PAPER

# Simulation of Radar Sea Clutter in Correlated Generalized Compound Distribution Based on Improved ZMNL

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**SUMMARY** In modern radar systems, the Generalized compound distribution model is more suitable for describing the amplitude distribution characteristics of radar sea clutter. Accurately and efficiently simulating sea clutter has important practical significance for radar signal processing and sea surface target detection. However, in traditional zero memory nonlinearity (ZMNL) method, the correlated Generalized compound distribution model cannot deal with non-integral or non-semi-integral parameter. In order to overcome this shortcoming, a new method of generating correlated Generalized compound distributed clutter is proposed, which changes the generation method of Generalized Gamma distributed random sequences in traditional Generalized compound distribution models. Firstly, by combining with the Gamma distribution and using the additivity of the Gamma distribution, the Probability Density Function (PDF) of Gamma function is transformed into a second-order nonlinear ordinary differential equation, and the Gamma distributed sequence under arbitrary parameter is solved. Then the Generalized Gamma distributed sequence with arbitrary parameter can be obtained through the nonlinear transformation relationship between the Generalized Gamma distribution and the Gamma distribution, so that the shape parameters of the Generalized compound distributed sea clutter are extended to general real numbers. Simulation results show that the proposed method is not only suitable for clutter simulation with non-integral or non-semi-integral shape parameter values, but also further improves the fitting degree.

***key words:*** *clutter simulation, Generalized compound distribution model, Generalized Gamma distribution, Gamma distribution*

## 1. Introduction

Radar sea clutter modeling and simulation technology has become a research topic that attracts broad attention. Accurately and quickly simulating sea clutter is of great significance for radar signal processing and sea surface target detection [1], [2]. A lot of analysis has been conducted on the measured radar sea clutter data both domestically and internationally, and the traditional radar clutter models include Rayleigh distribution, Log-normal distribution, Weibull distribution, and K-distribution [3]. The Rayleigh distribution can better fit the amplitude distribution of radar sea clutter at low resolution. However, at higher sea conditions and higher radar resolution, the clutter has a longer trailing tail and the Log-normal distribution fits the measured data better [4]. The dynamic range of the Weibull distribution is between the Log-normal and Rayleigh distributions, and it can more accurately describe the amplitude changes in the actual marine environment [5]. The K-distribution is a compound model composed of speckle and texture components, which can more accurately simulate sea clutter. However, with the increase of radar broadband, the speckle component of radar clutter deviates from the Gaussian distribution, the texture component deviates from the Gamma distribution, so that the K-distribution is no longer applicable [6], [7]. In response to this phenomenon, Anastassopoulos et al. proposed the Generalized compound distribution model suitable for broadband radar clutter [8]–[10], and this model treats the distributions of both speckle component and texture component of broadband radar clutter as Generalized Gamma (GΓ) distribution.

On this basis, Hou et al. [11] proposed a simulation method for correlated Generalized compound distributed radar clutter based on zero memory non-linear (ZMNL) method. This method is suitable for incoherent clutter model, the drawback is that the shape parameter of the clutter model must be an integer or semi-integer, which will cause clutter simulation bias, and it cannot independently control the power spectrum and amplitude distribution. To satisfy the requirements of power spectrum characteristics, the calculation of the correlation coefficients is relatively complex. A new method for simulation of Generalized compound distributed clutter is proposed in Ref. [12], which allows the generation of clutter with an arbitrarily specified power spectrum and relatively simple operation compared to the traditional ZMNL method, but an approximate approach is made for the simulation when the shape parameter is non-integer or non-semi-integer. Conte et al. [13] and Zhu and Tang [14] used the additivity of the Gamma distribution to simulate K-distributed clutter, dividing the shape parameter into the sum of the integral or semi-integral part named $\upsilon_1$ and the non-integral or non-semi-integral part named $\upsilon_2$, solving the problem of approximating the shape parameter $\upsilon$, but the specific Gamma distribution with $\upsilon_2$is generated by the product of Beta distributed random numbers and exponential distributed random numbers. Although the approximation problem of shape parameters has been solved, the simulation of Beta distribution may deviate when the parameters are small, which will lead to a certain error between the final clutter simulation curve and the theoretical Probability Density Function (PDF). The GΓ distribution does not have the

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additivity and cannot solve the problem of approximation when the shape parameters are non-integers or non-semi-integers by adding branches of the GΓ distribution.

