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Nonlinear estimation for 60GHz millimeter-wave radar system based on Bayesian particle filtering

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Abstract

In the 60GHz millimeter-wave radar communication systems, the nonlinear power amplifier is inevitable. In order to combat this problem, a promising estimation algorithm based on the particle filtering (PF) is presented here. By employing the conception of Bayesian approximation and sequential importance sampling, this appealing Monte Carlo random sampling method can address this complicated statistic estimation problem. In sharp contrast to the classical linear equalization problem, nevertheless, in the considered situation the PF-based method may become invalid due to the hardware nonlinearity and the resulting non-analytical importance function. To remedy this difficulty, based on the linearization technique a novel PF framework is suggested, and we show in particular how to linearize the involved nonlinearity transform in the formulated discrete dynamic state-space modeling (DSM). The merit of this method is that it can efficiently deal with discrete DSMs that are practically nonlinear and non-Gaussian. Experimental simulations verify the superior performance of our presented PF-based detection scheme, which may properly be applied to 60GHz millimeter-wave radar communication systems.

Keywords: 60GHz millimeter-wave communication radar systems, PA nonlinearity, Particle filtering, Taylor series, Linearization technique

1. Introduction

Because of large bandwidth, small size, high-resolution, and all-weather characteristics, 60GHz millimeter-wave radar has widely been used in many fields such as military communication systems and civilian communication. The most common types of 60GHz millimeter-wave radars include anti-collision radar and 60GHz Quadrature Doppler radar [1].

With the growing demand for high-speed wireless transmissions, 60GHz millimeter-wave communication has attracted an increasing amount of interests over the past few years as an effective method of gaining high-speed data rate [2]. In the 60GHz millimeter-wave radar communication, in order to achieve the ultra-high data rate with the regulated transmission bandwidth, high-order modulations have widely been adopted to make efficient use of the spectrum. Two of the most common high-order modulations are QPSK and 16QAM [3,4].

The absorption from oxygen is most obvious in 60GHz band, and therefore, the significant path-loss may have adverse effects on the transmission quality. To compete against the negative effects, high emission power is usually indispensable in 60GHz millimeter-wave communication. Thus, the resulting high peak-to-average power ratio may pose great challenges to the design of radio components. Unfortunately, it seems that the nonlinear characteristics of power amplifier are practically inevitable for 60GHz millimeter-wave radar devices [5]. As a consequence, it is recognized that there is serious distortion in emission signals which may significant increase the bit error ratio (BER) in receiver. To sum up, improving the performance of signal detections in 60GHz millimeter-wave radar communication in the presence of nonlinear power amplifier remains as a significant challenge and has become one of the major concerns in practice.

Currently, there are two commonly used methods for overcoming the nonlinearity of 60GHz millimeter-wave radar systems. One approach is to simply reduce the radiation power, and apparently the basic idea of this approach is to alleviate the nonlinear distortions directly

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[6]. An important advantage of this method is that it is easy to implement. Unfortunately, such an output power back-off (OBO) method, however, may directly result in the decline of the signal-to-noise ratio (SNR) in receiver. Another compensation approach can be summarized as a variety of linearization techniques [7,8]. The deficiency of these techniques is that the complexity is extraordinary and at the same time, the hardware realization is impractical.

In this article, relying on the Bayesian statistical inference and sequential importance sampling (SIS) technique [9,10], we propose a novel signal detection algorithm for 60GHz millimeter-wave radar communication to effectively address the involved nonlinearity distortion.

The SIS method aims essentially to establish a Monte Carlo (MC) numerical representation of the desired probability distribution which may be too complicated to derive the analytic expression, which primarily consists of a group of discrete particles and the associated weights [11,12]. Then, these particles and associated weights will be recursively updated, which can then be used to numerically approximate the desired probability distribution [9]. In other words, the discrete particles with their importance weights will provide the Bayesian estimates of the input signal sequence. In this investigation, we apply the SIS method to the signal estimation in 60GHz millimeter-wave radar communication systems in the presence of nonlinear distortion. First, in order to derive the practically feasible importance function (or the related likelihood function) by taking the complex nonlinear transform, we introduce the first-order Taylor expansion and develop a new representative dynamic state-space modeling (DSM) system via the local linearization technique.

Therefore, the involved importance function can conveniently be obtained. And on this basis, the signal detection with nonlinear distortion is realized by resorting to the particle filtering (PF) technique [13]. The experimental simulations are finally provided, which may essentially demonstrate that our suggested method can effectively solve the nonlinear estimation, and hence provide a promising solution to the emerging problem of 60GHz millimeter-wave radar communication systems.

