Research on Low Sampling Rate Digital Pre-distortion Technology Based on Improved Chebyshev Polynomial

LU Xu[1], ZHOU Xianchun[2], ZHANG Ying[3], YE Yuxuan[3]

(1. *School of Electronic and Information Engineering*, *Nanjing University of Information Science and Technology*, *Nanjing 210044*; 2. *School of Artificial Intelligence*, *Nanjing University of Information Science and Technology*, *Nanjing 210044*; 3. *School of Electronic and Information Engineering*, *Nanjing University of Information Science and Technology*, *Nanjing 210044*)

Abstract: This paper presents a low sampling rate digital pre-distortion technique based on an improved Chebyshev polynomial for the non-linear distortion problem of amplifiers in 5G broadband communication systems. An improved Chebyshev polynomial is used to construct the behavioural model of the broadband amplifier, and an undersampling technique is used to sample the output signal of the amplifier, reduce the sampling rate, and extract the pre-distortion parameters from the sampled signal through an indirect learning structure to finally correct the non-linearity of the amplifier system. This technique is able to improve the linearity and efficiency of the power amplifier and provides better flexibility. Experimental results show that by constructing the behavioural model of the amplifier using memory polynomials (MP), generalised polynomials (GMP) and modified Chebyshev polynomials respectively, the adjacent channel power ratio of the obtained system can be improved by more than 13.87dB, 17.6dB and 19.98dB respectively compared to the output signal of the amplifier without digital pre-distortion. The Chebyshev polynomial improves the neighbourhood channel power ratio by 6.11dB and 2.38dB compared to the memory polynomial and generalised polynomial respectively, while the normalised mean square error is effectively improved and enhanced. This shows that the improved Chebyshev pre-distortion can guarantee the performance of the system and improve the non-linearity better.

Keywords: Digital Pre-distortion, Improved Chebyshev Polynomials, Undersampling Techniques, Indirect Learning Structures

1 Introduction

With the rapid development of mobile communications, the fifth generation of wireless mobile communications (5G) has become a hot spot in wireless communications, which has the advantages of higher data transmission rates, lower latency, higher capacity and lower energy consumption, providing technical support for the realisation of the Internet of Everything and the construction of an intelligent society. In the process of achieving these technological breakthroughs, the role of power amplifiers (PA) is particularly important. However, the limitations of device manufacturing technology have led to the linear operating area of power amplifiers (PA).As the input amplitude increases, producing distortion in the output amplitude, the power amplifier works in a non-linear operating area, the amplifier efficiency will be significantly reduced and produce more serious non-linear distortion, making the whole signal transmission system unstable[1].

Therefore, the study of amplifier distortion compensation techniques is essential to improve the performance of wireless communication systems[2] . The rapid development of wireless communications requires wider bandwidths and more sophisticated modulation schemes. With the upcoming 5th generation wireless technology as shown, it is expected that the signal bandwidth may exceed 500 mhz. Typically, the bandwidth of the power amplifier (PA) output signal is 3-5 times that of the original signal according to Nyquist's sampling law[3]. In this case, it is impractical for a high precision analogue-to-digital converter (ADC) to capture the output signal of the PA at the Nyquist sampling (NS) rate. Therefore, an improvement in the sampling rate of the output signal is also an area of interest[4].

To address these issues, many academics and engineers have conducted extensive research into linearisation techniques for power amplifiers. These linearisation techniques include power fallback techniques, negative feedback techniques, feedforward techniques and digital pre-distortion techniques[5]. Power fallback techniques are used to reduce the power of the amplifier input signal so that the amplifier operates in the linear region, but with reduced amplifier efficiency[6]. Negative feedback techniques rotate the amplifier output by a certain phase and superimpose it on the input, adapted in communication systems with narrow bandwidths[7]. Feed-forward techniques amplify the error signal by introducing an auxiliary amplifier and compensate for the non-linearity at the output using signal pair cancellation, but are complex and costly[8]. The core idea of digital pre-distortion techniques is to predict the non-linear characteristics of the power amplifier in advance and to avoid distortion in the power amplifier by pre-processing the compensation signal so that the amplifier can still operate in the linear region when the input signal amplitude is too high. The digital pre-distortion technique is a low-cost, high-performance and easy to implement hardware method, and is therefore widely used in power amplifier distortion compensation. In order to make the digital pre-distortion technique perform better, it is important to use a suitable mathematical model to describe the behaviour of the power amplifier[9].

