noise. In order to make use of the advantages of direct and indirect learning and avoid their disadvantages, a new composite learning architecture is proposed in Fig. 1. This architecture consists of two sub-architectures, the indirect and the direct learning architecture. The indirect learning is composed of predistorter, PA, predistorter training, and adaptive algorithm 1. The direct learning includes predistorter, PA and algorithm 2.

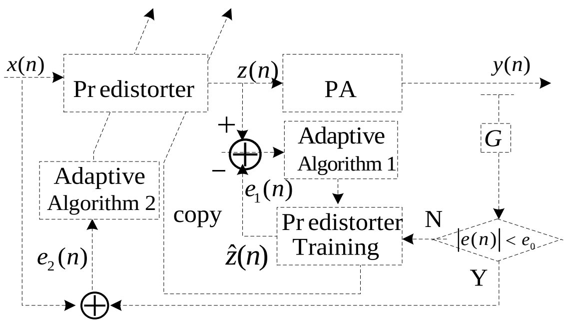

Fig. 1. Proposed composite learning architecture

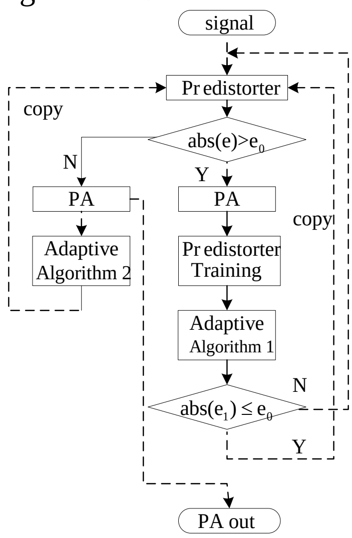

Fig. 2 Flow chart of composite learning

Once the algorithm 1 convergences by setting an appropriate threshold, the direct learning begins, taking the weight vector obtained from indirect learning as the initial value. This approach can not only effectively suppress additive noise and quantization noise of ADC in the feedback loop, but also improve the convergence stability.

The desired signal vector is denoted as $\boldsymbol{d}$ and the error vector $\boldsymbol{e}$. The PA output signal sampled is transformed and denoted as $\boldsymbol{v}$. Thus $\boldsymbol{d} = \boldsymbol{e}\text{-}\boldsymbol{v}$.

Composite Learning Algorithm. The flow chart of composite learning algorithm is shown in Fig. 2. Firstly, setting the error determinant threshold $|e_1(n)| = |e_0(n)| = 1$, $|e(n)| \ge e_0$, the algorithm 1 estimates DPD parameters. Secondly, checking $e_1(n)$, if $|e(n)| < e_0$, then $|e_1(n)| = |e(n)|$, Algorithm 2 in direct learning is activated to continue DPD parameter estimation until optimal convergence.

A number of adaptive algorithms can be applied in this composite learning architecture. In this paper, we take the well-known RLS algorithm as algorithm 1 in indirect learning for its fast convergence characteristics. The error value of the learning curve of the RLS can be used as the discrimination threshold. Algorithm 2 responsible for fine adjustment in direct learning has a crucial effect on the final performance of DPD. Therefore, we present an improved algorithm for direct learning in next section.

Kernel Memory Polynomial Model. The DPD kernel memory polynomial model adopted in the paper is [1]

$$y(n) = \sum_{k=1}^{K} \sum_{m=0}^{M} C_{km} \left| x(n-m) \right| \left| x(n-m) \right|^{k-1} \tag{2}$$

where K is the nonlinear order. M is depth of memory. C_{km} is DPD coefficient.

4 LNCVSS-LMS Algorithm

A low noise and low complexity variable step size LMS (LNCVSS-LMS) is proposed in this section, which is not only effectively suppress the uncorrelated noise, but also reduces the computational complexity. The variable step size function $\mu(n)$ is defined as

$$\mu(n+1) = \alpha\mu(n) + \beta e^2(n) \tag{3}$$

where $0 < \alpha < 1$, $\beta > 0$.