The merits of our proposed algorithm could be summarized into twofold. First, the new method has the characteristic of real-time process. More specifically, the output estimation could be prepared in time as the new observation arrives without the sequential parameter learning. Second, this approach can significantly reduce the complexity and cost of the hardware. For these reasons, the presented detection algorithm could widely be applied in practice.

The remainder of this article is organized as follows. Section 2 provides a model of considered nonlinear 60GHz millimeter-wave radar communication systems, i.e., the received signals are seriously distorted by a power amplifier. In Section 3, we briefly review the PF algorithm and provide computational details for implementing the method in blind estimation. In Section 4, we propose a novel PF method based on the Taylor expansion which is utilized to linearize the nonlinear model. Computer simulations are provided in Section 5. Finally, conclusions are presented in Section 6.

2. Nonlinear system model

2.1. Nonlinear power amplification

In practice, the power amplification procedure at the transmitter end will inevitably introduce the nonlinear distortion due to hardware imperfections. As a consequence, both amplitude and phase of the output signal in receiver will sharply be distorted, and hence the serious detection error will occur by remarkably degrading the transmission performance. The effects of PA nonlinear include the distortion generated by amplitude modulation–amplitude modulation (AM–AM) conversion and AM–phase modulation (AM–PM) conversion. In this article, the nonlinear PA model regulated by IEEE 802.11ad task group (TG) is adopted [4].

More specifically, the AM–AM model is expressed as follows:

$$G(V_{in}) = \frac{gV_{in}}{\left(1 + (gV_{in}/V_{sat})^{2\sigma_s}\right)^{\frac{1}{2\sigma_s}}}, \tag{1}$$

where V_{in} and $G(V_{\text{in}})$ represent the input and output voltage amplitude range in root mean square; g denotes the linear gain and we practically set g = 4.65; σ_s is the smoothness factor and σ_s = 0.81; V_{sat} is the saturation level and is considered to be 0.58 V.

The AM–PM model is given by

$$\Psi(V_{in}) = \frac{\alpha {V_{in}}^{q_1}}{1 + (V_{in}/\beta)^{q_2}}, \tag{2}$$

where Ψ (V_{in}) is the additional phase in degrees. The values of α, β, q_1, and q_2 are set to be 2560, 0.114, 2.4, and 2.3, respectively. For the convenience of analysis, we assume a set (G, Ψ) = $[g, \sigma_s, V_{sat}, \alpha, \beta, q_1, q_2]$ consist of the associative parameters which can denote the AM–AM and AM–PM models.

Figure 1 depicts the curves of AM–AM and AM–PM models given output saturation voltage of V_{sat}. We can ignore the amplitude distortion and phase distortion when the amplitude of input is less than 0.1 V. But when the input signal amplitude is greater than 0.1 V, the amplifier will work in nonlinear region; this may result in severe nonlinear distortion, and therefore the performance of the receiver signal will deteriorate seriously.

In order to alleviate the unflavored effects from the inevitable nonlinear distortion, a simple solution but not

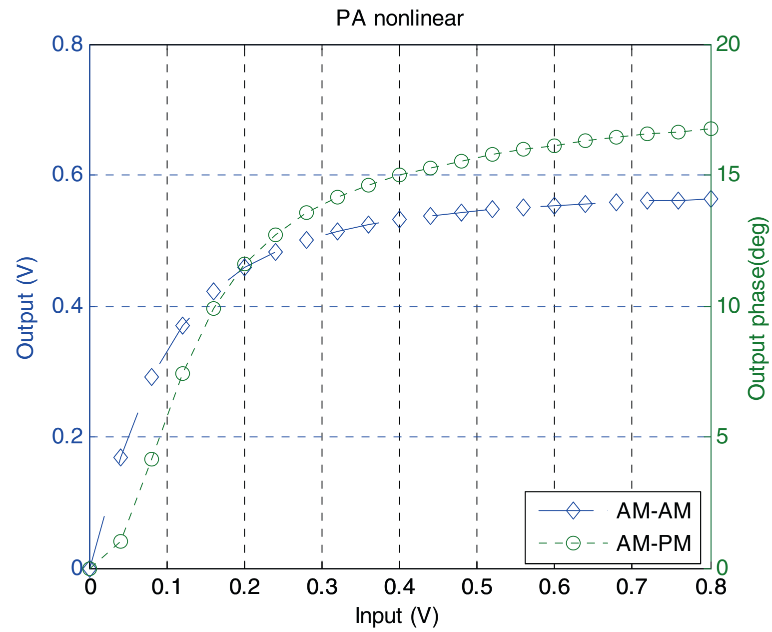

Figure 1 IEEE 802.11ad PA model.

