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Research Article

A Novel Digital Predistortion Identification Algorithm Based on Variable Forgetting Factor Recursive Least Square Method

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The transmitting signal of wireless communication system is impaired by the nonlinearity of RF power amplifier (PA) which leads to signal distortion and spectrum spillover, by which the signal transmission quality is affected. Digital predistortion (DPD) is an efficient and economical way to correct the nonlinear effects of power amplifiers. The recursive least square (RLS) recognition algorithm is commonly used to extract the correction coefficients of the DPD model, and the accuracy of the extraction directly affects the system performance. In this paper, a new variable forgetting factor identification algorithm (new variable forgetting factor recursive least square, NVFFRLS) is proposed for recursive least square (RLS) identification algorithm. The 64-QAM signal is combined with a memory polynomial (MP) predistortion model for predistortion system simulation. The experimental results show that, compared with the RLS identification algorithm and two kinds of variable forgetting factor RLS identification algorithms, the algorithm has smaller estimation error, faster convergence, and better tracking capability, stability, and adaptability; the predistortion system based on NVFFRLS identification algorithm can compensate the nonlinear memory effects of power amplifier more effectively.

1. Introduction

Adaptive identification algorithms are widely used in various fields, such as adaptive filtering and model identification. Least mean square (LMS), recursive least square (RLS), and other adaptive algorithms are commonly used to identify unknown systems. The mathematical methods and constraints are used to process the input and output data of the unknown system, namely, estimating the model parameters.

Among them, with low computational complexity, single iterative update expression, and the advantage that there is only one intermediate parameter of estimation error in the iterative process, the LMS algorithm is one of the nonbatch processing algorithms, which is good at tracking and easy to implement in engineering but slow algorithm convergence speed. The RLS algorithm performs the inverse operation of the matrix by iterative update, which reduces the calculation amount of the algorithm and has a fast convergence speed. However, in the iterative process, there are multiple intermediate parameters, which occupy the mass storage space, such that the utilization rate of storage resources and tracking ability is lowered.

Improving the tracking ability of the RLS algorithm can increase the identification accuracy of the system model. The traditional RLS algorithm changes the performance of the system by adjusting the size of the forgetting factor, but as this forgetting factor is fixed, it is not that effective to reach with the real-time changes. Reference [1] proposed a variable forgetting factor recursive least square (VFFRLS (1)) algorithm, which improves the system tracking ability, but with inconvenient forgetting parameter adjusting, general system adaptability, and poor real-time dynamic filtering. Literature [2] proposes a variable forgetting factor RLS (VFFRLS (2)) algorithm for discriminative systems, and the algorithm improves the error convergence speed and tracking ability, but the system adaptability is weak and the stability is poor. The iteration term of the forgetting factor is complicated.

The stability, convergence speed, and tracking ability of RLS algorithm are affected by the forgetting factor. The closer it is to the true value, the faster the algorithm converges and the more stable it is, while exacerbating the deterioration of the tracking performance. To improve the tracking performance, the forgetting factor must be reduced. Therefore, NVFFRLS algorithm is proposed by introducing adjacent estimation error term and cubic root to affect the value of forgetting factor to solve the above problems. The traditional RLS, VFFRLS (1), and VFFRLS (2) algorithm and the proposed new algorithm are used to identify the predistortion module. The simulation results show that the improved algorithm has small parameter estimation error, fast convergence speed, strong tracking ability, and more stability and system adaptability.

The organization of this paper includes the following aspects: Section 2 introduces the model of digital predistortion and the model of power amplifier. Section 3 represents the identification structure of the digital predistortion system and analyzes the principle of different structures and describes the identification algorithm, including the function of the forgetting factor and the transformation of the new variable forgetting factor. Section 4 gives the simulation results of the algorithm and compares it with several algorithms. Section 5 summarizes the article and makes a concise conclusion.

2. Digital Predistortion Model

Digital predistortion technology is the most widely used in current communication system linearization technology. The commonly used digital predistortion models include Volterra series and memory polynomial (MP) model. Volterra series, as a kind of Taylor series with strong memory effect, contains high-order terms of independent variables and delayed memory effects, which makes it become a series with a strong modeling ability and capability of deeply restoring the physical characteristics of nonlinearity and memory of power amplifier. However, as the memory depth rises and model nonlinear order increases, the model coefficients of the Volterra series will be so excessive that it will improve the calculation amount and complexity. Obtained by cutting the Volterra series and only retaining the parameters on the main diagonal of the Volterra series matrix, the MP model is less complex and better able to characterize the nonlinear memory effect of the RF power amplifier [3]. Frequency band in which even order produces nonlinear distortion is far away from the central frequency and can be filtered by the band-pass filter. When the nonlinear order is an even number, the frequency band with nonlinear distortion is far from the center band and can be rejected by band-pass filter; therefore, the spectrum aliasing and intermodulation distortion are generated by the odd order, which cause the power amplifier nonlinear distortion. The mathematical expression is as follows:

$$h(n) = \sum_{k=1}^{K} \sum_{q=0}^{Q} a_{k,q} r(n-q) |r(n-q)|^{k-1}, \tag{1}$$

where $r(n)$ and $h(n)$ are the input and output signals of the MP model, respectively; k is the nonlinear order and odd; q is the delay term of the model, which represents the memory depth; and $a_{k,q}$ is the coefficient of the model.

The predistorter model can be regarded as the inverse model of the power amplifier model, so both can be modeled using the memory polynomial. Literature [4] uses memory polynomials as amplifier models, and the power amplifier model coefficients are extracted from the actual class AB power amplifier, where the memory depth and nonlinear order of the model are 2 and 5, respectively; the coefficients are as follows:

$$\begin{cases} a_{10} = 1.015 + 0.0903j, \\ a_{11} = 1.13918 - 0.1003j, \\ a_{12} = 0.2531 - 0.00982j, \\ a_{30} = -0.045 + 0.2900j, \\ a_{31} = -0.1689 + 0.00323j, \\ a_{32} = 0.2532 - 0.0982j, \\ a_{50} = -0.9651 + 0.0238j, \\ a_{51} = -0.2451 - 0.3733j, \\ a_{52} = 0.1229 + 0.1503j. \end{cases} \tag{2}$$

Therefore, the article cites this amplifier model for experimental analysis. The input and output characteristics of the power amplifier model used in the simulation are shown in Figure 1.

