

DIRECT LEARNING ARCHITECTURE FOR DIGITAL PREDISTORTION WITH REAL-VALUED FEEDBACK

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Abstract: The power efficiency is a key parameter of modern communication systems. Efficient non-linear power amplifiers are linearised using digital predistorters. Conventional predistorters require two ADCs in the feedback. In this paper we have proposed a modification of the direct learning architecture using solely one ADC in the feedback and an RF mixer instead of a quadrature mixer. This allows us to minimise the system complexity and power consumption and maximise the efficiency. The proposed architecture has been verified experimentally and compared to the conventional digital predistorters. We have shown that it can achieve same linearisation performance as the conventional architecture with two ADCs. Moreover the proposed method outperformed the conventional DPD with indirect learning architecture.

Keywords: digital predistortion, direct learning architecture, real-valued feedback

1 INTRODUCTION

Modern wireless communication systems are required to provide still more and more data throughput. This demand is usually satisfied by increased communication bandwidth and utilisation of spectrum-efficient modulations. The most of these modulations are linear, e.g. quadrature amplitude modulation (QAM), orthogonal frequency-division multiplexing (OFDM), or filter bank multicarrier (FBMC) and its variants as candidates for 5G cellular networks, and require usage of linear power amplifiers (PA). The linear PAs are usually low power-efficient. Therefore they operate close to saturation in the nonlinear region and are linearised or compensated to achieve linear behaviour.

One of the linearisation technique is digital predistortion (DPD) which is based on sensing the PA output, comparing it with the desired signal, and introducing a correction of the transmitted signal (predistortion) to get the desired signal at the PA output. A typical representative of such DPD can be a baseband predistorter depicted in Fig. 1a. All the signal processing is performed in the digital domain which assumes an analogue-to-digital converter (ADC) to be used for sampling the PA output and a digital-to-analogue converter (DAC) to generate the transmitted signal.

Wideband communication systems require two high-speed ADCs in the feedback path. These ADCs are power hungry and increase design complexity and price. Nowadays research shows the interest to relax demands on these ADCs. Liu [1], and Huang [2] focused in their work mainly on lowering the sampling frequency of the ADCs. Wang in the paper [3] and Zhang in [4] extended the undersampling DPD for multiband and wideband transmitters. Zhang et al. followed different approach in their papers [5] where they presented the DPD with the feedback ADCs replaced by high-speed DACs accompanied with high-speed comparators which allowed them to reduce system power consumption.

Power consumption and the system simplification was also main object of Chani-Cahuana et al. in their paper [6]. They proposed an architecture with a single ADC and an RF mixer instead two ADCs with a quadrature mixer employing the iterative learning control (ILC) algorithm which they

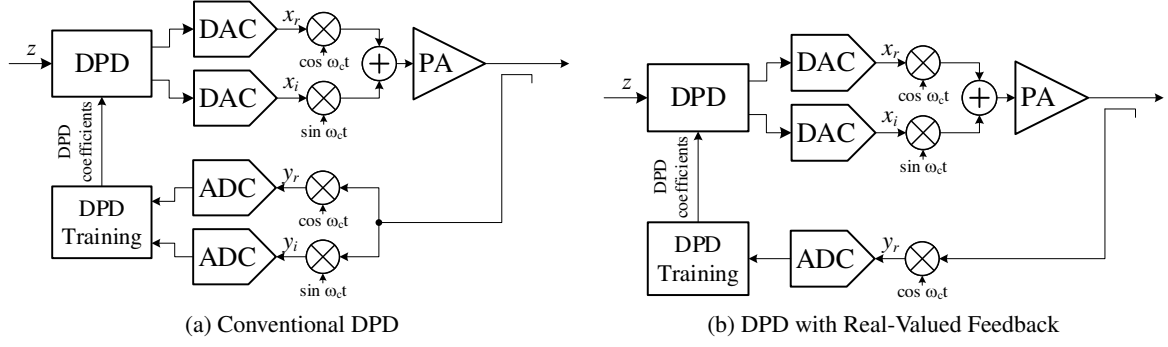


Figure 1: Diagrams of the baseband DPDs

presented formerly in [7]. Besides the reduced power consumption and system complexity, the real-valued feedback provides certain advantage of reduced sensitivity to in-phase and quadrature (IQ) imbalance of the feedback quadrature mixer which we have presented in [8].

