Chebyshev orthogonal approximation cascaded with Functional Link Neural Network for Adaptive Digital Predistorter

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Chebyshev orthogonal approximation cascaded with Functional Link Neural Network for Adaptive Digital Predistorter

Jijun Ren

***Abstract*—Chebyshev orthogonal approximation cascaded with functional link neural networks (FLNN) for short-wave adaptive digital predistorter (ADPD) is proposed. The Kalman filter method is used to update the coefficients for analyzing the nonlinear behavior of the power amplifier (PA). Furthermore, considering the system implementation and resources, we simplify the Chebyshev polynomials in the actual realization on the premise of guaranteeing the fitting accuracy. Experimental results on HF (High-Frequency) PA of short-wave communication show that more accurate linearization results can be obtained by using the proposed Chebyshev orthogonal approximation cascaded with FLNN.**

Index Terms—**power amplifier linearization; adaptive digital predistorter; Chebyshev orthogonal approximation; Functional link neural network**

I. INTRODUCTION

Power amplifier is a non-linear device of base stations, will inevitably lead to adjacent interference, in-band distortion, and the crossing intermodulation. It has long been considered as an effective technology to improve the linearity and efficiency of the system. DPD has long been recognized as an effective technique to improve system linearity and efficiency [1–5].

The LUT structure is the effective implementing method by evaluating polynomial functions with evenly spaced amplitude values, and then these values stored [6] [7]. Volterra series is usually used to describe the PA with memory and can be further simplified to memory polynomial model (MPM) in practical engineering applications [8]. In the past two decades, many researchers have studied DPD in detail [9-12].

This Letter proposes a method of Chebyshev orthogonal approximation cascaded with FLNN for ADPD to obtain more accurate approximation value of LUT and is organized as follows. The following section discusses the LUT approximation by Chebyshev orthogonal polynomial and it is cascaded with FLNN to obtain more accurate linearization with low-complexity. Experimental validation results are shown in the section 'experimental design', followed by a brief conclusion in the last section.

II. APPROXIMATION OF LUT BY CHEBYSHEV SERIES METHOD

As a closed-loop control system realized in digital domain, DPD compares PA output with input through a feedback path to make PA output reach a certain level [13], [14].

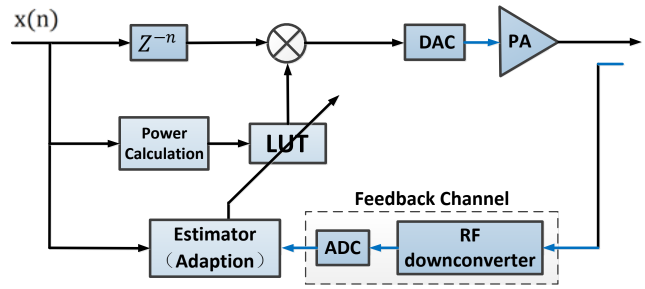


Fig 1. Schematic diagram of DPD LUT system

Chebyshev orthogonal approximation is based on Chebyshev polynomials.

$$T_k(x) = \cos(k * \arccos(x))(-1 \le x \le 1) \tag{1}$$

Although $T_k(x)$ can be regarded as a trigonometric function, with some algebraic identities and multiplications, the Eq. (1) can be written as a true polynomial. The first six polynomials are as follows:

$$\begin{cases} T_0(x) = 1;\ \ T_1(x) = x;\ \ T_2(x) = 2x^2 - 1 \\ T_3(x) = 4x^3 - 3x;\ \ T_4(x) = 8x^4 - 8x^2 + 1 \\ T_5(x) = 16x^5 - 20x^3 + 5x; T_6(x) = 32x^6 - 48x^4 + 18x^2 - 1 \end{cases} \tag{2}$$

Chebyshev polynomials usually follow the following iterative rules:

$$T_k(x) = 2xT_{k-1}(x) - T_{k-2}(x) \qquad \forall k \ge 2 \tag{3}$$

Function approximation can be written into

$$f(x) = \sum_{k=0}^{N-1} c(k)T_k(x) \tag{4}$$

Since all the discrete Chebyshev polynomials are orthogonal to each other, it is shown that both the forward and inverse transformations are unique, i.e. bidirectional monomorphism.

Based on this Chebyshev orthogonal approximation model, we can obtain architecture for DPD LUT system shown as Fig. 2.

