Three-dimensional power segmented tracking for adaptive digital pre-distortion

Lie Zhang\(^{(a)}\), Yan Feng\(^{1}\)

\(^1\) School of Electronics and Information, Northwestern Polytechnical University, Xi’an, 710129, China

\(^{a}\) liezhang@mail.nwpu.edu.cn

Abstract: A three-dimensional power segmented tracking for adaptive digital pre-distortion is presented to stabilize the linearization of radio frequency power amplifiers (PAs). It contains long term average power segmented dimensional, short term average power segmented dimensional and instant power segmented dimensional that can correct and track the various nonlinear characteristics of PAs. Moreover, a constraint least square algorithm by indirectly learning structure is employed to initial the parameters and a least mean square algorithm by directly learning structure is used to adaptive calculate the parameters. Experimental results show that the proposed method has stable improvements in comparison with previous methods.

Keywords: radio frequency power amplifiers, digital pre-distortion, long term memory effect, short term memory effect, adaptive tracking

Classification: Microwave and millimeter wave devices, circuits, and systems

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1 Introduction

The green communication requirement of high efficiency for wideband transmitters is a critical issue in modern wireless communication system. Since the power consumption and linearization performance of radio frequency (RF) wideband power amplifiers (PAs) greatly affect transmitters, the relevant researchers want to optimize them to meet system requirements. In order to achieve the targets, digital pre-distortion (DPD) techniques [1, 2] are widely applied. However, the wideband multi-carriers signals, such as long-term evolution (LTE) signals, with high power average peak ratio (PAPR) are commonly used in the transmitters. The wideband bandwidth and high PA-PAR can increase the influence of the nonlinear and memory effects of PAs. Especially, according to the 3GPP technique specification [3], the total power dynamic range of wideband LTE transmitters had almost 20 dB in 20 MHz bandwidth when the power of orthogonal frequency division multiplexing (OFDM) symbols were varied. The long term varieties of thermal memory effects [4] and short term varieties of electrical memory effects [5] can be worsen accompanying with these power varieties. Hence, DPD should correct and track these various characteristics of PAs.

In the past decade, based on the idea of segmenting amplitude of DPD input signal, several methods were proposed to improve DPD performance, such as the decomposed piecewise volterra series [6], the piecewise linear polynomials model [7], and the overlapped segment piece-wise polynomial [8]. These methods improved the instant linearization but can’t compensate dynamic nonlinear very well. The research of O.Hammi [9] showed that average power tracking was much more important to the various characteristics of PAs. Thus, DPD should track these dynamic varieties to improve stability of linearization. For implementation of DPD, multi-Lookup Tables (LUTs) were used by P. L. Gilabert in [10].

In this letter, we proposed a robust and higher performance method, a
three-dimensional power segmented tracking (TPST) for adaptive digital pre-distortion, to follow the varieties of the long term memory effects and short term memory effects. Firstly, a long term average power segmented (LAPS) block is used to divide the long term characteristics of RF PAs into different power regions. Secondly, in each long term average power segment, a short term average power segmented (SAPS) block is used to divide the short term characteristics of RF PAs as well. Thirdly, in each short term average power segment, an instant power segmented (IPS) block is used to divide the instant term characteristics of RF PAs into different power regions. Furthermore, a constraint least square algorithm by indirectly learning structure is employed to initial coefficients of TPST DPD. Then an adaptive least mean square algorithm by directly learning structure is used to track and update the coefficients of TPST DPD. Finally, multi-dimensional LUTs are applied to implement TPST DPD and experiments are performed to show that linear performance is robust and stable.

2 TPST for adaptive DPD

2.1 Transmitted power dynamic range in LTE transmitters

According to the 3GPP TS 36.104 [3], each radio frame is 10 ms long and consists of 140 OFDM symbols of length 71µs. The OFDM symbols have different transmitted power, such as a 20 MHz bandwidth signal have about 20 dB transmitted power dynamic range. These varieties of power can be drastic or smooth which depend on the accessed numbers and the locations of user equipments (UEs) in one cell. These can be shown in Fig.1.

![Fig. 1. Average power of OFDM symbols in LTE transmitters.](image-url)

The drastic fluctuate of short term average power and instant power can make short term electrical memory effects of PAs deteriorate and transform. Similarly, the slow fluctuate of long term average power can make thermal memory effects of PAs smooth varieties. In order to tracking the memory effects caused by the power varieties, DPD should fine compensate these distortions to ensure the stability of the linear performance.
2.2 TPST DPD structure
In order to further improve the flexibility of transmitted power dynamic range in LTE transmitters, a three-dimensional power segmented tracking DPD structure is shown in Fig.2.