As the inputting power increases, the power amplifier appears nonlinear distortion and presents gain compression phenomenon. When the input power is close to -1.5 dB, the power amplifier is at the 1 dB gain compression point, and the overworking range of the power amplifier after digital predistortion should be less than this value.

3. Identification Structure and Algorithm

3.1. Identification Structure. Digital predistortion system identification structure is mainly divided into direct learning and indirect learning. The direct learning structure [5] is shown in Figure 2, in which $x(n)$ is the input signal of the predistorter, $z(n)$ is the output signal of the predistorter, $y(n)$ is the output signal of the power amplifier, and $e(n)$ is the estimation error between the output signal and the input signal.

The indirect learning structure [6] is shown in Figure 3, where $z'(n)$ is the output signal of the power amplifier trained by the adaptive algorithm.

This structure (open loop) constructs a post-predistortion module which is completely consistent with the predistortion training module. The difference between the input $z(n)$ of the power amplifier and the output signal $z'(n)$ of the adaptive identification training is calculated until the error value between the output signal of the predistortion module and the output signal trained by the adaptive algorithm approaches 0, and the

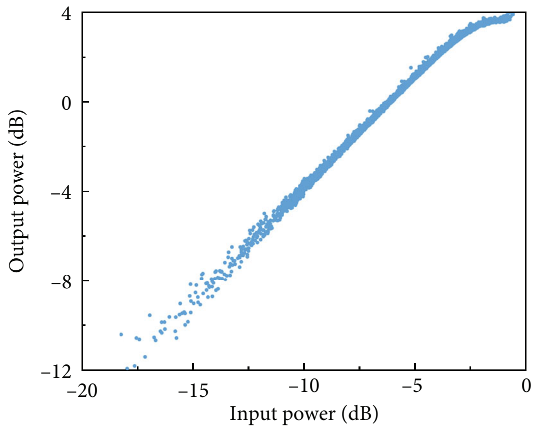


Figure 1: Characteristics of power amplifier.

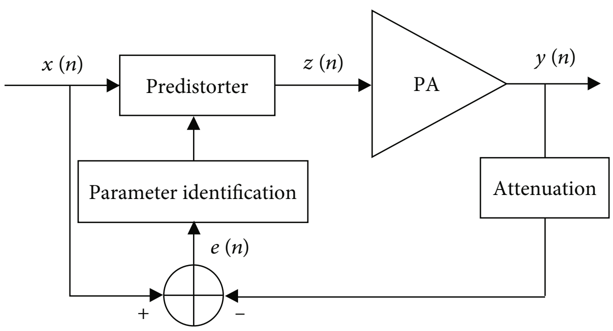


Figure 2: Direct learning of structural principle.

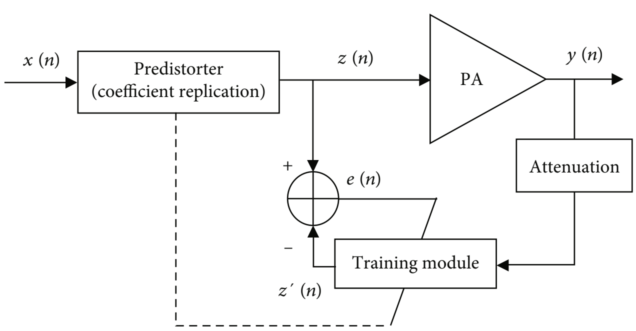


Figure 3: Indirect learning structure principle.

identified coefficient is directly copied to the post-predistortion module when it converges.

When implementing DPD projects, most researchers use either indirect learning or direct learning structures (closed loop). Those with RF or PA design experience usually choose indirect learning due to they consider DPD to be a reverse operation of PA, while those with signal processing or control theory tend to choose closed-loop estimation because they view adaptation as a closed-loop control process [7]. In this paper, the indirect learning structure is used to identify the system model parameters.

3.2. Forgetting Factor. The proportional weight of the data after iteration can be improved by the forgetting factor, which makes nonstationary data adaptable [8]. The error signal of the recursive least square method is determined by the expected and estimated signal, and the small value of λ will increase the dependence of the estimated signal to the expected signal; i.e., the error value of the signal close to the moment of n will be given a smaller weight, and the output signal will approach the expected signal, but this behavior will lead to the correct operation of the system depending entirely on the desired signal, so part of the literature shows that the forgetting factor $0.95 \leq \lambda \leq 0.995$ achieves the best results.

3.3. RLS Identification Algorithm. In the digital predistortion system, the inverse model of the power amplifier can be regarded as a predistorter [9], in which the nonlinear distortion characteristic is opposite to the power amplifier; due to the large amount of calculation of the inverse matrix of the power amplifier, an adaptive identification algorithm is introduced to quickly approximate the inverse model of the power amplifier.

The recursive least square algorithm with faster convergence rate is used to identify the unknown system so that it can reduce the system mean square error [10]. During the initialization process, determine the initial value of the forgetting factor ($0 < \lambda < 1$), the cost function made of the error squared, and the forgetting factor. The cost function can be expressed as

$$\mathrm{Jn} = \sum_{n=0}^{i} \lambda^{i-n} |e(n)|^2, \tag{3}$$

where λ is the forgetting factor (generally0.98) and $e(n)$ is the estimation error; the algorithm converges when the cost function Jn takes the minimum value.