In this paper we propose the DPD employing direct-learning architecture DLA for estimation of DPD parameters. DLA is an iterative algorithm which usually estimates DPD coefficients better than the used indirect learning architecture (ILA) [9]. The most recent paper [10] independently published by Guan partially overlaps with results in our paper.

2 DPD WITH REAL VALUED FEEDBACK USING DLA

Consider that PA is modelled by memory polynomial model [11]. The discrete baseband PA output y is given as [11]

$$y(n) = \sum_{k=1}^K \sum_{q=0}^Q b_{k,q} x(n-q) |x(n-q)|^{k-1} \quad (1)$$

where x is the PA input, $b_{k,q}$ is a coefficient of the PA model, and P and Q represent the maximum PA nonlinearity order and memory length respectively. The product $x(n-q) |x(n-q)|^{k-1}$ is often called a basis waveform or a basis function. We denote it as

$$\phi_{k,q}(n) = x(n-q) |x(n-q)|^{k-1}. \quad (2)$$

The input samples x , model coefficients $b_{k,q}$, and the basis waveforms $\phi_{k,q}(n)$ can be arranged into vectors and a matrix as

$$\begin{aligned} \phi_{k,q} &= [\phi_{k,q}(0) \quad \phi_{k,q}(1) \quad \dots \quad \phi_{k,q}(N)]^T \\ \mathbf{x} &= [x(0) \quad x(1) \quad \dots \quad x(N)]^T \\ \mathbf{y} &= [y(0) \quad y(1) \quad \dots \quad y(N)]^T \\ \mathbf{b} &= [b_{1,0} \quad b_{1,1} \quad \dots \quad b_{1,Q} \quad b_{2,0} \quad \dots \quad b_{K,Q}]^T \\ \mathbf{X} &= [\phi_{1,0} \quad \phi_{1,1} \quad \dots \quad \phi_{1,Q} \quad \phi_{2,0} \quad \dots \quad \phi_{K,Q}]^T \end{aligned}$$

where \mathbf{b} is column vector with $K(Q+1)$ rows, and the size of the matrix \mathbf{X} is $N \times K(Q+1)$.

DLA is a method which tries to directly solve $A(x) = y$ as $x = A^{-1}(y)$ with $A(\cdot)$ being a nonlinear transfer function of the PA. A solution of this nonlinear problem can be obtained by the Gauss-Newton method. This method can be defined for DPD as [12]

$$\mathbf{b}(m+1) = \mathbf{b}(m) - \mu \mathbf{e}(m) \quad (3)$$

where m is the iteration, $\mathbf{b}(m)$ and $\mathbf{b}(m+1)$ are previous and new DPD coefficients, μ is the iteration step size, and $\mathbf{e}(m)$ is the coefficient error vector. For the m -th iteration it is given as the least square (LS) solution of

$$\mathbf{x} - \mathbf{y} = \mathbf{X}\mathbf{e}. \quad (4)$$

Eq. 4 can be split into the real and imaginary parts, denoted as $(\cdot)_r$ and $(\cdot)_i$ respectively, with $\Delta = \mathbf{x} - \mathbf{y}$ as

$$\begin{aligned} \Delta_r + j\Delta_i &= (\mathbf{X}_r + j\mathbf{X}_i)(\mathbf{e}_r + j\mathbf{e}_i) \\ \Delta_r + j\Delta_i &= \mathbf{X}_r\mathbf{e}_r + j\mathbf{X}_i\mathbf{e}_r + j\mathbf{X}_r\mathbf{e}_i - \mathbf{X}_i\mathbf{e}_i \\ \Delta_r &= \mathbf{X}_r\mathbf{e}_r - \mathbf{X}_i\mathbf{e}_i \quad \wedge \quad \Delta_i = \mathbf{X}_i\mathbf{e}_r + \mathbf{X}_r\mathbf{e}_i \end{aligned}$$