This paper proposes an improved Chebyshev polynomial model to model the behaviour of a 5G system amplifier. The Chebyshev polynomial model is a common mathematical model that can be used to describe the non-linear characteristics of a power amplifier. Compared to traditional modelling methods, the use of an improved Chebyshev polynomial model not only improves the accuracy of the modelling, but also effectively avoids the problems of over- and under-fitting. The under-sampling method is used to sample the signal of the feedback loop at a low rate. To extract the coefficients in the digital pre-distorter, an indirect learning structure and a least squares algorithm are used in this paper. The indirect learning structure is an error back-propagation based learning structure that can effectively extract the coefficients in the digital pre-distorter. The least squares algorithm is a common optimisation algorithm that minimises the sum of squares of the prediction errors to obtain the optimal coefficients.

The paper is organised as follows, section 2 provides a theoretical analysis of the various aspects of digital pre-distortion. In Section III, improved Chebyshev and undersampling techniques proposed for this paper are presented. Experimental results are given in Section IV, and a comparative analysis with memory polynomials and generalised polynomials is presented.

2 Theoretical Analysis

The digital pre-distortion technique is a widely used linearisation technique in wireless communication systems with high accuracy, large bandwidth and good stability. Its basic structure is shown in Fig.1. The input signal $X(n)$ is processed by the pre-distorter to

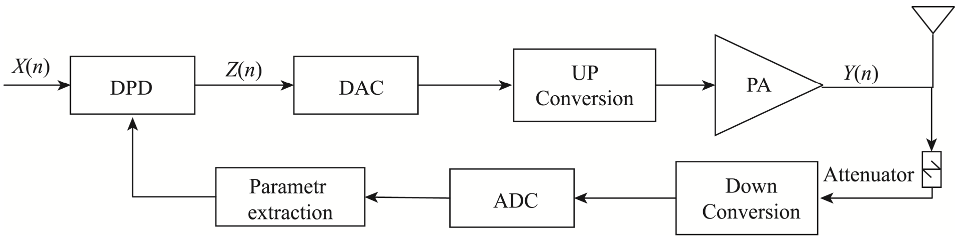


Fig.1 Digital Pre-distortion Architecture Diagram

obtain the pre-distortion signal Z(n), Z(n) goes through the DAC and up-conversion, and then through the amplifier to output the signal as $Y(n)$. $Y(n)$ goes through the attenuator and down-conversion and ADC for pre-distortion parameter extraction. The role of the digital pre-distortion module is to linearise the amplifier by pre-distorting the input signal so that its amplitude and phase characteristics are opposite to the non-linear characteristics of the amplifier, in order to counteract the non-linear distortion of the amplifier module[10]. The implementation of this pre-distortion can be divided into several main steps, including the selection of memory polynomials, learning structures and parameter identification algorithms.

2.1 Polynomial Model

In wideband transmitters, pre-distortion models can be analysed in terms of the behavioural model of the power amplifier. Power amplifiers are usually non-linear in nature, which introduces distortion and interference signals. In order to achieve linearisation of the amplifier, pre-distortion techniques are introduced. The pre-distortion model and the behavioural model of the amplifier are inverse models of each other and there is an inverse relationship between them. The behavioural model of an amplifier device describes the non-linear conversion relationship between its input and output signals. The pre-distortion model models and compensates for the non-linear characteristics of the amplifier device by inverse modelling.