significant approach is to adopt the OBO mechanism. Back-off power is usually defined as

$$R_{backoff} = 10\log_{10}(P_{sat}/P_{in}), \tag{3}$$

where P_{sat} is the output saturation power, P_{in} is the input power, and $R_{backoff}$ is the power back-off value in dB. Obviously, the greater back-off value means the smaller the output power, and the smaller the output power means the smaller the nonlinear distortion. More specifically, the nonlinear distortion may partly be alleviated by reducing the input power P_{in}. Unfortunately, lower transmit power will lead to the lower SNR, this will result in decreasing anti-jamming capability. At the same time, the performance of amplifier devices may greatly be deteriorated. Therefore, the power back-off mechanism can only avoid the negative effects of nonlinear distortion in a certain extent, but fail to effectively improve the system performance under the nonlinear device. It is difficult to be adopted widely in the practical design.

2.2. Signal model

The transmitter-end block diagram of nonlinear communication system considered in this study has been illustrated in Figure 2. For the convenience of analysis, we assume that the wireless propagation channel to be single-path with additive white Gaussian noise (AWGN). However, from our later formulation, it still may be straightforward to extend to multi-path propagation.

The transmitter-end operates as follows. In the beginning, the binary source sequence $\{b_i\}$ (i = 0,1,2,. . .) is sequentially fed into an M-order linear modulator (such as M-PSK or M-QAM). Subsequently, the modulated data symbols $\{x_k\}$ (k = 0,1,2,. . .) are passed though a front-end nonlinear PA, and after this process, we can get the emitted symbols $\{x_k^\dagger\}$ whose voltage amplitudes and phases are seriously distorted. Finally, the emission symbols are propagated through single-path channel with AWGN.

It is noteworthy that, although we mainly consider the single-path Gaussian propagation senior in this article, we may still adopt an extended multi-path model in

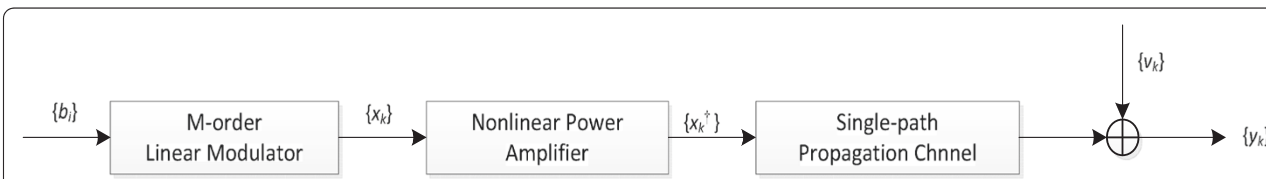

Figure 2 Transmitter-end block diagram.

order to conveniently formulate the dynamic system model in (5) and (6), i.e., this memory model may be always necessary when considering the applications of PF to the specific nonlinear estimation problem. And hence, the generalization to the realistic multi-path channel is also practically feasible. Thus, the observed signals denoted by $\{y_k\}$ (k = 0,1,2,. . .) at the receiving end can be given by

$$\begin{aligned} y_k &= \mathbf{h}^H \mathbf{x}_k^\dagger + \nu_k \\ &= \sum_{l=0}^{L-1} h_l x_{k-l}^\dagger + \nu_k \\ &= \sum_{l=0}^{L-1} h_l g(x_{k-l}) + \nu_k, \quad k = 0, 1, \ldots, K-1 \end{aligned} \tag{4}$$

where L denotes the length of the communication channel impulse response. The complex symbol x_k is a high-order modulated uniform random variable, i.e., $x_k \in \{A\}$, k = 0,1,2,. . ., and it is independent from the obvious and future symbols. In practice, we set the prior probability of each transmitted symbol equal. And ν_k represents the noise value at time k, whereas it is an AWGN process with zero mean and variance σ^2, i.e., $\nu_k \sim N(0, \sigma^2)$. The coefficient of channel $\mathbf{h}$ is assumed to be invariant and follow the Gaussian distribution with the mean vector of $\overline{\mathbf{h}}$ and the covariance matrix Σ, i.e., $\boldsymbol{h} \sim N(\overline{\boldsymbol{h}}, \Sigma)$, whereas, it can conveniently be represented by the $L \times 1$ vector, $\mathbf{h} = [h_0, h_1, \ldots, h_{L-1}]^T$.