![Fig. 2. TPST DPD structure.](image)

Here signal $x(n)$ and $\hat{x}(n)$ are the input and output of TPST DPD at time $n$, respectively. Long term average power block is used to tracking the long term thermal memory effects of PAs, short term average power block is used to tracking short term electrical memory effects of PAs, and instant power block is used to tracking the instant electrical memory effects of PAs. The three-dimensional power index is shown in the Fig.3. The order of these indexes is from long term average power index to short term average power index, finally to instant power index.

![Fig. 3. Three-dimensional power index.](image)

2.3 Power segmented index
According to the TPST DPD structure, it has three-dimensional power index. Let long term average power $LAP$ is presented by

$$LAP = \left( \sum_{n=0}^{N_{LAP}-1} |x(n)|^2 \right) / N_{LAP}$$  \hspace{1cm} (1)

Short term average power $SAP$ is presented by

$$SAP = \left( \sum_{n=0}^{N_{SAP}-1} |x(n)|^2 \right) / N_{SAP}$$  \hspace{1cm} (2)
Instant power IP is presented by

$$IP = |x(n)|^2$$ (3)

Here \( N_{LAP} \) denotes accumulative points in LAP, \( N_{SAP} \) denotes accumulative points in SAP. \(|.|^2\) denotes calculation of power. Then three-dimensional power index can be given by

$$(Ind_{LAP}, Ind_{SAP}, Ind_{IP}) = (i,j,k)$$ (4)

Here \( I_i \leq \ LAP < I_{i+1} \), \( J_j \leq \ SAP < J_{j+1} \), and \( K_k \leq \ IP < K_{k+1} \). \( i = 0,...,S_{LAP} - 1 \), \( j = 0,...,S_{SAP} - 1 \) and \( k = 0,...,S_{IP} - 1 \). \( I, J, K \) are the thresholds of three-dimensional power indexes. \( S_{LAP}, S_{SAP} \) and \( S_{IP} \) are the maximum segmented numbers of three-dimensional power index. The power segmented regions can be uniformity or not. Note that we only consider uniformity in this letter.

### 2.4 Calculation of TPST adaptive DPD

The calculation of TPST adaptive DPD is composed of two steps. The first step is that a constraint least square algorithm by indirectly learning structure is employed to initial the parameters of the TPST DPD. This can accelerate the convergence of the proposed TPST DPD model. The indirectly learning structure is shown in Fig.4.

Here signal \( y(n) \) and \( \hat{y}(n) \) are the input and output of TPST DPD B. Indirect learning structure uses TPST DPD B to calculate coefficients and then copy to TPST DPD A. The formula of TPST DPD is shown in

$$\hat{y}_{i,j,k}(n) = \sum_{p=0}^{P-1} \sum_{l_1=0}^{L_1-1} \sum_{l_2=0}^{L_2-1} c_{i,j,k,p,l_1,l_2} y_{i,j,k}(n - l_1)|y_{i,j,k}(n - l_2)|^p$$ (5)

Here \( l_1 \) is the memory depth of the signal, \( l_2 \) is the memory depth of the power, \( p \) is the order of the polynomial, and \( c_{i,j,k,p,l_1,l_2} \) is coefficient of the TPST DPD. \( y_{i,j,k}(n) \) is \( y(n) \) in one location of three-dimensional power regions when \( x(n) \) find the corresponding three-dimensional power index by comparing with the thresholds. \( \hat{y}_{i,j,k}(n) \) is the output of \( \hat{y}_{i,j,k}(n) \) in the TPST DPD B. Note that the location of three-dimensional power regions is only use \( x(n) \) to compare with the thresholds. The memory depth terms such
as $x_{i,j,k}(n-l_1), |x_{i,j,k}(n-l_2)|$, $y_{i,j,k}(n-l_1)$ and $|y_{i,j,k}(n-l_2)|$, don’t need to compare with the thresholds anymore. These terms use the same location with the $x_{i,j,k}(n)$.