The memory polynomial approach describes the non-linear characteristics of the amplifier by building a polynomial model and predicting the relationship between the input signal and the output signal by fitting a polynomial based on pre-collected amplifier input and output sample data[11]. In this way, the pre-distorter can compensate accordingly to the predicted non-linear distortion, bringing the amplifier output signal closer to a linear response. Typically, the behavioural model of an amplifier device can be represented using a memory polynomial (MP) model, which is simple in structure and easy to extract parameters. The pre-distortion model is linearised by selecting the appropriate pre-distorter function and parameters so that the output signal cancels out with the input signal of the amplifier device. The model's number sequence expression is:

$$y(n)=\sum_{p=0}^{P}\sum_{m=0}^{M}a_{pm}\,|\,x(n-m)\,|^{p}\;x(n-m) \tag{1}$$

Where $x(n)$ and $y(n)$ are the baseband normalised input and output signals of the amplifier, respectively. P is the non-linear order, and M is the model memory depth.

The memory polynomial model is a commonly used behavioural model for amplifier devices and is widely used in broadband transmitters. Its structure block diagram is shown in Fig.2 and includes a delay unit and a memoryless polynomial unit. The delay unit is used to delay the input signal to account for the dynamic response of the amplifier device. The delay unit can be one or more clock cycles of delay. By introducing an appropriate delay, the timing behaviour of the non-linear characteristics of the amplifier device can be captured. The memoryless polynomial cell is a key component of the model and is used to describe the non-linear conversion characteristics of the amplifier device. It uses a series of polynomial functions to approximate the relationship between the input and output of the amplifier device. These polynomial functions are usually based on a power term of the input signal and the non-linear characteristics and can be selected and adjusted to approximate the non-linear conversion characteristics of the actual amplifier device.

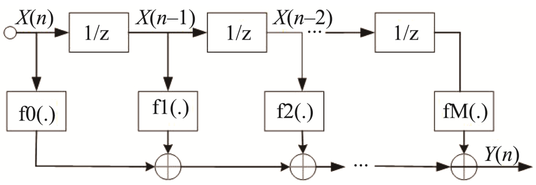
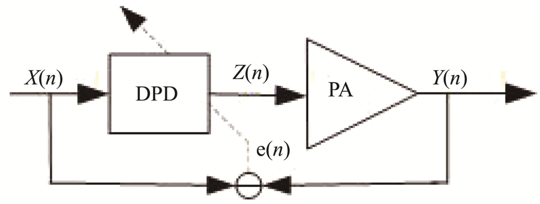


Fig.2 Memorizing Multiple Block Diagrams

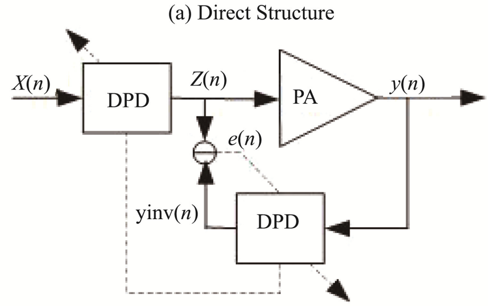
2.2 Learning Structure

The direct learning structure is shown in Fig.3(a), which uses complex adaptive algorithms such as the LMS algorithm (Least Mean Square algorithm) or the RLS algorithm (Recursive Least Squares algorithm). The structure uses the difference between the input and output signals as a condition for iteration, and updates the parameters through continuous iteration, eventually making the difference between the input and output signals converge to zero. This method is capable to achieve high pre-distortion, but due to the instability of the adaptive algorithm, it may result in the whole system not working properly[12].