Based on the consideration above, the DSM model can be expressed as follows [14]

$$\mathbf{x}_k = \mathbf{T}\mathbf{x}_{k-1} + \mathbf{u}_k \tag{5}$$

$$y_k = \mathbf{h}^H g(\mathbf{x}_k) + \nu_k \tag{6}$$

Equation (5) is usually referred as to the state equation, which essentially describes the evolution process of the hidden state x_k [14]. Correspondingly, $\mathbf{u}_k = [0,0,\ldots,x_k]^T$ is an $L \times 1$ vector, $\mathbf{T}$ is the $L \times L$ state-transition matrix.

$$\mathbf{T}_{L\times L} = \begin{pmatrix} 0\ 1\ 0 \cdots 0 \\ 0\ 0\ 1 \cdots 0 \\ \vdots\ \vdots\ \vdots \ddots \vdots \\ 0\ 0\ 0 \cdots 1 \\ 0\ 0\ 0 \cdots 0 \end{pmatrix}$$

Equation (6) is the observation equation, which gives the relationship between the received (or observed) signal y_k and the hidden (or unobserved) state x_k. The nonlinear transform $g(.)$ specifies the mapping between the input signal and output signal of the nonlinear power amplifier.

It should be noted that the focus of this study is the single-path Gaussian propagation channel, so we should make choice of the value of $\overline{\mathbf{h}}$ and Σ with the purpose that let the generated channel $\mathbf{h}$ approach single-path. For this reason, under the nonlinear distortion we may simplify the observation model (6) into (7).

$$y_k = g(x_k) + \nu_k, \quad \nu_k \sim N(0, \sigma^2) \tag{7}$$

Also, in the formulated model above, the propagation channel is assumed to be time-invariant and the gain is normalized to 1.

3. PF

3.1. Bayesian inference

According to the model given in Equation (6), assume that the coefficient of single-path channel $\mathbf{h}$ is known but the transmitted symbols $\{x_{0:K}\}$ are unknown. From a Bayesian perspective, the optimal signal detection can be achieved by MAP detection of the transmitted $x_{0:K}$, based on the observed sequence $y_{0:K}$. The aim of this study is to compute the MAP estimate of state symbols $\{x_{0:K}\}$ based on the observed symbols$\{y_{0:K}\}$ and the coefficient of channel $\mathbf{h}$. The MAP estimate of the transmitted symbols is given by

$$\hat{x}_{0:K}^{(MAP)} := \underset{x_{0:K}}{\arg\max} \{p[x_{0:k}|y_{0:k}, \mathbf{h}, (G, \Psi)]\} \tag{8}$$

In order to simplify the computation, we can solve this problem sequentially and recursively. More specifically, we can calculate the $x_{0:k}^{(\mathrm{MAP})}$ from $x_{0:k-1}^{(\mathrm{MAP})}$ when the recent observation y_k is received. The posterior probability mass function (pmf) is shown as follows [15]

$$\begin{aligned} p(x_{0:k}|y_{0:k}, \mathbf{h}, (G, \Psi)) &\propto p(y_k|x_{0:k}, y_{0:k-1}, \mathbf{h}, (G, \Psi)) \\ &\times p(x_{0:k-1}|y_{0:k-1}, \mathbf{h}, (G, \Psi)) \end{aligned} \tag{9}$$

Unfortunately, the involved posterior distribution of interest above is often analytically intractable and hard to derive in practice. More specifically, because of the high-dimensional marginalization integration and the nonlinear process, we have to resort to the approximation method.

3.2. Blind estimation using the SIS

As an important expansion of Kalman filtering, the PF method shows great promise to blind nonlinear equalization in 60GHz millimeter-wave communication. With PF, continuous distribution could be approximated by discrete random measures. In the implementation of the PF, SIS plays a crucial role. Relying on the MC method and discrete numerical approximation approach, SIS could deal with many complicated statistic estimations. In this section, we mainly focus on the SIS algorithm and the re-sampling approach which can combat the degeneracy of particles.

Based on the idea of sequential and recursive estimation, we can achieve real-time detection via SIS, which is regarded as the extension of importance sampling (IS). According to the SIS algorithm, we may build the state trajectories and compute the importance weights sequentially. More specifically, SIS could obtain the estimation of target probability via particles $x^{(i)}$ with associated weights $\widetilde{w}^{(i)}$ (i = 1,2,. . .,N). On this basis, the MAP estimation (8) could be drawn and marginal data detection at time k are given by [14]

$$\hat{x}_{0:K}^{(MAP)} := \underset{x\in\{\mathbb{A}\}}{\arg\max}\left\{\sum_{i=1}^{N}\delta\left(x_k - x_k^{(i)}\right)w_k^{(i)}\right\} \tag{10}$$

Here, N represents the total number of particles at the same sampling time. δ = 1 if $\mathbf{x}_{0:k} = \mathbf{x}_{0:k}^{(i)}$ and δ = 0 otherwise.