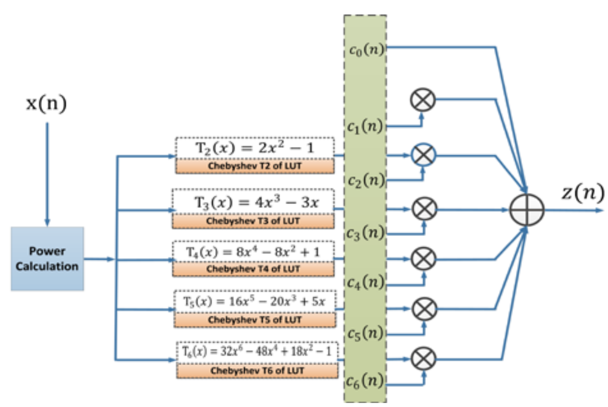


Fig 2. Schematic diagram of Chebyshev orthogonal approximation model in DPD system

III. PARAMETERS EXTRACTION OF FLNNCPADPD BEHAVIORAL MODEL

Different from the FLNN and Chebyshev orthogonal polynomial function approximation [15], [16], we cascade FLNN and Chebyshev polynomials and use a Kalman filter method to update the coefficients of the algorithm. Furthermore, considering the system implementation and resources, we simplify the Chebyshev polynomials on the premise of guaranteeing the approximation accuracy.

A. Mathematical analysis

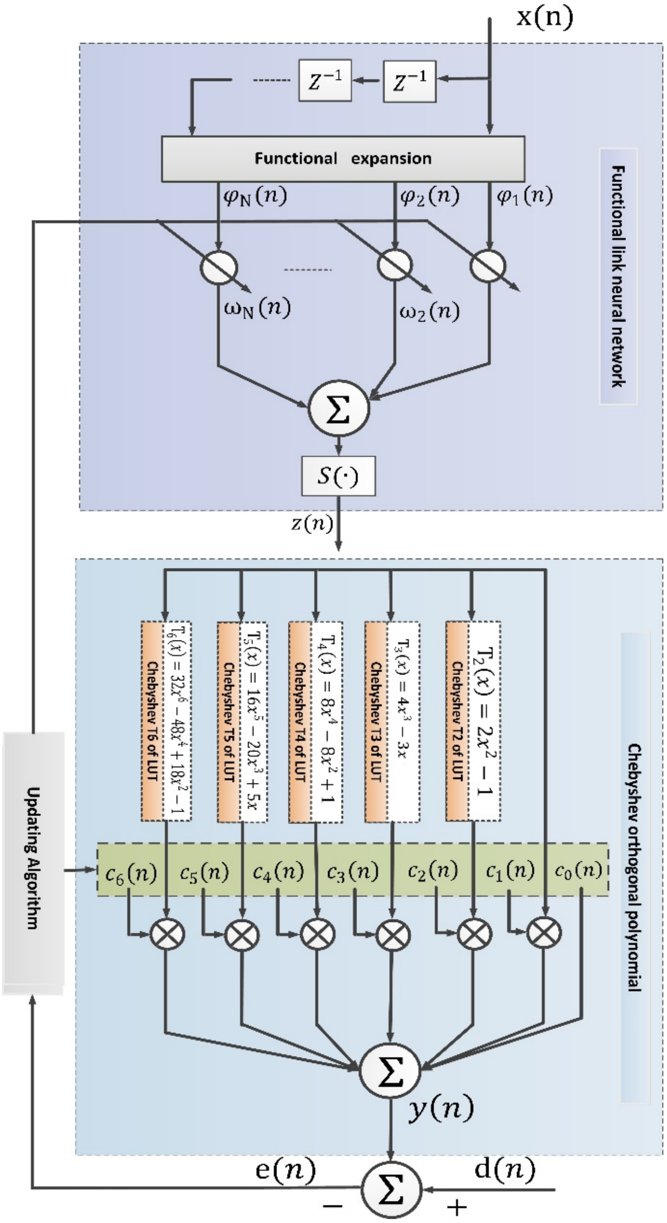


Fig 3. Schematic diagram of the FLNNCPADPD

As depicted in Fig. 3, by combining the characteristics of the Chebyshev orthogonal polynomial and FLNN, we propose a novel structure nonlinear ADPD as FLNNCPADPD.