The design idea of the RLS algorithm: the predistorter coefficient $w(n-1)$ at moment $n-1$ and the data samples at moment n are known, and the coefficients $w(n)$ at moment n are obtained by iteration [11]. The derivation process is tedious of the RLS algorithm which will not be narrated. The specific iteration process is shown in Algorithm 1, where$P(n)$ is the autocorrelation matrix, δ is a small positive number, $k\,(n)$ is the Kalman gain vector, $z(n)$ is the output signal of the predistorter, $u(n)$ is the input signal of algorithm, $u^H(n)$ is the conjugate transpose matrix of $u(n)$, $w(n)$ is the coefficients of the predistorter,$w^H(n-1)$ is the conjugate transpose matrix of $w(n-1)$, $d(n)$ is the desired signal, and$e*(n)$ is the covariance matrix of $e(n)$.

According to the coefficients at time $n-1$, the input signal $u(n)$ is trained to obtain the output signal of the predistorter at time n. The expected output $d(n)$ and $z(n)$ are subtracted to obtain the error $e(n)$, which combine the adaptive algorithm to calculate the predistorter coefficient at the moment n.

3.4. NVFFRLS Identification Algorithm. The smaller forgetting factor helps to improve the tracking ability of the system but aggravates the noise sensitivity; on the contrary, the system tracking ability and estimation error reduced and enhanced noise resistance [12]. The forgetting factor can indirectly affect the convergence of the recognition algorithm and

$$
\begin{aligned}
&\textbf{\textit{Initialize}}: \boldsymbol{w}(\mathbf{0}) = \mathbf{0}, \boldsymbol{P}(\mathbf{0}) = \boldsymbol{\delta I}, \boldsymbol{\delta} = \mathbf{0.001},\\
&\boldsymbol{I} \text{ is the } \textbf{\textit{identity matrix}}, \boldsymbol{\lambda} = \mathbf{0.98}.\\
&\textbf{\textit{Input}}: \boldsymbol{u}(\boldsymbol{n}), \boldsymbol{d}(\boldsymbol{n}).\\
&\textbf{\textit{Iteration}}: \text{for } \boldsymbol{n} = \mathbf{1} \text{ to } \boldsymbol{N}\\
&\textbf{\textit{Compute}}\, \boldsymbol{z}(\boldsymbol{n}) = \boldsymbol{w}^{H}(\boldsymbol{n})\, \boldsymbol{u}(\boldsymbol{n})\\
&\boldsymbol{e}(\boldsymbol{n}) = \boldsymbol{d}(\boldsymbol{n}) - \boldsymbol{z}(\boldsymbol{n})\\
&\boldsymbol{k}(\boldsymbol{n}) = \boldsymbol{P}(\boldsymbol{n})\boldsymbol{u}(\boldsymbol{n})/[\boldsymbol{\lambda} + \boldsymbol{u}^{H}(\boldsymbol{n})\boldsymbol{P}(\boldsymbol{n})\boldsymbol{u}(\boldsymbol{n})]\\
&\boldsymbol{w}(\boldsymbol{n}) = \boldsymbol{w}(\boldsymbol{n}-\mathbf{1}) + \boldsymbol{k}(\boldsymbol{n})\boldsymbol{e}^{*}(\boldsymbol{n})\\
&\boldsymbol{P}(\boldsymbol{n}) = \boldsymbol{\lambda}^{-1}[\boldsymbol{P}(\boldsymbol{n}-\mathbf{1}) - \boldsymbol{k}(\boldsymbol{n})\boldsymbol{u}^{H}(\boldsymbol{n})\boldsymbol{P}(\boldsymbol{n}-\mathbf{1})]\\
&\textbf{\textit{end}}\\
&\textbf{\textit{Output}}: \boldsymbol{e}(\boldsymbol{n}), \boldsymbol{z}(\boldsymbol{n}), \text{and } \boldsymbol{w}(\mathbf{1}), \boldsymbol{w}(\mathbf{2}), \cdots, \boldsymbol{w}(\boldsymbol{n})
\end{aligned}
$$

Algorithm 1: RLS algorithm calculation process.

$$
\begin{aligned}
&\textit{Initialize}: w(0) = 0, P(0) = \delta I, \delta = 0.001,\\
&\boldsymbol{I} \text{ is the } \textbf{\textit{identity matrix}}, \boldsymbol{\lambda}(\mathbf{1}) = \mathbf{0.98}.\\
&\textbf{\textit{Input}}: \boldsymbol{u}(\boldsymbol{n}), \boldsymbol{d}(\boldsymbol{n})\\
&\textbf{\textit{Iteration}}: \text{for } \boldsymbol{n} = \mathbf{1} \text{ to } \boldsymbol{N}\\
&\textbf{\textit{Compute}}\, \boldsymbol{z}(\boldsymbol{n}) = \boldsymbol{w}^{H}(\boldsymbol{n})\, \boldsymbol{u}(\boldsymbol{n})\\
&\boldsymbol{e}(\boldsymbol{n}) = \boldsymbol{d}(\boldsymbol{n}) - \boldsymbol{z}(\boldsymbol{n})\\
&\boldsymbol{k}(\boldsymbol{n}) = \boldsymbol{P}(\boldsymbol{n})\boldsymbol{u}(\boldsymbol{n})/[\boldsymbol{\lambda}(\boldsymbol{n}) + \boldsymbol{u}^{H}(\boldsymbol{n})\boldsymbol{P}(\boldsymbol{n})\boldsymbol{u}(\boldsymbol{n})]\\
&\boldsymbol{w}(\boldsymbol{n}) = \boldsymbol{w}(\boldsymbol{n}-\mathbf{1}) + \boldsymbol{k}(\boldsymbol{n})\boldsymbol{e}^{*}(\boldsymbol{n})\\
&\boldsymbol{P}(\boldsymbol{n}) = \boldsymbol{\lambda}(\boldsymbol{n})^{-1}[\boldsymbol{P}(\boldsymbol{n}-\mathbf{1}) - \boldsymbol{k}(\boldsymbol{n})\boldsymbol{u}^{H}(\boldsymbol{n})\boldsymbol{P}(\boldsymbol{n}-\mathbf{1})]\\
&\boldsymbol{\lambda}(\boldsymbol{n}+\mathbf{1}) = \boldsymbol{C} - \boldsymbol{a}\sqrt[v]{|\boldsymbol{e}(\boldsymbol{n}) - \boldsymbol{e}(\boldsymbol{n}-\mathbf{1})|}\\
&\textbf{\textit{end}}\\
&\textbf{\textit{Output}}: \boldsymbol{e}(\boldsymbol{n}), \boldsymbol{z}(\boldsymbol{n}), \text{and } \boldsymbol{w}(\mathbf{1}), \boldsymbol{w}(\mathbf{2}), \cdots, \boldsymbol{w}(\boldsymbol{n})
\end{aligned}
$$