The indirect learning structure, shown in Fig.3(b), uses the posterior part of the amplifier device to replace the pre-inverse of the pre-distortion device in order to achieve the update of the pre-distortion parameters. This structure has no closed-loop feedback and the identification algorithm of the pre-distortion parameters is able to converge, therefore the stability problem in the direct learning structure does not exist. In contrast to the direct learning structure, the indirect learning structure does not require iterations and is able to update the pre-distortion parameters in real time. In the indirect learning structure, the parameters of the pre-distortion device can be obtained by offline training or online learning. In offline training, the parameters of the predistortion device are trained by providing a set of known input signals and corresponding output signals. When learning online, the pre-distortion device updates its parameters based on the difference between the real-time input and output signals, achieving a dynamic pre-distortion effect.



(a) Direct Structure



(b) Indirect Structure

Fig.3 Learning Structure

Therefore, this paper uses an indirect learning structure, which has the advantage of higher stability, convergence of the parameter identification algorithm and the ability to update the pre-distortion parameters in real time. The digital pre-distortion system with the indirect learning structure can effectively compensate for the non-linear characteristics of the amplifier device and realise the linearisation of the amplifier.

2.3 Parameter Recognition Algorithms

Coefficient discrimination algorithms for digital predistorters include least squares, linear discrimination algorithms such as recursive least squares (RLS), least mean square error (LMS) and normalized least mean square error method (NLMS)[13].

In this paper, the least squares algorithm (LS) is used as the identification algorithm for the most pre-distorter coefficients. The least squares algorithm, is a commonly used algorithm for fitting data in scientific experiments. Normally, the observed data derived from an experiment cannot find a unique solution, so only similar solutions can be found. The least squares method enables the smallest difference between the solution data and the actual data values to be found, thus enabling a globally optimal fitted curve to be derived[14]. The key to least squares is to find the difference between the observed data and the target data and to minimise the sum of squares, i.e. the sum of squares of the errors. The expression for the least sum of squares of the error is:

$$\| \vec{\varepsilon} \|_2^2 = \sum_{i=0}^{n} \varepsilon_i^2 = \sum_{i=0}^{n} [A(x_i) - y(i)]^2 \quad (2)$$

$y(i)$ is the fitted target signal and $A(x_i)$ is the expression of the polynomial.

The steps of the least squares method are as follows:

(1) Collect the observed data from the experiment and the target data, with the observed data being the input signal of the pre-distorter and the target data being the corresponding output signal.

(2) Construct a mathematical model with the coefficients of the pre-distorter as the parameters to be solved. Based on the model and the known input and output data, establish the mathematical relationship between the observed data and the target data.

(3) Based on the principle of least squares, the difference between the observed data and the target data is solved for and the sum of squares is minimised. This can be achieved by solving an optimisation problem, usually using numerical optimisation methods such as gradient descent algorithms or matrix operations methods.

(4) Solve to obtain the optimal pre-distorter coefficients that minimise the difference between the observed and target data. These coefficients can be used to configure the digital pre-distorter to achieve a linearising effect on the amplifier.

3 Presentation Method

3.1 Improving the Chebyshev Behavioural Model

The memory polynomial (MP) model is capable of accurately modelling amplifiers in weakly nonlinear systems, but its modelling accuracy is low when the power amplifier is strongly nonlinear. In this paper, the Chebyshev polynomial model is improved, Eq(3) improves the complex orthogonal Chebyshev polynomial as in Eq. and Eq (4) is a recursive formula between the orders：

$$\phi_{2k+1,q}(y(n)) = (2k+1)\sum_{m=0}^{k} \frac{(-1)^m (2k-m)!}{m!(2k-2m+1)!} 2^{2(k-m)} \quad (3)$$
$$y(n-q)\,|\,y(n-q)\,|^{2(k-m)}$$

$$\phi_{k,q}(y(n)) = 2y(n)\phi_{k-1,q}(y(n)) - \phi_{k-2,q}(y(n)) \quad (4)$$

where $\phi_{k,q}(y(n))$ is the losing orthogonal basis, $y(n)$ is the normalised output data，k is the non-linear order, and q is the memory depth.