We begin SIS algorithm by drawing N particles from posterior pmf $p(x_{0:k}|y_{0:k},\mathbf{h},(G,\Psi))$. In practice, it is usually intractable to sample directly from the target distribution $p(x_{0:k}|y_{0:k},\mathbf{h},(G,\Psi))$, so we design an important distribution $\pi(x_{0:k}|y_{0:k},\mathbf{h},(G,\Psi))$ from which the particles are more easily to drawn. The design of the important distribution is a critical step in PF, and it varies according to the actual situation. We will present the important distribution adopted in Section 4.

With the particles sequentially sampled from the importance function as each new observation arrives, the importance weights can be computed recursively in time as follow [16]:

$$\widetilde{w}_k^{(i)} = \widetilde{w}_{k-1}^{(i)}\frac{p\left(y_k|x_{0:k}^{(i)}, y_{0:k-1}, \mathbf{h}, (G,\Psi)\right)}{\pi\left(x_k^{(i)}|x_{0:k-1}^{(i)}, y_{0:k}, \mathbf{h}, (G,\Psi)\right)}, \tag{11}$$

where $\widetilde{w}^{(i)}$ is a set of importance weights. After this step completed, normalize the importance weights using (12):

$$w_k^{(i)} = \frac{\widetilde{w}_k^{(i)}}{\sum_{i=1}^{N}\widetilde{w}_k^{(i)}} \tag{12}$$

Unfortunately, as has been illustrated by most investigations and noted from (10), the degeneracy of SIS algorithm is usually inevitable, which is referred to the decrease of importance weights over time. Along with a consequence of weight degeneracy, the approximation of posterior probability may seriously deteriorate and even become useless. An efficient approach to alleviate this difficulty is to conduct a re-sampling procedure in the SIS algorithm. The basic idea of such method is to eliminate particles with small normalized importance weight while concentrating upon those particles having larger normalized importance weight.

A suitable measure to the serious degeneracy can be estimated from

$$N_{eff} = \frac{1}{\sum_{i=1}^{n}\left(w_k^{(i)}\right)^2} \tag{13}$$

Thus, in practice, when N_{eff} is below a fixed threshold, the re-sampling procedure is used.

Bayesian signal detection

In this section, we will address the problem of designing the optimal importance function which could be adopted in this nonlinear communication system relying on the local linearization technique. In addition, the implementations of nonlinear equalization are presented.

4.1. PF with local linearization

Because we mainly consider the single-path Gaussian propagation under the nonlinear distortion in this study, we could adopt model (7) to represent the system observations. In order to derive the feasible importance function with the complex nonlinear transform, by performing a Taylor expansion up to first-order of the observation equation at the point $x_k = x_k^*$, we may further get

$$\begin{aligned} y_k &= g(x_k) + v_k \\ &\simeq g\left(x_k^*\right) + \frac{\partial g(x_k)}{\partial x_k}\Big|_{x_k=x_k^*}\left(x_k - x_k^*\right) + v_k, \end{aligned} \tag{14}$$

where x_k^* represents the hypothetical signal with known value, which can be drawn from the finite alphabet of modulated symbols. It is conveniently to calculate the optimal importance function $\pi(x_k|x_{0:k-1}^{(i)},y_{0:k},\mathbf{h},(G,\Psi))$ with mean m_* and covariance Σ_* which could be evaluated for each trajectory using the following formula

$$\begin{aligned} &\pi(x_k|x_{0:k-1}^{(i)}, y_{0:k}, \mathbf{h}, (G,\Psi)) \\ &\triangleq p(\mathsf{x}_k|\mathsf{x}_{0:k-1}^{(i)}, \mathsf{y}_{0:k}, \mathbf{h}, (G,\Psi)) \sim \mathsf{N}(\mathsf{m}_*, \Sigma_*) \end{aligned} \tag{15}$$

Here, the variance Σ_* could be calculated by

$$\Sigma_*^{-1} = \frac{1}{\sigma^2}\times\left[\frac{\partial g(x_k)}{\partial x_k}\Bigg|_{x_k = x_k^*}\right]^T \frac{\partial g(x_k)}{\partial x_k}\Bigg|_{x_k=x_k^*} \tag{16}$$

and the mean m_* is given by

$$m_* = \frac{\Sigma_*}{\sigma^2}\times\left[\frac{\partial g(x_k)}{\partial x_k}\Bigg|_{x_k = x_k^*}\right]^H\left[y_k - g\left(x_k^*\right) + \frac{\partial g(x_k)}{\partial x_k}\Bigg|_{x_k = x_k^*} X_k^*\right] \tag{17}$$

Thus, after sampling from the importance function $\pi(x_k|x_{0:k-1}^{(i)},y_{0:k},\mathbf{h},(G,\Psi))$, we may get the particles $\{x_k^{(i)}\}$ at time k, and then send these particles to the power amplifier and get new particles $\{x_k^{(i)}\}$whose voltage amplitude and phase are distortional.