Algorithm 2: NVFFRLS algorithm calculation process.

plays a key role in the performance of the system, so the NVFFRLS recognition algorithm is proposed. On the basis of recursive small squares (RLS), the forgetting factor is modified to obtain this algorithm, which not only improves the tracking ability and convergence speed of the system but also reduces the estimation error. The algorithm iterative process is shown in Algorithm 2, where v is greater than 1 odd number and increasing this value can improve the convergence speed of the algorithm, but it affects the later modeling accuracy; C is the maximum of λ; v and C can be adjusted according to the actual situation; and a is used to change the flatness of the function image to prevent negative numbers. The initial value of λ is set to 0.98 and can be adaptively adjusted according to the estimation error. By comparing the current estimation error with the error at the previous time, the forgetting factor at the next time is affected.

4. Algorithm Simulation Analysis and Validation

4.1. Evaluation Indexes. Digital predistortion systems have a variety of evaluation indicators. The normalized mean square error (NMSE) can reflect the modeling accuracy metric, and the error vector magnitude (EVM) can fully reflect the divergence of the signal constellation map after modulation and is easy to calculate. Therefore, both are widely used to evaluate the accuracy of digital predistortion modeling. So NMSE and EVM are selected to evaluate the

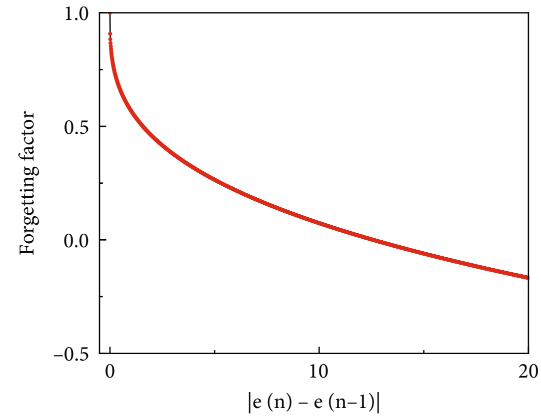


Figure 4: Forgetting factor correction function.

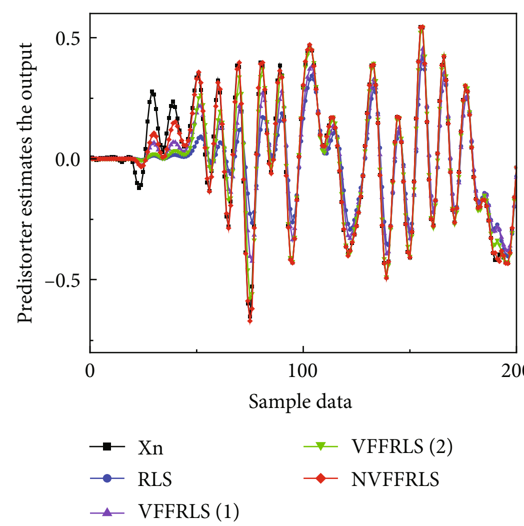


Figure 5: Comparison of tracking performance.

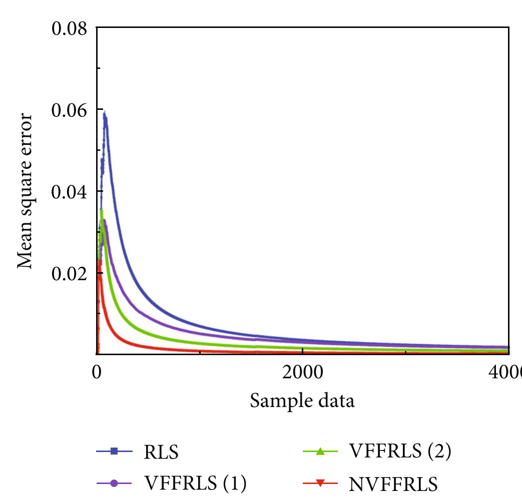


Figure 6: Comparison of the convergence performance.

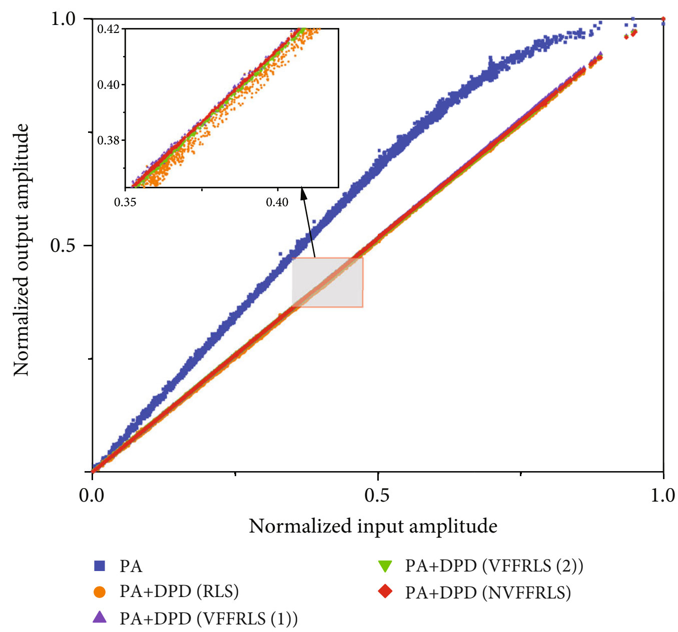


FIGURE 7: AM-AM characteristic curves.