and by matrix reordering we get two matrix equations

$$\Delta_r = \mathbf{x}_r - \mathbf{y}_r = [\mathbf{X}_r \quad -\mathbf{X}_i] \begin{bmatrix} \mathbf{e}_r \\ \mathbf{e}_i \end{bmatrix} \quad \wedge \quad \Delta_i = \mathbf{x}_i - \mathbf{y}_i = [\mathbf{X}_i \quad \mathbf{X}_r] \begin{bmatrix} \mathbf{e}_r \\ \mathbf{e}_i \end{bmatrix}. \quad (5)$$

To get the solution of \mathbf{e} , it is sufficient to solve only one of the two equations in Eq. 5. Advantageously each equation requires only real or imaginary samples of the PA output \mathbf{y} . Since the matrix \mathbf{X} is fully known and Eq. 5 are overdetermined we can get \mathbf{e} as the LS solution of Eq. 5 using real feedback samples

$$\begin{bmatrix} \mathbf{e}_r \\ \mathbf{e}_i \end{bmatrix} = (\mathbf{M}_a^H \mathbf{M}_a)^{-1} \mathbf{M}_a^H (\mathbf{x}_r - \mathbf{y}_r) \quad (6)$$

or using imaginary feedback samples

$$\begin{bmatrix} \mathbf{e}_r \\ \mathbf{e}_i \end{bmatrix} = (\mathbf{M}_b^H \mathbf{M}_b)^{-1} \mathbf{M}_b^H (\mathbf{x}_i - \mathbf{y}_i) \quad (7)$$

where

$$\mathbf{M}_a = [\mathbf{X}_r \quad -\mathbf{X}_i] \quad \wedge \quad \mathbf{M}_b = [\mathbf{X}_i \quad \mathbf{X}_r]. \quad (8)$$

Back substitution of the vector \mathbf{e} solution to the Eq. 3 yields the new DPD coefficients

$$\begin{bmatrix} \mathbf{b}_r(m+1) \\ \mathbf{b}_i(m+1) \end{bmatrix} = \begin{bmatrix} \mathbf{b}_r(m) \\ \mathbf{b}_i(m) \end{bmatrix} - \mu (\mathbf{M}_a^H \mathbf{M}_a)^{-1} \mathbf{M}_a^H (\mathbf{x}_r - \mathbf{y}_r). \quad (9)$$

A similar solution can be obtained for imaginary feedback samples.

Usage of only real or imaginary feedback samples allows us to modify DPD structure and dispose of one feedback ADC. The resulting structure is depicted in Fig. 1b.

3 EXPERIMENTAL RESULTS

We have verified the above procedure by simulation of a system with a nonlinear PA model and predistorter for its linearisation. For predistorter performance comparison we have simulated three different architectures – ILA, DLA, and DLA with real valued feedback denoted as R-DLA. The PA model has been extracted from measurements of a real PA of the AB type with LDMOS transistors¹. For the testing, FBMC signal has been used. For the further evaluation of results, we have done 200 iterations, in the each a new FBMC signal with random data has been generated.

¹For the extraction of the PA coefficients a signal with 2 MHz channel bandwidth at carrier frequency of 450 MHz was used. Output power has been set to 33 dBm with back-off of 4 dB. Measurements were performed using direct-conversion radio architecture with 8-times oversampling.