The proposed FLNNCPADPD may be considered as interpolating or approximating a multivariate, continuous function $f(X)$ by approximating function $\hat{f}(x)$ of the FLNN cascaded with Chebyshev orthogonal polynomial. Assume that $\Phi(n) = [\varphi_1(n)\ \varphi_2(n) \cdots \varphi_N(n)]^T$ is the input pattern vector and $\Omega(n) = [\omega_1(n)\ \omega_2(n) \cdots \omega_N(n)]^T$ is the coefficient vector of the FLNN.

So, the $u(n)$ is

$$u(n) = \Phi(n)\Omega(n)^T \tag{5}$$

And we can have

$$z(n) = S(u(n))$$

In which, the function $S(u(n))$ is defined by

$$S(u(n)) = \frac{2}{1+e^{-2(u(n))}} - 1 \tag{6}$$

Thus, the output $z(n)$ of the FLNN is rewritten by

$$z(n) = S(\Phi(n)\Omega(n)^T) = \frac{2}{1+e^{-2(\Phi(n)\Omega(n)^T)}} - 1$$

Based on the strong approximation ability of Chebyshev orthogonal polynomial, we choose to simplify the Chebyshev orthogonal polynomial to 6th order and lead to the formula described in Eq. (7) to 6 coefficients (one of which is constant 1) for engineering implementation.

$$f(x) = \sum_{k=1}^{6} c(k)T_k(x) \tag{7}$$

Further, the output y(n) in the matrix form is obtained by

$$y(n) = f(z(n)) = C(z(n))T(z(n))^T \tag{8}$$

Where the vectors $C(n)$ and $T(n)$ are defined respectively by

$$C(n) = [1\ C_1(n) \cdots C_6(n)]^T$$
$$T(n) = [1\ T_1(n) \cdots T_6(n)]^T$$

B. Kalman filter adaptive algorithm

As described in Eq. (7), the output of the model at instant k can be represented by the following Eq. (9):

$$\begin{cases} y(k) = C\left(\frac{2}{1+e^{-2(\Phi(k)\Omega(k)^T)}} - 1\right) T\left(\frac{2}{1+e^{-2(\Phi(k)\Omega(k)^T)}} - 1\right)^T \\ C(k) = [1\ C_1(k) \dots C_6(k)]^T \\ T(k) = [1\ T_1(k) \dots T_6(k)]^T \end{cases} \tag{9}$$

How to find the appropriate weight vector Ω_k and C_k to obtain the approximate $y(k)$ within the error ε is the objective of the learning algorithm.

The low complexity Kalman filter adaptive algorithm with better performance for instantaneous error is proposed to adjust the coefficient vector Ω_k and C_k.

Thus, the output $y(k)$ can be rewritten by

$$y(k) = \mu^T(k)\Omega_k \tag{10}$$

The coefficient's adaptation can be divided into two parts because of the cascade model.

When the algorithm is convergence, we can have

$$\Omega_k = \Omega_{k-1} \tag{11}$$

And the error between estimate value and actual value is

$$e(k) = y(k) - \mu^T(k)\Omega_k$$

So, the $y(k)$ is

$$y(k) = e(k) + \mu^T(k)\Omega_k \tag{12}$$

We can assume that (10) and (11) are process equations and measurement equations respectively, and the state-space equation is

$$\begin{cases} \Omega_k = \Omega_{k-1} \\ y(k) = e(k) + \mu^T(k)\Omega_k \end{cases}$$

According to the adaptive filter theory, we can attain the steps as follows:

Known parameters:State transition matrix$T(k,k-1) = I \in \Omega^{N\times N}$, state noise vector $v_1(n) = 0$,Measurement matrix$M(k) = \mu^T(k) \in \Omega^{1\times N}$, measurement $v_2(k) = e(k)$.

1) Initial:$\Omega_0 = 0 \in C^{N\times 1}$;$P(0) = I \in C^{N\times N}$;

$Q_2 = 0.01$(Based on performance metric) ;

2) Step 1: $n = 1,2 \dots, N$, n are the iteration times

$$\alpha(k) = y(k) - M(k)\Omega_{k-1};$$

$$B(k) = M(k)P(k-1)M^H(k) + Q_2(k)K(k)$$
$$= P(k-1)M^H(k);$$

$$\widehat{\Omega}_k = \widehat{\Omega}_{k-1} + K(k)\alpha(k)P(k) = [I - K(k)M(k)]\, P(k-1);$$

3) Step 2: $k = k+1$;

4) Go to step 1.

By the same way, we can obtain further results of C_k.