accuracy of digital predistortion systems in this paper. The expressions of NMSE and EVM are shown as follows:

$$\mathrm{NMSE} = \frac{10\lg\left(\sum_{n=0}^{N-1}\left|y(n)-y'(n)\right|^2\right)}{\sum_{n=0}^{N-1}\left|y(n)\right|^2}, \tag{4}$$

where $y(n)$ is the actual output signal of the power amplifier, $y'(n)$ is the ideal output signal of the power amplifier, and N indicates the number of samples of the input signal, unit in dB; the NMSE reflects how close the actual output is to the ideal output, and the smaller the value, the better.

$$\mathrm{EVM} = \sqrt{\frac{\sum_{n=1}^{N}\left(I_n'-I_n\right)^2+\left(Q_n'-Q_n\right)^2}{\sum_{n=1}^{N}I_n^{\,2}+Q_n^{\,2}}}\times 100\%, \tag{5}$$

where I_n and Q_n are the I_n/Q_n component values of the n terms of the reference signal, I'_n and Q'_n are the I'_n/Q'_n component values of the n terms of the actual signal, and N is the length of the input vector signal. EVM describes the error between the actual output and the expected output and represents the in-band distortion characteristics of the signal; the smaller the value, the lower the distortion degree.

4.2. Simulation Analysis. In this article, MATLAB experimental platform is used to verify the proposed NVFFRLS predistortion identification algorithm. The experiments simulate the effect of the algorithm on the predistortion effect in the ideal case, and the CSI condition at the receiver side is ignored; i.e., the data feedback from the receiver is the ideal value by default.

The 64-QAM signal is used for verification analysis, where the intercepted 64-QAM signal has 27000 sampling points and 13 MHz bandwidth. The predistortion system uses AWGN channels with SNR of 40, an indirect learning structure, and combines RLS, VFFRLS (1), VFFRLS (2), and NVFFRLS algorithms to identify the predistorter parameters. Here, the nonlinear order K of the MP model is 7, the memory depth Q is 3, and the power amplifier magnification is set to 3.2.

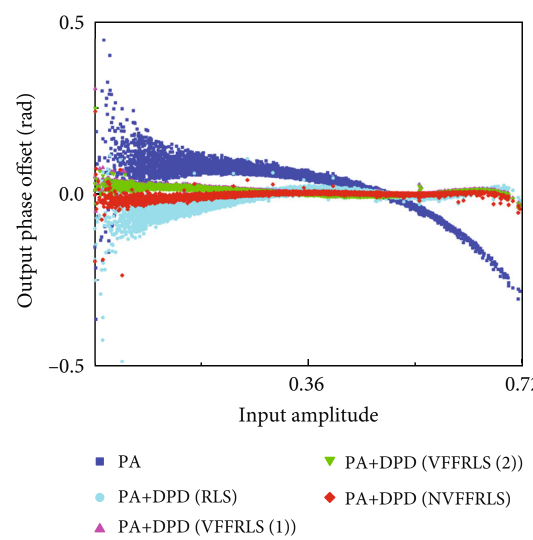


FIGURE 8: AM-PM characteristic curves.

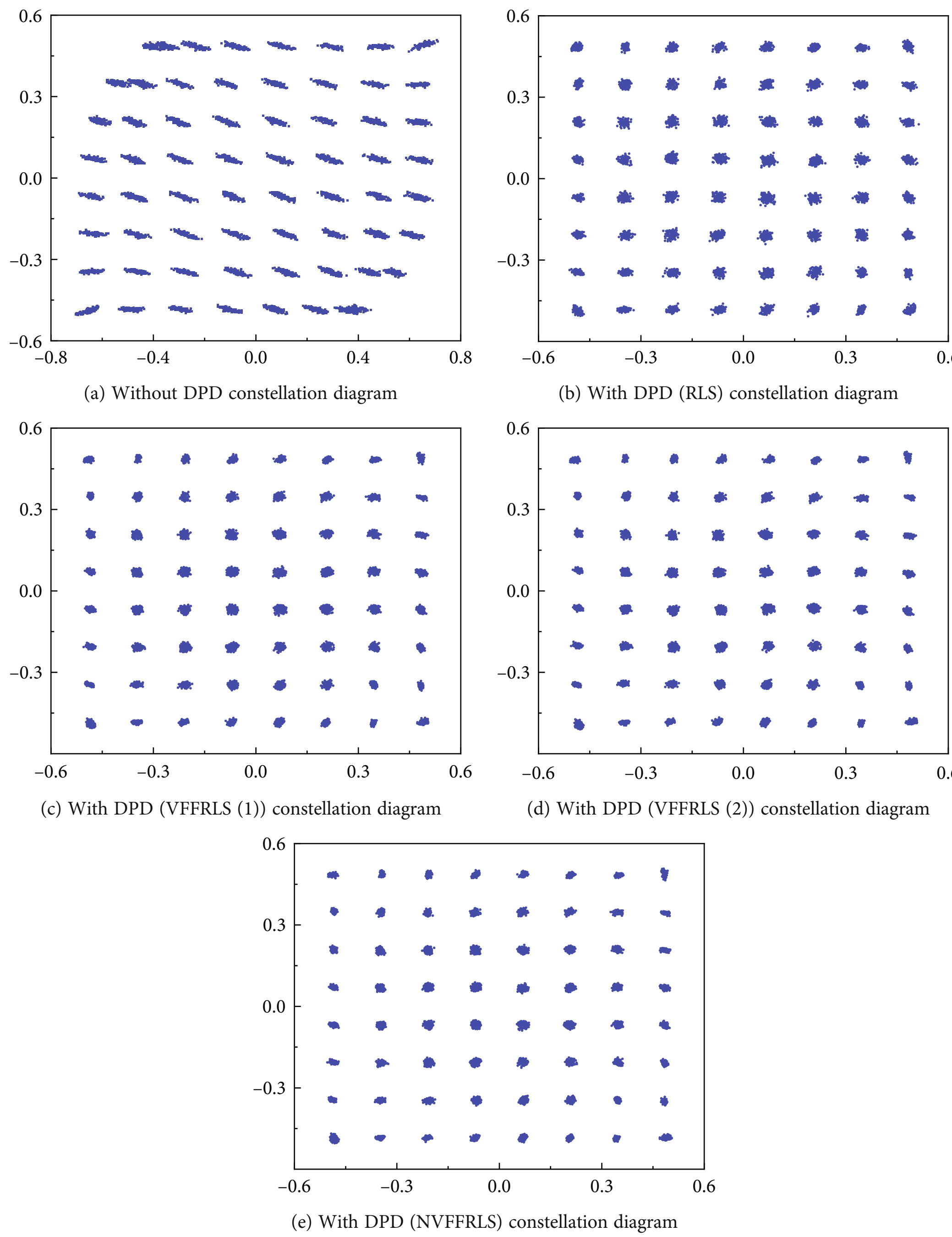
In the experiment of this paper, $C = 1$, $a = 0.43$, and $v = 3$ in the iterative formula of forgetting factor, and the image of correction function of forgetting factor is shown in Figure 4.