From equations (3) and (4) we can obtain the first order modified Chebyshev polynomial as Eq:

$$\phi_{1,q}(y(n)) = y(n-q) \quad (5)$$

By analogy the third order modified Chebyshev polynomial is given by Eq:

$$\phi_{3,q}(y(n)) = 4y(n-q)\,|\,y(n-q)\,|^2 - 3y(n-q) \quad (6)$$

The fifth order modified Chebyshev polynomial is given by Eq:

$$\phi_{5,q}(y(n)) = 16(n-q)\,|\,y(n-q)\,|^4 - 20y(n-q) \quad (7)$$
$$|\,y(n-q)\,|^2 + 5y(n-q)$$

Meanwhile, the size of the data matrix determinant is used to judge the degree of matrix pathology, and the data matrix determinants for the MP model and the modified Chebyshev polynomial model are shown in the Table 1.

Table 1 Data Matrix Determinant

	Items	MP	Chebyshev
K=5,Q=2	9	26.4842+1.4886i	18.4501+10.223i
K=7,Q=3	16	–3.4784–77.4509i	–2.7759–61.3632i
K=9,Q=4	25	4.6035+21.2609i	7.3975+34.1263i

Table 1 shows that the determinant of the MP model is smaller than that of the improved Chebyshev model, indicating that the data matrix of the MP model is easily pathologised and more resources are consumed to ensure the accuracy of the numerical operations when performing inverse operations. The improved Chebyshev model is worth adopting because of its superior performance. Therefore, the fifth-order improved Chebyshev polynomial is used in this design.

3.2 Low Rate Sampling Technology

Using a low rate ADC to sample the amplifier output signal, the under-sampling of the amplifier output signal is captured. The data collected is the undersampled data of the amplifier output signal, and the data will generate aliasing distortion. Here, the data obtained by sampling with a high-speed ADC without aliasing distortion is referred to as fully sampled data. The corresponding pre-distortion structure is called full sampling pre-distortion. This design uses the Under-Sampling Restoration (USR) technique[15]. As shown in Fig.4.

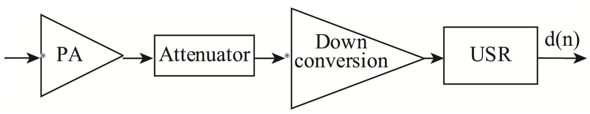


Fig.4 Sampling Flowchart

$x(n)$ is the amplifier input signal and $y(n)$ the amplifier output signal. $y(n)$ is passed through an attenuator for power attenuation, then through a down-conversion for carrier frequency transformation, and finally through an ADC to obtain the sampled signal.

Undersampling recovery techniques are a method used to reconstruct high frequency signals from low sample rate signals. When sampling is performed, the sampling rate of the signal may be reduced in order to reduce the complexity of data acquisition and processing, or to save bandwidth and storage resources. However, reducing the sampling rate can result in the loss or aliasing of the high frequency components of the original signal, resulting in a loss of information. The goal of undersampling recovery techniques is to reconstruct the high frequency components of the original signal from the reduced sample rate signal by using suitable signal processing algorithms and mathematical models[16].

This compensates for the information loss to a certain extent and restores the quality and accuracy of the signal.

In the case of undersampling, the original signal is sampled and confused as shown in Equation (8):

$$x(n) = s[nT] \tag{8}$$

where $x(n)$ is the sampled signal, $s[nT]$ is the value of the original signal at the sampling moment nT, and T is the sampling interval.

If the sampling rate is $1/M$, i.e. only one of every M samples is retained, then the undersampled signal is as shown in Equation (9):

$$x_{down}[n] = x[nM] = s[nMT] \tag{9}$$

where x_{down} is the undersampled signal, n is the undersampling moment, and in order to recover the original signal, linear interpolation is used, as shown in Equation (10):

$$s_{recon}[nT] = (1/M)^{*} \sum_{k=(n-1)M}^{nM} x_{down}[k] \tag{10}$$

where s_{recon} is the value of the reconstructed signal moment nT and x_{down} is the value of the undersampled signal moment k.