Let $u_{i,j,k} = y_{i,j,k}(n-l_1)|y_{i,j,k}(n-l_2)|^p$ be the kernel vector of the TPST DPD. $U_{i,j,k}$ is the kernel matrix of TPST DPD which is composed of sampling data in three-dimensional power regions. $U_i$ is that in two-dimensional power regions, $C_{i,j,k}$ is the coefficient vector of TPST DPD. $\hat{X}_{i,j,k}$ is the output vector of TPST DPD which belongs to three-dimensional power regions. $\hat{X}_i$ is that in two-dimensional power regions. $\hat{X}_j$ is that in one-dimensional power regions. Thus a constraint cost function is shown in

$$
\begin{align*}
\min \| & C_{i,j,k} U_{i,j,k} - \hat{X}_{i,j,k} \| \\
\text{subject to : } & C_{i,j,k} U_{i,j,k-1} - \hat{X}_{i,j,k-1} = 0 \\
& C_{i,j,k} U_{i,j,k+1} - \hat{X}_{i,j,k+1} = 0 \\
& C_{i,j,k} U_i - \hat{X}_i = 0
\end{align*}
$$

(6)

Since the number of indirectly sampling data in each iteration is limited, the sampling data can’t ensure cover all three-dimensional power regions. Maybe one power region only has few sampling data. It is unstable for calculation at this time. Consequently power constraint should add in this calculation. The constraint least square algorithm is shown in

$$
C_{i,j,k} = (U_{i,j,k}^H U_{i,j,k} + \alpha U_{i,j,k-1}^H U_{i,j,k-1} + \beta U_{i,j,k+1}^H U_{i,j,k+1} + \eta U_{i,j}^H U_i + \gamma U_i^H U_i)^{-1}(U_{i,j,k}^H \hat{X}_{i,j,k} + \alpha U_{i,j,k-1}^H \hat{X}_{i,j,k-1} + \beta U_{i,j,k+1}^H \hat{X}_{i,j,k+1} + \eta U_{i,j}^H \hat{X}_i + \gamma U_i^H \hat{X}_i)
$$

(7)

Here $0 \leq \alpha < 1$, $0 \leq \beta < 1$, $0 \leq \eta < 1$ and $0 \leq \gamma < 1$. $(.)^H$ denotes the conjugated transpose of a matrix. Note that constraint factors depend on the numbers of sampling data in current power regions. The fewer numbers are employed, the lower value of factor is used.

The second step is that a least mean square algorithm by directly learning structure is used to adaptively calculate the parameters of the TPST DPD. It is shown in Fig.5.

![Fig. 5. Directly learning structure of TPST adaptive DPD.](image)

Let error signal be presented by

$$
e_{i,j,k}(n) = x_{i,j,k}(n) - y_{i,j,k}(n)
$$

(8)
Then we can get
\[ c_{i,j,k,p,l_1,l_2}(n + 1) = c_{i,j,k,p,l_1,l_2}(n) + \mu e^{i,j,k}(n)x_{i,j,k}(n - l_1)x_{i,j,k}(n - l_2)^* \]  
(9)

Here \(\mu\) is the iterative length of step, \((\cdot)^*\) denotes the conjugated of signal. The TPST adaptive DPD can real-time track the nonlinear characteristic of PAs which caused by transmitted power varieties.

2.5 LUTs implementation of TPST adaptive DPD
TPST adaptive DPD can employ multi-dimensional LUTs to implement in the wireless transmitters which is easy to be realized. It is shown in Fig.6.

\[ \hat{x}(n) = \sum_{l_1=0}^{L_1-1} \sum_{l_2=0}^{L_2-1} x_{i,j,k}(n - l_1)LUT_{i,j,k,l_1,l_2}(|x_{i,j,k}(n - l_2)|) \]  
(10)

3 Experimental results
The experimental setup, which is used to validate the proposed approach, is shown in Fig.7.

An LTE-advanced 60 MHz signal with double carriers is used in the test. The two carriers with 20 MHz bandwidth are −20 MHz and +20 MHz offset to RF center frequency, respectively. There are 20 radio frames which are used in the test and the power of signal is varied in each OFDM symbol. The digital baseband signal is generated in MATLAB on a personal computer.
(PC). It passes through the TPST DPD block, then to the arbitrary waveform generator (AWG). The RF signal from AWG is filtered and driven by a driver at 26 dBm. A 32-W Doherty PA, constructed by two LDMOS transistors working at 2.14 GHz, with 19 dB gain is used to amplify the RF signal. The PA output signal is sampled in a spectrum analyser. Then these data are used for the calculation of TPST adaptive DPD in the MATLAB. The configurations are as follows: \( N_{\text{LAP}} = 8192, N_{\text{SAP}} = 128, \alpha = 0.08, \beta = 0.08, \eta = 0.03, \gamma = 0.02, \mu = 0.01, L_1 = 4, L_2 = 4, S_{\text{LAP}} = 4, S_{\text{SAP}} = 4, S_{\text{IP}} = 4. \) The length of each LUT is 128.