After the process of IS, updating the associated weights of the discrete particles should be carried out, the main idea of weight update over nonlinear channel is same as the method over linear system, so the normalized importance weights can be evaluated from (11) and the probability distribution function (pdf) $p(y_k|x_{0:k}^{(i)},y_{0:k-1},\mathbf{h},(G,\Psi))$can be expressed for likelihood [9,15], shown in (18)

$$p\left(y_k|x_{0:k}^{(i)},y_{0:k-1},\mathbf{h},(G,\Psi)\right)=\frac{1}{\sqrt{2\pi\left(\mathbf{x}_k^{(i)T}\Sigma\mathbf{x}_k^{(i)}+\sigma^2\right)}}\times\exp\left\{-\frac{\left[y_k-\mathbf{h}^H g\left(\mathbf{x}_k^{(i)}\right)\right]^2}{2\left(\mathbf{x}_k^{(i)T}\Sigma\mathbf{x}_k^{(i)}+\sigma^2\right)}\right\}, \tag{18}$$

where $\mathbf{\Sigma}$ is the initial covariance matrix of channel and $\mathbf{x}_k^{(i)}$ is an $L \times 1$ vector contained by particles at time $k - 2$, $k - 1$, and k in the same trajectory i. It is important to note that $\mathbf{h}$ represents the single-path channel, so the value of $\mathbf{h}$ is approximated to be $[1\ 0\ 0]^T$.

Notice that, Equation (18) indicates that the likelihood function follows a Gaussian distribution, i.e., $p\left(y_k\middle|x_{0:k}^{(i)},y_{0:k-1},\mathbf{h},(G,\Psi)\right)\sim N\left(m_k^{(i)},\sigma_k^{(i)2}\right)$, with its mean and variance calculated from

$$m_k^{(i)}=\mathbf{h}^H g\left(\mathbf{x}_k^{(i)}\right) \tag{19}$$

$$\sigma_k^{(i)2}=\mathbf{x}_k^{(i)T}\Sigma\mathbf{x}_k^{(i)}+\sigma^2 \tag{20}$$

Relying on the likelihood function above, the associated weights of the new particles can be updated by using

$$\widetilde{w}_k^{(i)}\propto\frac{1}{\sqrt{2\pi}\sigma_k^{(\mathrm{i})}}\exp\left[-\frac{\left(y_k-m_k^{(i)}\right)^2}{2\sigma_k^{(i)2}}\right]\times\widetilde{\mathrm{w}}_{\mathrm{k}-1}^{(\mathrm{i})} \tag{21}$$

Then, use Equation (12) to normalize the associated weights into $w_k^{(i)}$.

Up to now, the discrete random measures $\{x_k^{(i)},\ w_k^{(i)}\}$ have been derived, so the MAP criterion should be carried on to get the estimated symbols.

4.2. Implementations

Based on the elaborations above, the Bayesian nonlinear detection algorithm comes in its fullness. At the receiving end, we may simulate the blind signal detection of nonlinear communication systems in the presence of nonlinear distortions in the following four steps:

for $k = 0{:}K - 1$

1 Draw N particles from the importance function $\pi(x_k|x_{0:k-1}^{(\mathrm{i})},y_{0:k},\mathrm{h},(G,\Psi)) \sim N(m_*, \Sigma_*)$, and feed these particles into the nonlinear power amplifier.
2 Compute importance weight of each particle according to (18) and (21), then normalize the weight.
3 Re-sample in accordance with (13).
4 Use the method of MAP estimate (10) to calculate the transmitted symbols.

end for

5. Computer simulation

In this article, we focus on a scenario of a time-invariant nonlinear channel with an impulse response with the extended length $L = 3$. We assumed a Gaussian prior for the channel coefficients, $\mathbf{h}\sim N\left(\overline{\mathbf{h}},\Sigma\right)$. The channel mean is assumed to $\overline{\mathbf{h}}=[1\ \ 0\ \ 0]$ and the covariance matrix is $\Sigma = \mathrm{diag}\{\delta\ \delta\ \delta\}$ with $\delta = 10^{-10}$. The main reason for this configuration is that it could practically approximate a single-path channel. In our experiment, the transmitted signals $\{b_i\}$ were modulated to $\{x_k\}$ by using 16QAM and QPSK schemes, respectively, and the *prior* distribution of $\{x_k\}$ is assumed known.