In order to further improve the effect of Generalized compound distributed sea clutter simulation, a new correlated Generalized compound distributed clutter simulation method is proposed to change the generation approach of GΓ distributed random sequences in the traditional correlated GΓ distribution model. Gamma distributed random sequences transformed by specific nonlinear transformation to obtain GΓ distributed random sequences. Using the additivity of the Gamma distribution, the PDF of the Gamma function is transformed into a second-order nonlinear ordinary differential equation by adding the Gamma distribution generating branches before performing the nonlinear transformation, and solving the Gamma distributed random numbers with the scale parameter of 1 and the shape parameter of arbitrary value. Then, nonlinear transformation is performed to obtain the GΓ distributed random numbers under arbitrary parameter. The proposed method not only extends the shape parameters of Generalized compound Gaussian distributed clutter to general real numbers, but also fits better with theoretical distribution.

## 2. Correlated Generalized Compound Distributed Clutter Simulation Data Model

### 2.1 Correlated Generalized Compound Distributed Clutter Mathematical Model

The compound model of radar sea clutter can be described using Eq. (1) [15]:

$$Z = XY \tag{1}$$

where $X$ and $Y$ are independent short-term correlated fast changing component (speckle component) and long-term correlated slow changing component (texture component), respectively. The PDF of $Z$ describes the distributions of the distribution of the results obtained by multiplying the speckle component and texture component. For Generalized compound distribution, $X$ and $Y$ are the independent GΓ distributions, which can be obtained from Gaussian distributed random sequences through nonlinear transformation:

$$X = \left(\sum_{m=1}^{M} \varepsilon_m^2\right)^{\frac{1}{b_1}}, \quad Y = \left(\sum_{n=1}^{N} \eta_n^2\right)^{\frac{1}{b_2}} \tag{2}$$

where $b_1$ and $b_2$ are positive parameters ($b_1 > 0$, $b_2 > 0$), and $\varepsilon_m$ and $\eta_n$ are independent and identically distributed random sequences which follow the Gaussian distributions $\varepsilon_m \sim N\left(0, \frac{1}{2}\right)$ and $\eta_n \sim N\left(0, \frac{a^{b_2}}{2}\right)$ with a scale parameter $a$, respectively.

If new parameters $v_1$ and $v_2$ defined by $M = 2v_1$ and $N = 2v_2$ are introduced, it can be seen that the PDF of X and Y are giveb by Eq. (3) [16], [17]:

$$\begin{aligned} f(X) &= \frac{b_1}{\Gamma(v_1)} X^{b_1 v_1 - 1} \exp\left(-X^{b_1}\right) \\ g(Y) &= \frac{b_2}{a \cdot \Gamma(v_2)} \left(\frac{Y}{a}\right)^{b_2 v_2 - 1} \exp\left(-\left(\frac{Y}{a}\right)^{b_2}\right) \end{aligned} \tag{3}$$

where $\Gamma(\cdot)$ is the Gamma function, the definition of which is given later (in Eq. (5)).

Based on Eqs. (1) to (3), the expression for the PDF of Generalized compound distribution clutter can be written as:

$$\begin{aligned} & f_{GC}(Z; a, b_1, b_2, v_1, v_2) \\ &= \int_0^{+\infty} \frac{1}{s} f(Z/s) g(s) ds \\ &= \frac{b_1 b_2}{\Gamma(v_1)\Gamma(v_2)} \cdot \frac{Z^{b_1 v_1 - 1}}{a^{b_2 v_2}} \\ &\quad \cdot \int_0^{+\infty} s^{b_2 v_2 - b_1 v_1 - 1} \exp\left(-\left(\frac{s}{a}\right)^{b_2} - \left(\frac{Z}{s}\right)^{b_1}\right) ds \end{aligned} \tag{4}$$

where $v_1$ and $v_2$ are the shape parameter; $b_1$ and $b_2$ are the power parameter; $a$ is the scale parameter; $\Gamma(\cdot)$ is the Gamma function, and its expression is:

$$\Gamma(x) = \int_0^{+\infty} t^{x-1} \exp(-t) dt \tag{5}$$

When the Generalized compound distribution takes a special value, it degenerates into other common distributions [18]: 1) When $b_1 = b_2$, it corresponds to the Generalized K-distribution; 2) When $b_1 = b_2$, $v_1 = 1$ and $v_2 = 0.5$, it corresponds to the Weibull distribution; 3) When $b_1 = b_2 = 2$ and $v_1 = 1$, it corresponds to the K-distribution. According to the different values of different parameters, the Generalized compound distribution can also evolve into other distributions, as shown in Fig. 1.