Anti-noise Performance. Let $\mathbf{w}_0$ be the global optimal solution of the LNCVSS-LMS algorithm and $\xi(n)$ the difference between the expected response $z(n)$ and the predistorted training network $\hat{z}(n)$ of the time n. We assume that the expectation and variance of noise are 0 and δ^2. Then we can get

$$z(n) = \mathbf{w}_0{}^H \mathbf{u}(n) + \xi(n) \tag{4}$$

$$\hat{z}(n) = \mathbf{w}(n)^H \mathbf{u}(n) \tag{5}$$

$$e(n) = z(n) - \hat{z}(n) \tag{6}$$

$$e(n) = \xi(n) - (\mathbf{w}(n)^H - \mathbf{w}_0)\mathbf{u}(n) \tag{7}$$

Let $\lambda(n) = \mathbf{w}(n)^H - \mathbf{w}_0$, then

$$E\{e(n)\cdot(e(n)-e(n-1))\} = E\{\lambda(n)\cdot u(n)\cdot(\lambda(n)\cdot u(n) - \lambda(n-1)\cdot u(n-1))\} \tag{8}$$

$$E\{e(n)^2\} = E\{\lambda(n)\cdot u(n)\cdot \lambda(n)\cdot u(n)\} + \delta^2 \tag{9}$$

By (7) and (8), we can know that the LNCVSS-LMS algorithm is only related to the input signal, and has nothing to do with the noise. Therefore, the LNCVSS-LMS algorithm has strong noise suppression ability.

Complexity Evaluation. In addition to the insensitivity to noise, LNCVSS-LMS does have a low complexity. A comparison of the computation complexity of three algorithms is shown in Table 1, where the complexity is measured by the total number of multiplication and addition operations.

TABLE I Computation Complexity Comparison

Algorithm	step-size factor	(multiply, add)
VSS-LMS	$\mu(n+1) = \alpha\mu(n) + \beta e^2(n)$	(2N+4， 2N+1)
MVSS-LMS	$\mu(n+1) = \alpha\mu(n) + \gamma p^2(n)$	
	$p(n+1) = \beta p(n) + (1-\beta)e(n)x(n)$	(2N+7， 2N+2)
LNCVSS-LMS	$\mu(n+1) = \alpha\mu(n) + \beta\,|e(n)|\cdot|(|e(n)| - |e(n-1)|)|$	(2N+4， 2N+2)

From Table 1, we can see that our proposed LNCVSS-LMS maintains about the same complexity as the other two algorithms, However it has more outstanding performance than the other two, which can be seen from the simulation results in section 5.

5 Simulation Result

In this section, we evaluate the performance of the proposed composite adaptive digital predistortion for RF power amplifier linearization. We set the input signal is 16 quadrature amplitude modulation (QAM). The PA model used for the predistorter is the S-GMP model discussed in section II with the quintic nonlinearity and 3 order memory. DPD kernel is a memory polynomial model with 5 order nonlinear and 8 order memory.

AM/AM and AM/PM. Fig. 3 shows the input and output amplitude (AM/AM), and the input amplitude and output phase (AM/PM), before and after the DPD processing. From the figure, we can see that the nonlinear PA is linearized significantly.

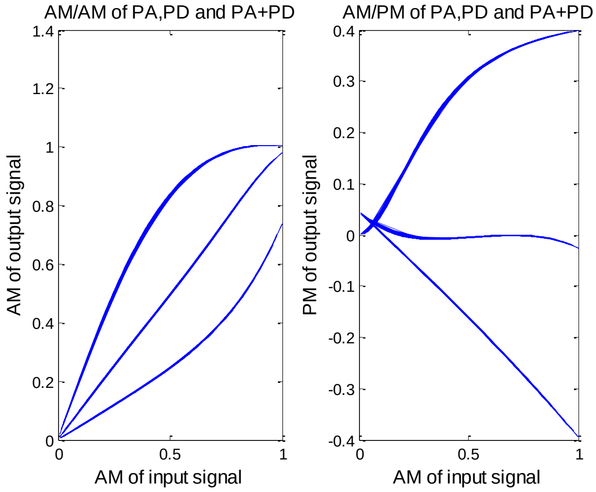

Fig. 3 AM/AM and AM/PM of S-GMP

Power Spectral Density. Fig. 4 presents a comparison of power spectral density among several PA models. The out-of-band spectrum suppression ability of the S-GMP model is better than that of the MP model, and is similar to the GMP model.

Fig. 5 shows the output power spectrum of PA with different adaptive algorithm. It shows that the power spectral density of LNCVSS-LMS adaptive algorithm proposed in this paper is much closer to the original spectrum than LMS, VSS-LMS and MVSS-LMS [6] algorithms.