4 Experimental Verification

4.1 Model Evaluation Indicators

Normalised Mean Square Error (NMSE) is a commonly used metric for assessing the accuracy of behavioural models. It is used to measure the difference between predicted values and actual observations, making comparisons between different data sets fairer and more reliable by normalising the errors. NMSE is calculated by squaring the difference between the predicted values and the corresponding actual observations and summing all squared errors. This summed value is then divided by the variance of the actual sequence of observations to obtain the normalised mean squared error. The purpose of this is to normalise the errors to a relatively uniform scale in order to better compare accuracy between different data sets[17]. Specifically, the NMSE is calculated as shown in Equation (11):

$$NMSE_{dB} = 10\log_{10}\left(\frac{\sum_{k=1}^{K} |y_{ymeas}(k) - y_{\mathrm{mod}}(k)|^2}{\sum_{k=1}^{K} |y_{meas}(k)|^2}\right) \tag{11}$$

where y_{meas} and y_{mod} represent the measured and modelled output waveforms respectively, and K is the number of output waveform sampling points.

NMSE values usually range from 0 to 1, where 0 indicates perfect agreement between predicted and actual observations, and 1 indicates a large difference between predicted and actual observations. Thus, a smaller NMSE value usually indicates higher model accuracy, while a larger NMSE value indicates lower model accuracy. By using normalised mean squared error as an assessment metric, we can gain a more comprehensive understanding of the performance of behavioural models in predicting DUT behaviour and make comparisons and selections between different models[18].

The Adjacent Channel Power Ratio (ACPR) is one of the metrics used to measure the frequency domain performance of signals in wireless communication systems. It is used to assess how much interference a wireless device causes to adjacent channels when transmitting a signal. In a wireless communication system, different signals are assigned to different channels for transmission[19], and ACPR measures the ratio between the signal power in the channel of interest and the signal power in its neighbouring channels. Typically, we would like the power in the channel of interest to be as high as possible, and the power in the adjacent channel to be as low as possible, in order to reduce interference between adjacent channels. Specifically, the ACPR calculation formula is shown in Equation (12):

$$ACPR = 10\log_{10}\left(\frac{P_{main}}{P_{adjacent}}\right) \tag{12}$$

where P_{main} and $P_{adjaent}$ represent the signal power of the primary channel and the signal power of the adjacent channel, respectively, in decibels (dB). A smaller value of ACPR indicates that the signal power in the channel of interest is higher relative to the signal power of the adjacent channel, indicating better frequency domain performance of the device and less interference to the adjacent channel[20].

4.2 Experimental Platform

The entire experiment was performed as follows, using Matlab on the computer side to generate the 5G digital baseband signal. First, the signal parameters required for the experiment are determined, including a bandwidth of 80MHz. Then, the signal processing toolbox in Matlab is used to generate the corresponding digital baseband signals. These signals can be randomly generated or generated according to a specific modulation method. The generated digital baseband signals are downloaded to a signal generator (VSG). Connect the PC to the signal generator and transfer the generated signals to the signal generator using suitable software or tools. Ensure that the Signal Generator is able to generate the required signal accurately.

Convert the signal from the signal generator (VSG) to the required frequency by means of an inverter and feed it into the drive power amplifier. Connect the output of the signal generator to the input of the driver amplifier to ensure that the signal is passed to the amplifier correctly. The output signal of the amplifier is attenuated by an attenuator. In order to control the input power of the experiment, the amplifier output signal can be properly attenuated using an attenuator. This ensures that the power range of the signal is within an acceptable range when performing subsequent analysis. The attenuated signal is acquired by a spectrum analyser. The attenuated signal is connected to the spectrum analyser and the appropriate parameters are set to acquire the power spectral density of the signal. With the spectrum analyser, the spectral information of the output signal of the amplifier can be obtained.