Thus, the parameters of the whole cascade model are extracted completely.

As shown in Fig.4 of the learning curves of Kalman filter algorithm and conventional LMS algorithm, the proposed algorithm is better than conventional LMS in convergence performance, especially in convergence rate.

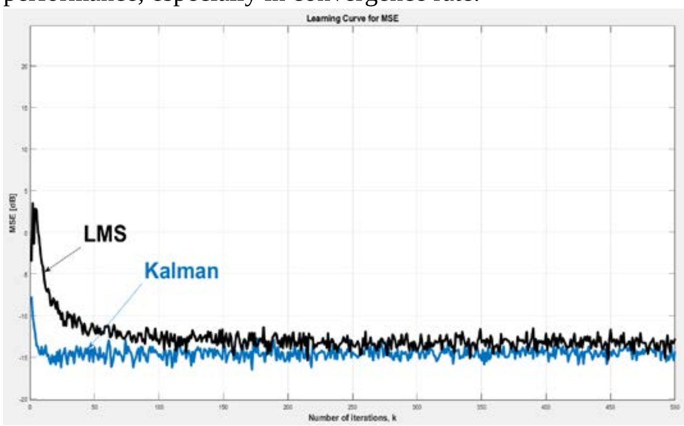


Fig 4. The learning curves of Kalman and LMS

The normalized mean-squared error (NMSE) defined by the Eq. (13) is a time-domain metric [17] which is used to validate the performance of DPD with this work.

$$NMSE_{dB} = 10log_{10}\left(\frac{\sum_{n=1}^{N}|z(n)-\tilde{z}(n)|^2}{\sum_{n=1}^{N}|z(n)|^2}\right) \qquad (13)$$

, where $z(n)$ is the desired output and $\tilde{z}(n)$ is the simulated output. The results are reported in Table I.

TABLE I

Comparison of NMSE and computation complexity between different method

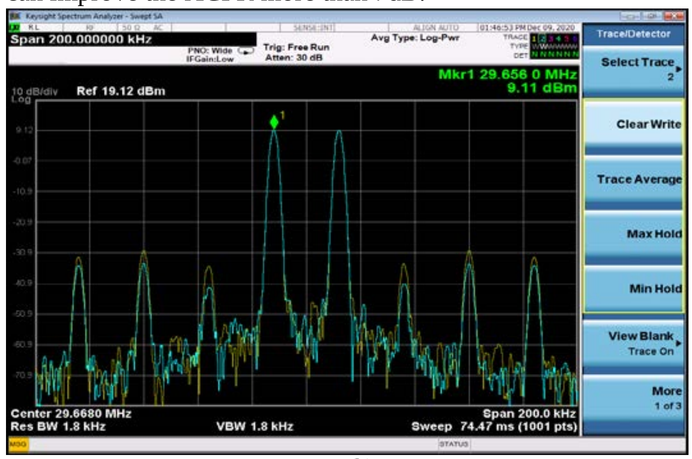
	NMSE	Number of weights
MPM (Q=3, K=9)	-46.13 dB	24
GMPM (Q=3, K=7)	-49.64dB	113
Proposed Model	-52.96 dB	42

IV. EXPERIMENTAL DESIGN

The DPD effect of HF PA is verified by AB class HF PA with output power of 150W and center frequency of 0.3 ~ 30MHz, as shown in Fig. 5.

Fig 5. Diagram of experimental testbed

The two-tone signal with an interval of 24KHz is used as the test verification signal according to the standard of HF system. Fig. 6 shows that compared with the MPM DPD LUT method (Q=3, K=9,yellow line), the proposed FLNNCPADPD can improve the ACPR more than 7dB.



(b)

Fig 6. DPD LUT with FLNNCPADPD in real HF system. Spectra of MPM method (yellow line) and FLNNCPADPD (blue line)

The results are reported in Table II.

TABLE II

Accuracy and IM3 of ACPR using different method

	$ACLR_{Lower}/ACLR_{Upper}$
Without DPD	-16.33dBc/-16.53dBc
MPM (Q=3, K=9)	-44.46dBc/-43.24dBc
Proposed Model	-51.82dBc/-50.37dBc

V. CONCLUSION

We have investigated the DPD method that cascades the FLNN with Chebyshev orthogonal polynomials and updates the coefficients with the Kalman filter method to obtain more accurate HF PA linearization. Experiment shows the method we mentioned can improve the ACPR of short-wave communication system more than 7dB.

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