![Graph](image)

Fig. 8. AM-AM and AM-PM of PAs. (a) AM-AM. (b) AM-PM.

The AM-AM and AM-PM of PA are shown in the Fig.8. (a) and Fig.8.(b). The TPST adaptive DPD can appropriate compensate the nonlinear distortions of PAs.

Fig.9.(a). shows the power varieties of OFDM symbols in the transmitted signal. Fig.9.(b). shows the normalized mean square error (NMSE) for TPST adaptive DPD compared with method in [2] and [6], where the NMSE is calculated using

\[
NMSE = 10 \times \log_{10} \left( \frac{\sum_{n=0}^{N-1} |x(n) - y(n)|^2}{\sum_{n=0}^{N-1} |x(n)|^2} \right) \quad (11)
\]

Here \( N \) presents the length of radio frame. We can see that the NMSE are deteriorate in [2] and [6] when drastic and smooth power varieties are occurred in the 20 radio frames LTE signal.
The average power spectral density of 20 radio frames signal is shown in Fig. 10. Table I shows the TPST adaptive DPD performance about Average NMSE of all radio frames, error vector magnitude (EVM) and adjacent channel leakage ratio (ACLR) in PA output. There are 15 dB improvements in NMSE by TPST adaptive DPD and EVM improves from 3.12% to 0.29%. The proposed approach is almost 20 dB reduction in ACLR, and it is 2 dB better than the approach in [6] and 4 dB better than that in [2].

| Methods  | Average NMSE, dB | EVM, % | ACLR, dBC (+/- 20MHz offset) |
|----------|------------------|--------|-----------------------------|
| w/o DPD  | -25.71           | 3.12   | -30.1/-30.2                 |
| In [2]   | -38.46           | 0.54   | -45.3/-45.4                 |
| In [6]   | -39.41           | 0.38   | -48.5/-48.3                 |
| TPST DPD | -40.14           | 0.29   | -50.4/-50.3                 |

Table II shows the comparison between the method in [2], the method in [6] and TPST DPD about the fluctuations of NMSE in 20 radio frames signal. Table III shows that of ACLR. We can see that the proposed TPST DPD is
the best one of the robustness and stability.

### Table II. The fluctuations of NMSE

| Methods     | Max. NMSE, dB | Min. NMSE, dB | Fluctuation of NMSE, dB |
|-------------|---------------|---------------|-------------------------|
| In [2]      | -37.6         | -39.4         | 1.8                     |
| In [6]      | -38.6         | -39.9         | 1.3                     |
| TPST DPD    | -39.7         | -40.4         | 0.7                     |

### Table III. The fluctuations of ACLR

| Methods     | Max. ACLR, dBc | Min. ACLR, dBc | Fluctuation of ACLR, dB |
|-------------|----------------|----------------|-------------------------|
| In [2]      | -43.5          | -46.3          | 2.8                     |
| In [6]      | -47.3          | -49.4          | 2.1                     |
| TPST DPD    | -49.9          | -50.7          | 0.8                     |

### Conclusion

In this letter, a TPST for adaptive DPD which can effectively compensate the nonlinear distortion in RF wideband PAs is proposed. Based on three-dimensional power segmented tracking, the proposed method can correct and follow the various nonlinear characteristics of RF PAs. Moreover, a constraint least square algorithm by indirectly learning structure is employed to initial coefficients of the TPST DPD. Then, a adaptive least mean square algorithm by directly learning structure is used to track the transmitted power varieties which can make linearization be more stable. Finally, multi-dimensional LUTs are used to implement TPST adaptive DPD. Experimental results validated that there are more than 2 dB stable ACLR improvements on a 60 MHz LTE-advanced signal with double carriers when comparing the proposed approach with the previous ones. Consequently, the proposed approach is very robust and suitable for RF transmitter to realize.