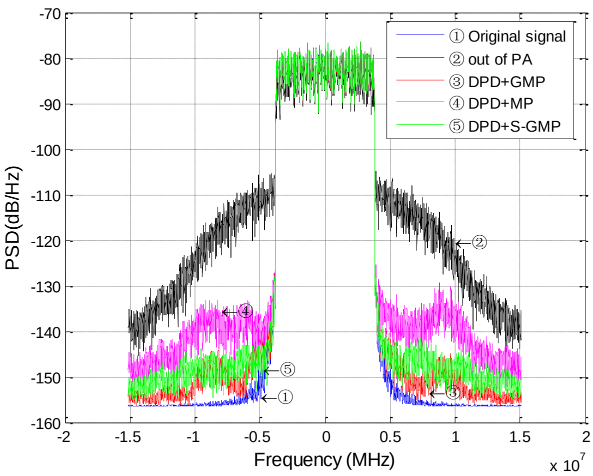

Fig. 4 Power spectrum of three PA model via DPD

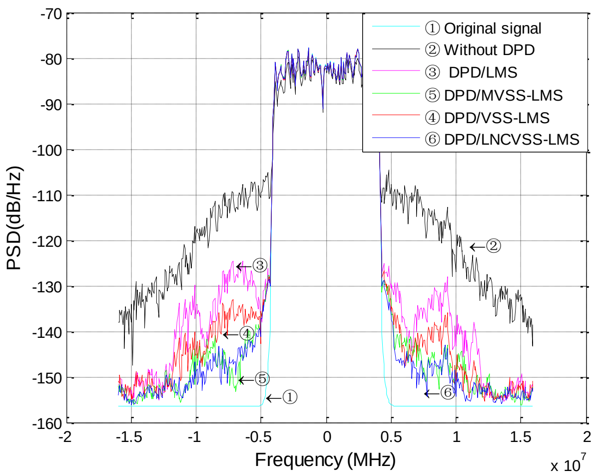

Fig. 5 Output power spectrum

Signal Constellation. In Fig. 6, compared with the indirect learning architecture and the hybrid indirect learning [8], the composite architecture proposed in this paper can more effectively improve the constellation dispersion.

Normalized Mean Square Error. The NMSEs of the VSS-LMS, the MVSS-LMS, and the LNCVSS-LMS are shown in Fig. 7. Obviously, the steady-state error of LNCVSS-LMS outperforms VSS-LMS about 5 dB, and better than MVSS-LMS 3 dB.

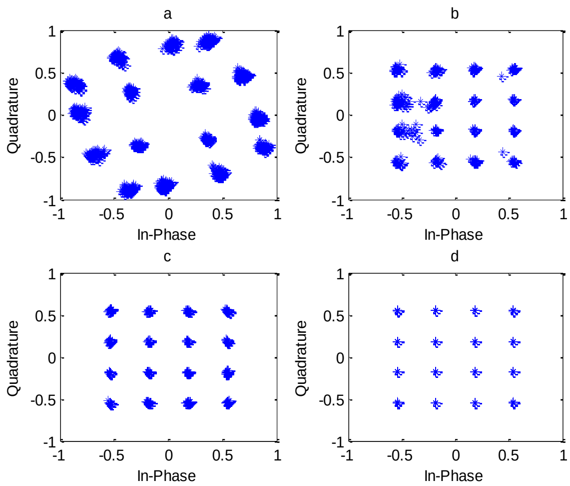

Fig. 6 Constellation diagram
(a) without DPD (b) indirect learning (c) hybrid indirect learning
(d) composite learning architecture

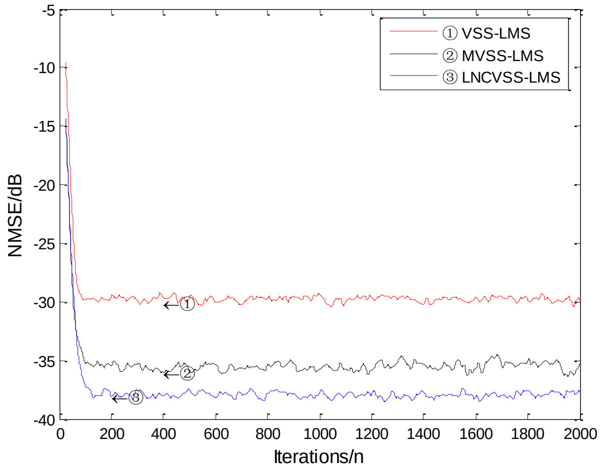

Fig. 7 NMSEs of three adaptive algorithms (SNR=10dB)

6 Conclusions

This paper proposed a threshold-determinant adaptive composite DPD architecture for PA linearization. To further improve the performances and reduce the effect of noise, a new variable step size LMS algorithm was proposed as well. The optimal approaches we investigated can effectively suppress the additive noise and quantization noise of ADC in the feedback loop. The simulation results showed that the linearization of the power amplifier is effective with the output spectrum, constellation and NMSE outperforming other learning architecture and algorithms.

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