The degree of linearisation of each model is finally analysed. Based on the experimentally acquired power spectral density of the amplifier output signal, the effects of the different pre-distortion models are compared. The performance of each model in terms of linearising the amplifier is assessed by comparing the difference between the output signal and the input signal of the different models. Throughout the experimental process, it is necessary to ensure that the instruments are correctly connected, the parameters are set accurately and attention is paid to the stability of the experimental environment. In addition, depending on the actual requirements, it may be necessary to carry out several experiments or adjust the experimental parameters to obtain accurate results.

4.3 Experimental Results

The results of this test are shown in Fig.5. Fig.5(a) shows the power spectral density of the input signal and Fig.5(b) shows the power spectral density of the output signal of the amplifier without digital pre-distortion, where distortion and leakage can be clearly observed. Fig.5(c) shows the power spectral density of the amplifier output signal using a memory polynomial and Fig.5(d) shows the power spectral density of a generalised polynomial. Fig.5(e) shows the power spectral density of the amplifier output signal using an improved Chebyshev polynomial, with better results in terms of improvement and enhancement compared to Fig.5(c) and Fig.5(d).

By comparing Fig.5(b), Fig.5(c), Fig.5(d) and Fig.5(e), it can be seen that the power spectral density of the amplifier output signal is significantly improved by the use of digital pre-distortion techniques. The memory polynomial and Chebyshev polynomial as pre-distortion models can effectively cancel out the non-linear distortion of the amplifier and make the output signal more closely resemble the characteristics of the input signal. In particular, the Chebyshev polynomial offers a greater improvement in performance compared to the memory polynomial and may be better suited to the linearisation requirements of this system.

The adjacent channel leakage ratio and normalized mean square error for this test are shown in Table 2, which shows that the ACPR for the no-digital pre-distortion technique is -20.96dB and the ACPR for the memory polynomial model is -34.83dB, an improvement of 13.87dB compared to the no-digital pre-distortion output. The ACPR of the generalised polynomial model is -38.5678dB, while the ACPR of the improved Chebyshev polynomial is -40.94dB, an improvement of 19.98dB compared to the no-digital pre-distortion, and an improvement of 6.11dB and 5.32dB compared to the memory polynomial and generalised polynomial outputs, respectively, which is worth adopting.