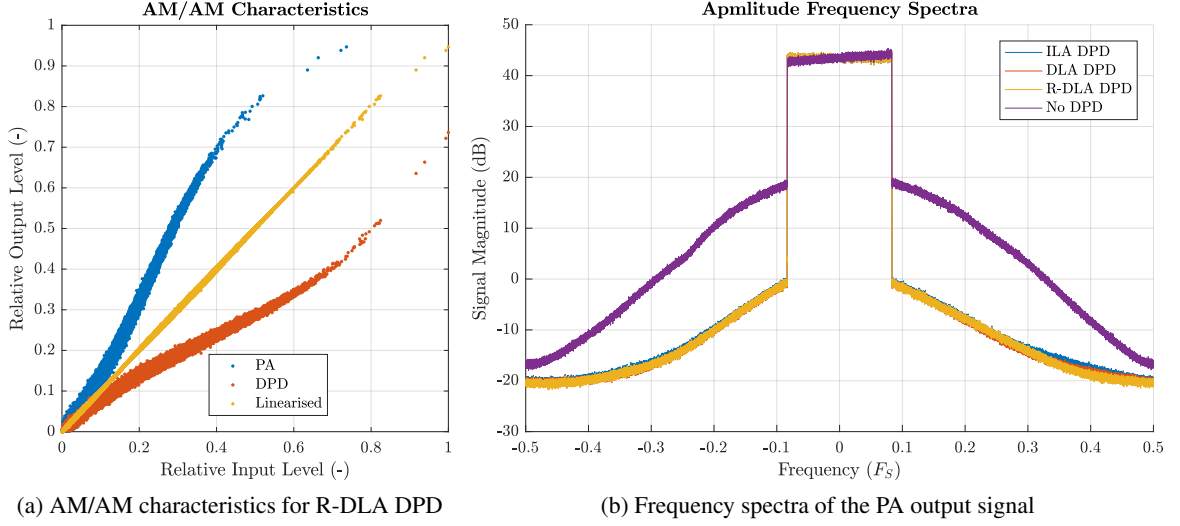


Figure 2: AM/AM characteristics and output signal spectra

Table 1: Simulation results of average NMSE, ACPR in 1st and 2nd adjacent channel

DPD architecture	NMSE (dB)	ACPR-1st (dB)	ACPR-2nd (dB)
No DPD	-19.9	-29.6	-46.4
ILA DPD	-40.5	-49.6	-60.4
DLA DPD	-40.8	-49.8	-61.0
R-DLA DPD	-40.8	-49.8	-61.0
No DPD	-19.9	-29.6	-46.4

Fig. 2a shows AM/AM characteristics for R-DLA after the R-DLA converged to the solution. The blue plot is the characteristics of the PA, the red is the predistorter and the yellow is the linearised characteristic of the system. The average spectra (calculated after convergence of DLA DPDs) are shown in Fig. 2b. In the spectra plots, we can see that the ILA, DLA, R-DLA perform very similar.

Performance of different architectures has been evaluated based on the normalised mean square error (NMSE), adjacent channel power ratio (ACPR) in the 1st and 2nd adjacent channels. We evaluated NMSE as $NMSE = 10 \log_{10}[(\mathbf{z} - \mathbf{y})^H (\mathbf{z} - \mathbf{y}) (\mathbf{z}^H \mathbf{z})^{-1}]$ and ACPR for the 1st adjacent channel which is $1B$ wide and with $1.1B$ offset, and for the 2nd adjacent channel which is $1B$ wide too and with $2.2B$ offset. ACPRs from the left and right channels are averaged separately for the 1st and 2nd adjacent channels and presented as a single value per the adjacent channel. The results averaged over the iterations are presented in Tab. 1.

4 CONCLUSION

In this paper we have proposed a new method for DPD with one ADC in the feedback path employing direct learning architecture to train DPD coefficients. The proposed method has been verified experimentally in simulations. The simulation results show that the proposed method linearisation performance is the same as for conventional architecture with two ADCs. In terms of linearisation performance the proposed method is better than commonly used DPD with the indirect learning architecture. While the linearisation performance of the presented DPD has been preserved, we achieved to minimise system design complexity, power consumption and system cost.

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