First, we compare the existing PF algorithm proposed for linear estimation problems and the new algorithm developed in this article. Because of the infeasible importance function, the estimation performance of the traditional algorithm will apparently be degraded when dealing with the nonlinear communication. From the simulation results in Figure 3, with the high-order modulation 16QAM, it is clear to see that the developed new approach shows the better performance, and the new algorithm can solve the problem of BER floor which is caused by lower power back-off in the presence of nonlinear distortion. Hence, the superiority of this suggested approach in dealing with nonlinear 60GHz millimeter-wave communication systems is rather obvious. In addition, from Figure 4 we may see in a clear logical way that the new algorithm shows better performance for the QPSK modulation likewise. For example, under the same condition of OBO value 12 dB, the desired SNR of new algorithm and traditional method is 5 and 7 dB, respectively, when the BER drops below 10^{-2}.

Then, we have plotted the BER curves of different value of the OBO which are derived from the MC simulation in Figures 5 and 6. The BER performance

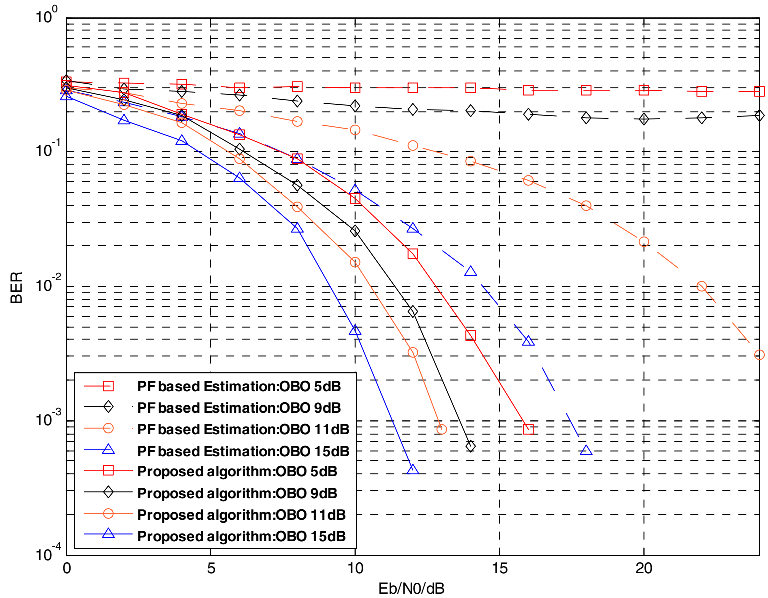

Figure 3 **Performance evaluations between the classical PF-based linear equalization and the developed nonlinear estimation method with 16QAM modulation.**

demonstrates that the smaller the output power is, the smaller the nonlinear distortion is produced. When the output power is small enough, the BER curve of PF becomes much close to the theoretical AWGN curve with linear PA. Besides, we may note that even if the OBO is 0 dB, the distorted signals could be estimated accurately as long as the SNR is large enough.

6. Conclusions

In this article, we have designed an effective estimation algorithm, which can conveniently be implemented in receiver-end, for nonlinear 60GHz millimeter-wave radar communication systems based on Bayesian inference. This algorithm is implemented by SIS and Taylor expansion. One of the main features of our

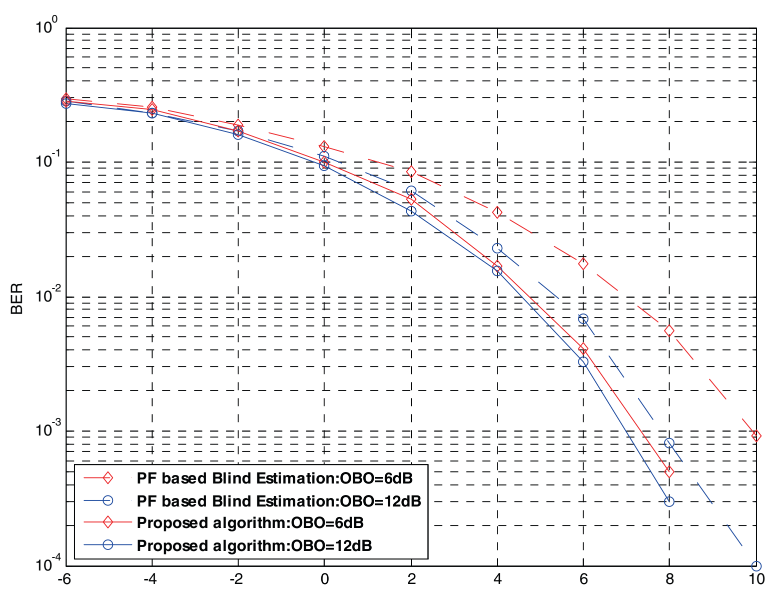

Figure 4 **Performance evaluations between the classical PF-based linear equalization and the developed nonlinear estimation method with QPSK modulation.**