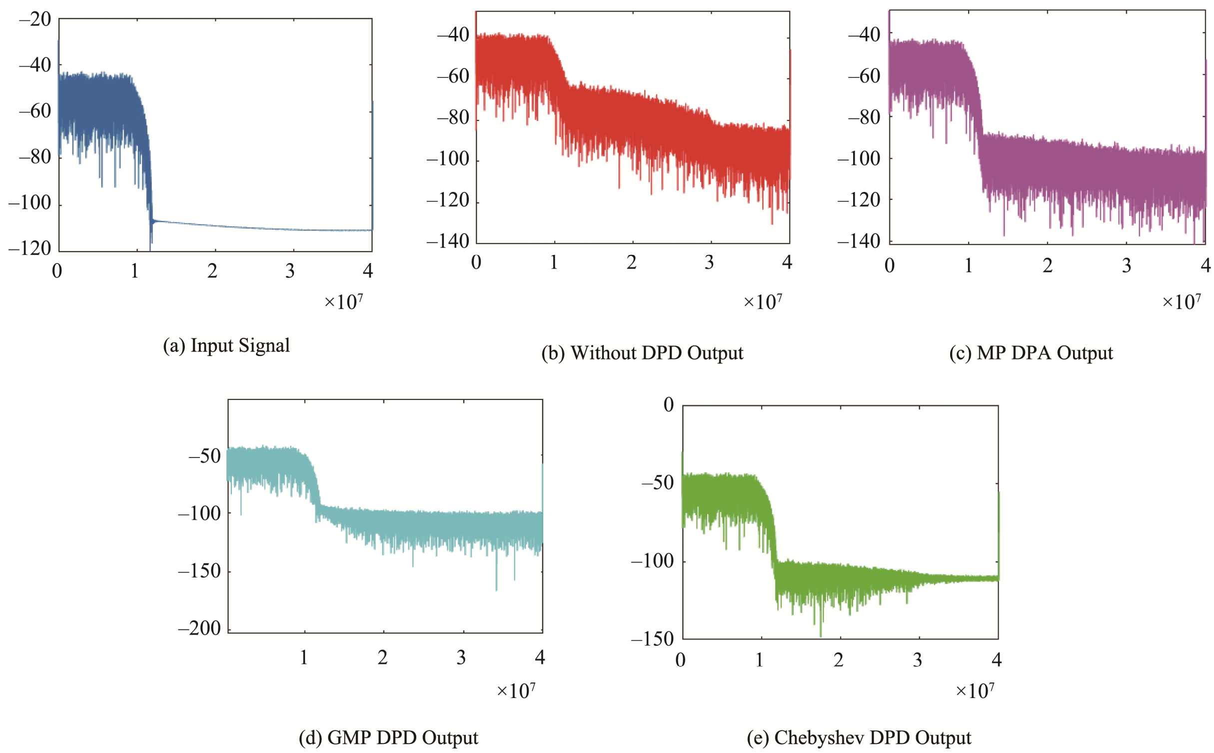


Fig.5 Power Spectral Density

Table 2 Comparison of Results

Signal	ACPR	NMSE
Input	–41.44dB	–48.01dB
Without	–20.96dB	–23.42dB
MP	–34.83dB	–40.94dB
GMP	–38.56dB	–46.25dB
Chebyshev	–40.94dB	–47.25dB

5 Conclusion

Improved Chebyshev polynomial pre-distortion has shown excellent results in terms of out-of-band rejection, as it can more effectively suppress leakage and distortion in the out-of-band frequency range of the amplifier output signal. Compared to existing memory polynomial pre-distortion devices, Chebyshev polynomial pre-distortion devices have a better ability to suppress out-of-band leakage. In addition, the Chebyshev polynomial pre-distorter has higher parameter identification accuracy and convergence speed, enabling accurate identification and updating of the pre-distorter parameters. Its unique recursive nature makes the hardware implementation of the pre-distorter more convenient, saving resources and improving performance.

The simulation results show that the improved Chebyshev polynomial pre-distortion has a significant improvement in ACPR performance compared to the memory polynomial pre-distortion and generalised polynomial, achieving improvements of 6.11dB and 5.32dB. This means that the improved Chebyshev polynomial pre-distortion is more effective in reducing the interference of the amplifier output signal in adjacent channels, improving the overall performance of the wireless communication system.

In summary, the improved Chebyshev polynomial pre-distortion outperforms the memory polynomial pre-distortion in terms of out-of-band rejection, parameter identification accuracy and convergence speed. Its recursive nature makes it easier to implement in hardware, while significantly improving the ACPR performance of the amplifier output signal. This makes the Chebyshev polynomial pre-distorter a promising and advantageous option for applications in wireless communication systems to improve linearisation and overall system performance. Composed to base layer and detail layer by multi-scale Retinex, the CLAHE-WGIF algorithm is proposed to increase the contrast and edge structure information of the detail layer, and the adaptive gamma.

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Author Biographies

LU Xu is now a M.Sc. candidate at Nanjing University of Information Science and Technology. His main research interests include signal and information processing.

E-mail: 2604590837@qq.com

ZHOU Xianchun (Corresponding author) received Ph.D. from Nanjing University of Information Science and Technology (NUIST) in 2011. He is now a professor and M.Sc. supervisor at NUIST, is also a senior member of China Electronics Society. His main research interests include signal and information processing.

E-mail: zhouxc2008@163.com