As can be seen from the graph, forgetting factor decreases as $|e(n) - e(n-1)|$ increases; i.e., the larger the estimation error, the smaller the value of the forgetting factor.

By comparing four kinds of predistortion evaluation indexes, the correctness of the algorithm is verified.

Table 1: The NMSE of the four algorithms.

Input signal	v/C	RLS/VFFRLS (1)/VFFRLS (2)/NVFFRLS ($K=7$, $Q=3$)			
64-QAM	3/1	-34.66	-40.10	-40.28	-41.36



(a) Without DPD constellation diagram

(b) With DPD (RLS) constellation diagram

(c) With DPD (VFFRLS (1)) constellation diagram

(d) With DPD (VFFRLS (2)) constellation diagram

(e) With DPD (NVFFRLS) constellation diagram

Figure 9: Constellation diagram after predistortion.

Figures 4 and 5 compare the tracking ability and convergence speed of the predistortion identification algorithm under the excitation signals, and the following output signals are all real part of the sampling data.

The legend Xn represents the ideal output of the predistorter training module, and the others are the estimated output of the algorithm. In Figure 4, the tracking ability size of the algorithm is NVFFRLS > VFFRLS (2) > VFFRLS (1) > RLS.

The mean square error function can describe the convergence rate of the function curve. In Figure 6, the order of convergence speed of the estimation errors for the different algorithms is NVFFRLS > VFFRLS (2) > VFFRLS (1) > RLS. In general, the convergence characteristics of NVFFRLS is relatively stable.

Figures 5 and 6 show that RLS, VFFRLS (1), and VFFRLS (2) algorithms have shortcomings in tracking effect and convergence speed. Compared with RLS algorithm, the VFFRLS (1) algorithm has stronger tracking ability and faster convergence speed. Compared with VFFRLS (1) algorithm, the VFFRLS (2) algorithm has more stable tracking ability and better adaptability. The NVFFRLS algorithm is comparable to the other three algorithms in all aspects and has stronger tracking ability and adaptability, faster convergence speed, better stability, and smaller estimation error.

The amplitude-to-amplitude modulation effect (AM-AM) curve and the amplitude-to-phase modulation effect (AM-PM) curve of input and output signals are ways to describe the input and output characteristics of the amplifier and can reflect the memory and nonlinear effects of the amplifier. Ideally, the AM-AM curve is approximately linear, and the AM-PM curve is approximately zero-degree straight line. Figures 7 and 8 compare the AM-PM and AM-AM curves of the amplifier output before and after the processing of the digital predistortion system based on the four identification algorithms, respectively.

The AM-AM curves before predistortion are rather divergent, and increasing the input amplitude results in gain compression, which shows strong nonlinearity. After the predistortion treatment, the AM-AM curves are close to linear. According to the three AM-AM curves after correction, compared with the other three algorithms, the output curve after the predistortion system, which is based on NVFFRLS algorithm, has smaller divergence degree and higher degree of linearization.

Before the predistortion treatment, the AM-PM curves deviated from the zero line. When the input signal amplitude was small, the curves were heavily influenced by the memory effect of the amplifier and were more divergent. Increasing the signal amplitude, the memory effect of the amplifier was clearly weakened, and the divergence of the curve was reduced, but the phase shift increased. After the predistortion treatment, the divergence of AM-PM curve is smaller and closer to linearity, and its nonlinearity and memory effect are weakened. Figure 8 clearly shows that the ability of correcting the phase distortion of the proposed algorithm is stronger than the other three algorithms. The corrected curves based on VFFRLS (1) and VFFRLS (2) algorithms in this image have a large divergence phenomenon, and the correctness of the conclusion of Figure 6 is verified at the same time.

This paper combines a memory polynomial predistortion model with an indirect learning identification structure and uses four adaptive identification algorithms to model. By calculating the NMSE values of different predistortion methods to evaluate the effect of predistortion linearization. The smaller the NMSE value, the better the effect of predistortion linearization. Table 1 gives the NMSE values, which are corrected by the four predistortion systems.

Compared with the other three predistortion systems, the predistortion system NMSE based on NVFFRLS algorithm is smaller and the modeling accuracy is higher. The NMSE of 64-QAM signal was increased by 6.7 dB, 1.26 dB, and 1.08 dB, respectively. The difference of NMSE shows that the proposed NVFFRLS algorithm has better predistortion modeling effect, strong adaptability, and stability. Compared with RLS algorithm, the modeling effect of VFFRLS (2) algorithm is slightly improved, and the modeling accuracy of VFFRLS (1) algorithm is better than RLS algorithm yet inferior to VFFRLS (2) algorithm. The VFFRLS (2) algorithm has significant modeling effect but is second to NVFFRLS algorithm. The NMSE difference shows that the NVFFRLS algorithm has better predistortion modeling effect and stronger adaptability and stability.