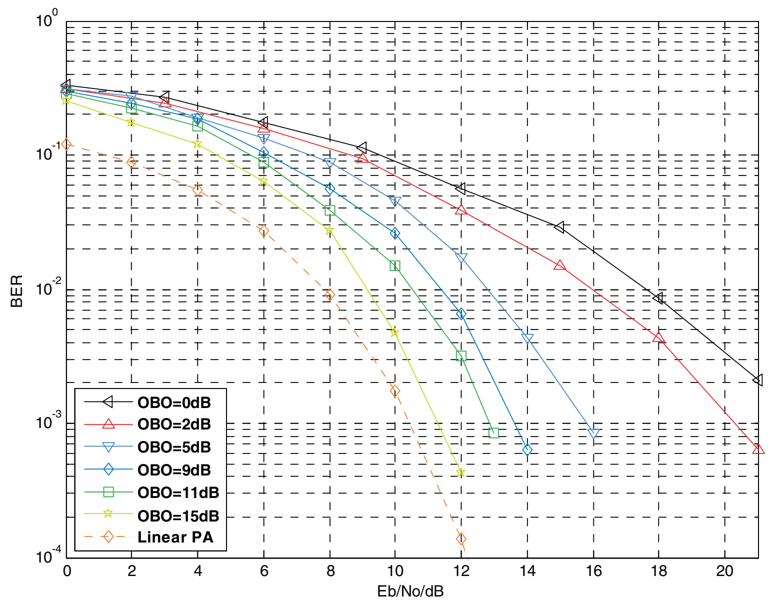

Figure 5 Detection performance of 16QAM modulation with different OBO values.

proposed estimator is that, as a promising solution to address nonlinear estimations, the first-order Taylor expansion is used to approach the involved nonlinear transform, and the associated weight is then recursively computed for each data trajectory in PF. The advantage of this method is its capability to estimate transmitted symbols sequentially and timely without a training sequence, even in the presence of nonlinear distortions due to hardware imperfections. As is shown by the experimental results, the combination of PF with Taylor expansion can effectively combat the nonlinearity distortion in the 60GHz millimeter-wave radar communication systems, which may hence provide a competitive solution to the practical design of 60GHz millimeter-wave communication and other radar communication systems.

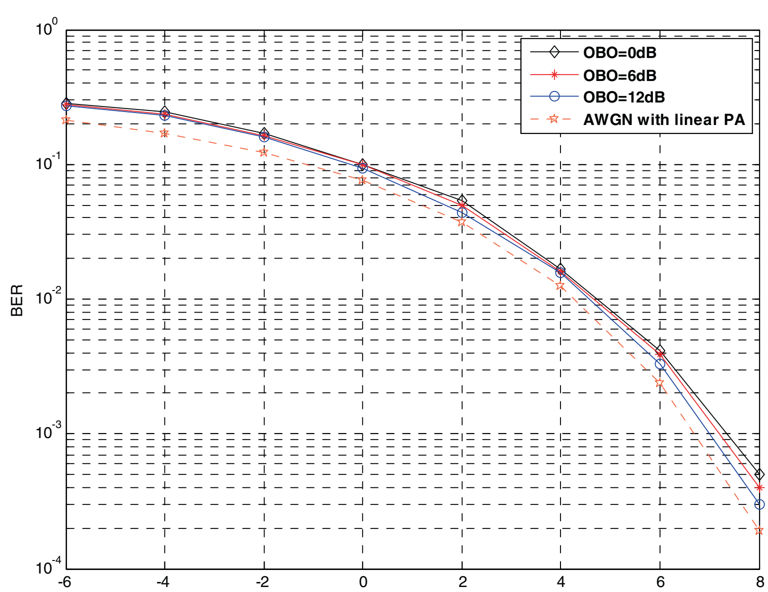

Figure 6 Detection performance of QPSK modulation with different OBO values.

Competing interests
The authors declare that they have no competing interests.

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