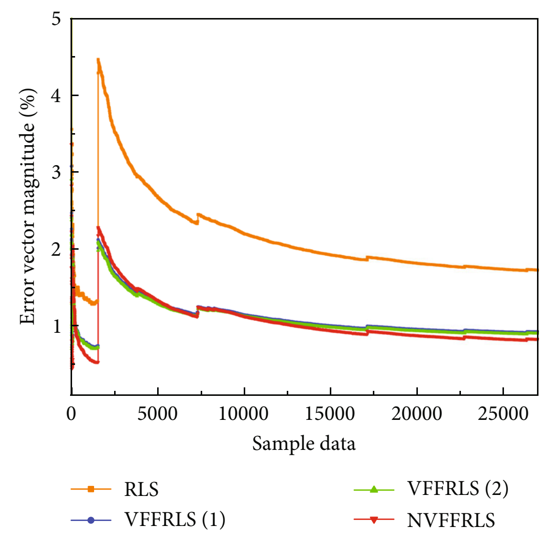


Figure 10: EVM of different algorithms.

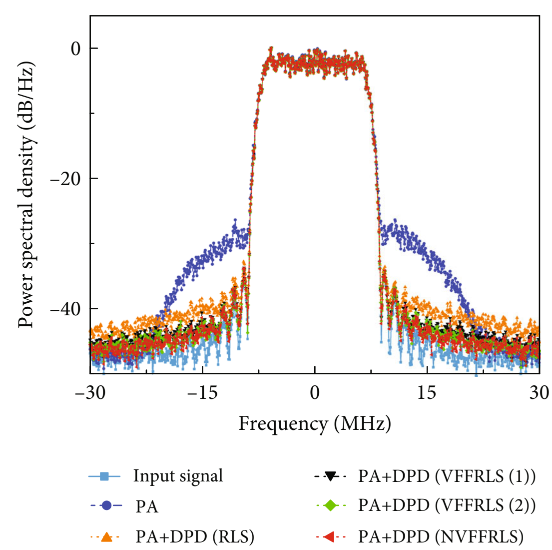
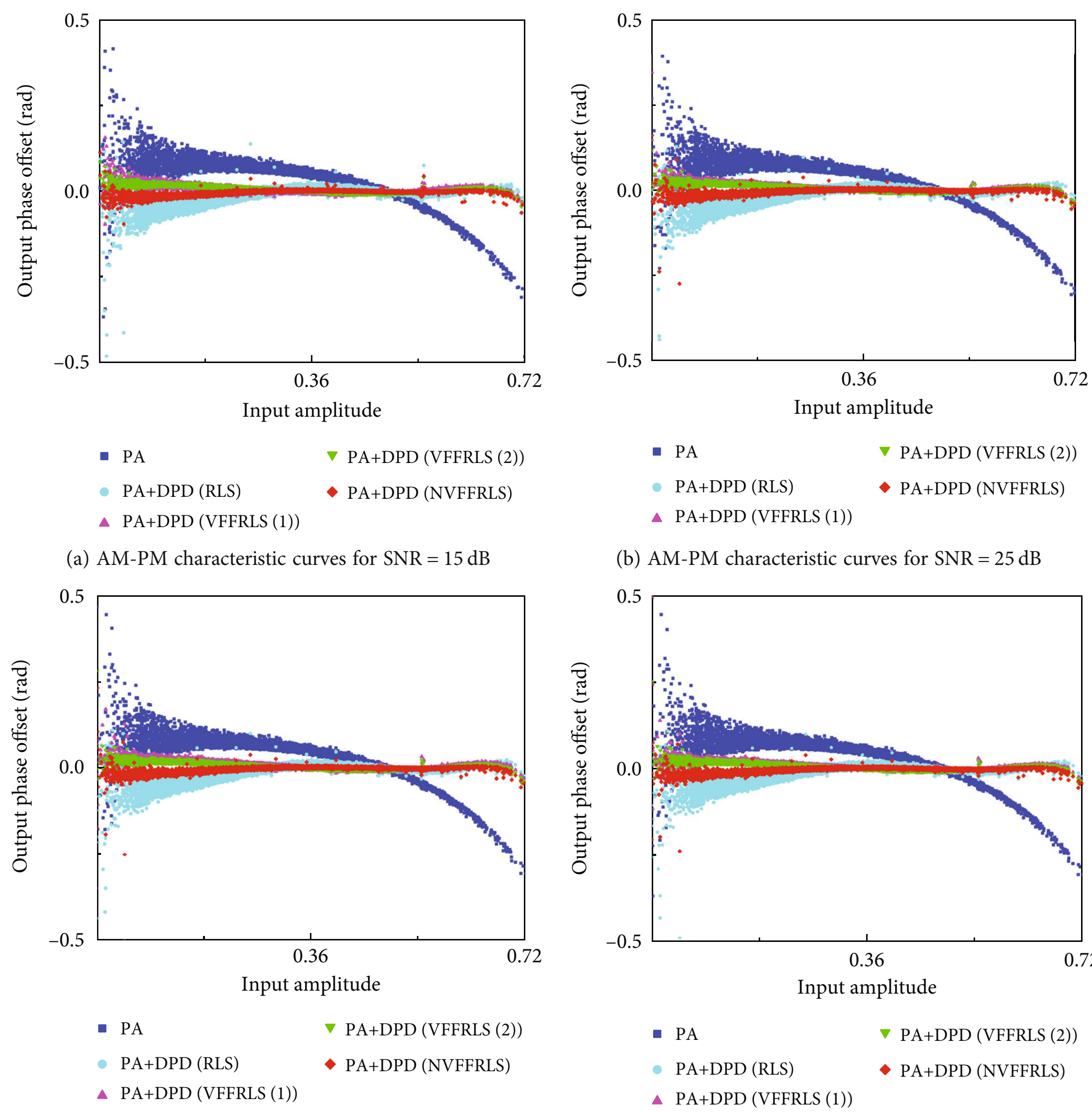


Figure 11: Power spectral densities of different input signals.

In the modulation domain, the effectiveness of the linearization is evaluated by analyzing the degree of convergence of the constellation diagram. The 27,000-point unshaped 64-QAM signal is taken as the input signal. Comparing the

Table 2: Comparison of ACPR under three input signals.

Input signal		RLS/VFFRLS (1)/VFFRLS (2)/NVFFRLS ($K = 7$, $Q = 3$)			
64-QAM	Low	-40.54	-42.34	-42.42	-43.00
	Up	-40.46	-42.13	-42.17	-42.83



(a) AM-PM characteristic curves for SNR = 15 dB

(b) AM-PM characteristic curves for SNR = 25 dB

(c) AM-PM characteristic curves for SNR = 35 dB

(d) AM-PM characteristic curves for SNR = 45 dB

Figure 12: AM-PM characteristics curves for different SNRS.

constellation diagrams processed by the four predistortion systems, the details are shown in Figure 9.

Before the predistortion process, the constellation diagram of the amplifier output is rather scattered, and the sampling point positions are deviated. After the linearization of the predistortion system, the constellation diagram is more neatly arranged. The predistortion system corresponding to NVFFRLS algorithm has the best correction capability, and the linearized constellation diagram is arranged neatly with a smaller degree of divergence. Figure 10 shows the vector errors corresponding to different algorithms.

The vector errors corresponding to RLS, VFFRLS (1), VFFRLS (2), and NVFFRLS are about 1.7236%, 0.9218%, 0.9208%, and 0.7978%, respectively. Compared with RLS, VFFRLS (1), and VFFRLS (2) algorithms, the vector error of NVFFRLS algorithm is increased by about 0.9258%, 0.124%, and 0.123%, respectively, and improves the predistortion effect.

Predistortion can suppress the out-of-band spectrum expansion of the signal and linearize the output of the power amplifier. The power spectral density (PSD) diagram can intuitively describe the effect of predistortion. Figure 11 shows the power spectral density of the input signal, the output signal of the power amplifier, and the output signal of the power amplifier after predistortion.

From Figure 11, it can be seen that the power amplifier improves the ability to suppress out-of-band spectrum expansion after predistortion. After DPD (NVFFRLS) correction, the out-of-band spectral expansion is more significantly suppressed, and the power spectrum is closer to the power spectral characteristics of the input signal. The adjacent channel power ratio (ACPR) characterizes the out-of-band spectrum expansion capability of the system [13]. Table 2 lists the ACPR (dB) values after four predistortion treatments.

The VFFRLS (1) algorithm is used to realize predistortion, which can effectively suppress the out-of-band spectrum expansion. The effect is better than the RLS algorithm. Based on the value of ACPR, when VFFRLS (2) algorithm is used to realize predistortion, the effect of suppressing out-of-band spectrum expansion is better than VFFRLS (1), but inferior to NVFFRLS algorithm. Compared with the DPD (RLS) system, the ACPR value corrected by the DPD (NVFFRLS) system is improved by 2.46 dB at most.

When using RLS identification algorithm for parameter identification, it is easy to be interfered by measurement noise, which leads to deviation of parameter identification results and makes the data processing effect worse. In this paper, the antinoise performance of different identification algorithms is analyzed by using additive Gaussian white noise with amplitude distribution obeying Gaussian distribution and power spectral density uniformly distributed. Figure 12 shows the AM-PM characteristic curves of the system under different SNR.

When the SNR = 15 dB, the AM-PM characteristic curves processed by the RLS algorithm are more divergent, especially when the input amplitude is around 0 and 0.7. The divergence of the VFFRLS (1) algorithm is greater than that of VFFRLS (2), and the proposed NVFFRLS algorithm has the best processing effect. The VFFRLS (1) and VFFRLS (2) algorithms gradually weaken the divergence of output characteristic curve with the increase of random noise signal-to-noise ratio, and the processing effect is still better than RLS algorithm. With the increase of SNR, the degree of divergence of the curve decreases. Compared with VFFRLS (1), the output characteristic curve of VFFRLS (2) algorithm diverges less and has better linearization effect.

Among the four figures, the NVFFRLS algorithm has the best processing effect, and the AM-PM characteristic curve after processing is closer to linear. It can be seen from the Figures 12(a)–12(d) that the AM-PM characteristics curves gradually obtained stabilization. When the SNR is greater than 35 dB, the output phase offset of NVFFRLS is closer to 0. Therefore, the proposed algorithm can have good processing results at a SNR of only 35.

The conclusion of Figure 12 shows that RLS algorithm is susceptible to noise interference, and NVFFRLS algorithm proposed in this paper improves the antinoise performance of the algorithm due to the introduction of estimation error related term and its identification result has smaller deviation.

5. Conclusion

Based on RLS algorithm, a new variable forgetting factor NVFFRLS algorithm is proposed and applied to the predistortion system. The test uses three common input signals and combines the MP predistorter model with the indirect learning system discrimination structure and uses the RLS, VFFRLS (1), VFFRLS (2), and NVFFRLS algorithms to extract the predistorter model coefficients. Experimental results show that, compared with the predistortion system based on RLS, VFFRLS (1), and VFFRLS (2) algorithms, the improved algorithm has smaller estimation error, stronger tracking ability and adaptability, better numerical stability, and faster convergence speed, and the NVFFRLS algorithm is used to implement the predistortion system, which has better effect of correcting nonlinearity and memory effects of power amplifier, smaller vector error of processed constellation diagram, and stronger ability to suppress out-of-band spectrum of power amplifier. The predistortion system based on NVFFRLS algorithm has lower ACPR and EVM than the RLS system, and its ACPR and EVM are improved by 2.46 dB and 0.9258% severally. The forgetting factor of NVFFRLS algorithm includes the estimation error term; it has lesser sensitivity to noise, better antinoise performance, and better practical engineering application value.

Data Availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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