### 2.2 Power Spectrum Model

The power spectrum characteristic of clutter is another important parameter to describe radar clutter, and the power

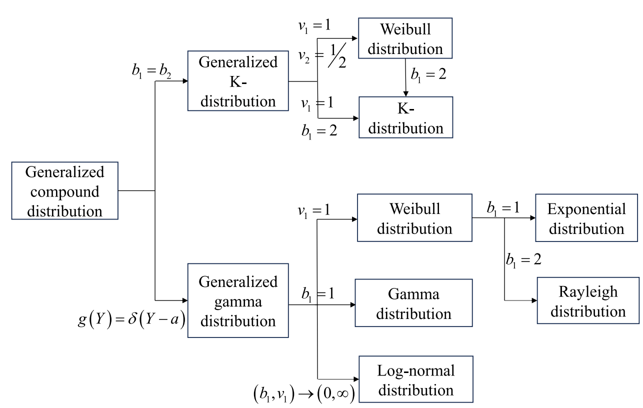


**Fig. 1** Relationship between generalized compound distribution and other distributions ($\delta(\cdot)$ is the Dirac delta function).

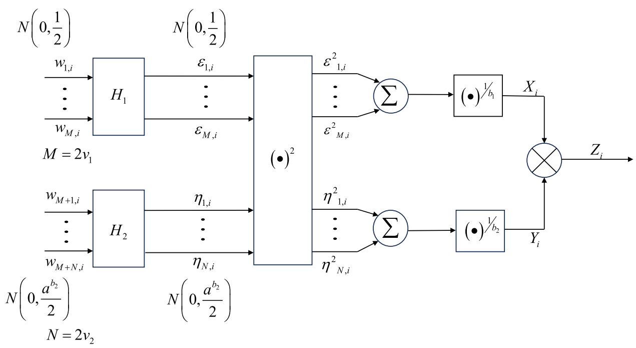


**Fig. 2** Simulation flow diagram of correlated generalized compound distributed clutter (in the figure, $H_1$ and $H_2$ are filters).

spectrum distribution of clutter is directly related to the design of filter. The Gaussian power spectrum model is expressed as follows [19]:

$$S(f) = S_0 \exp\left[-\left(\frac{(f-f_d)^2}{2\sigma_f}\right)\right] \tag{6}$$

where $S_0$ is the average clutter power, $f_d$ is the doppler frequency and $\sigma_f$ is the broadening of the power spectrum reflected by the standard deviation of the power spectrum.

### 2.3 Simulation of Generalized Compound Distributed Clutter

The ZMNL method is used to generate correlated Generalized compound distributed sea clutter sequences, the flowchart is shown in Fig. 2. The Generalized compound Gaussian distributed clutter simulation of ZMNL method consists of two branches, one of which is to generate $X_i$, which is generated by the sum of squares of $M$ independent Gaussian distributed random sequences $(w_{1,i}, w_{2,i}, \ldots, w_{M,i})$ to the power of $1/b_1$. The other branch is used to generate $Y_i$, which generates the $Y_i$ through the sum of squares of $N$ independent Gaussian distributed random sequences $(w_{M+1,i}, w_{M+2,i}, \ldots, w_{M+N,i})$ to the power of $1/b_2$. Among them, $M = 2v_1$, $N = 2v_2$, $M$ and $N$ are integers determined by the shape parameters $v_1$ and $v_2$. It can be seen that this simulation method can only simulate Generalized compound distributed sea clutter with shape parameters $v_1$ and $v_2$ being integers or semi-integers.

Xie et al. [15] derived the relationship between the autocorrelation coefficients $r_{ij}$ and $q_{ij}$ of the correlated Gaussian distributed random sequences $\{\varepsilon_i\}$ and $\{\eta_i\}$ under the condition of Generalized compound distribution and the autocorrelation coefficient $s_{ij}$ of the output sequence $\{Z_i\}$, as shown in Eq. (7):

$$s_{ij} = \left\{\left[\left(1-r_{ij}^2\right)^{v_1+\frac{2}{b_1}}\left(1-q_{ij}^2\right)^{v_2+\frac{2}{b_2}} {}_2F_1\left(v_1+\frac{k}{b_1}, v_1+\frac{l}{b_1}, v_1, r_{ij}^2\right) {}_2F_1\left(v_2+\frac{k}{b_2}, v_2+\frac{l}{b_2}, v_2, q_{ij}^2\right)-1\right]\right\}\cdot\frac{1}{\Lambda-1} \tag{7}$$

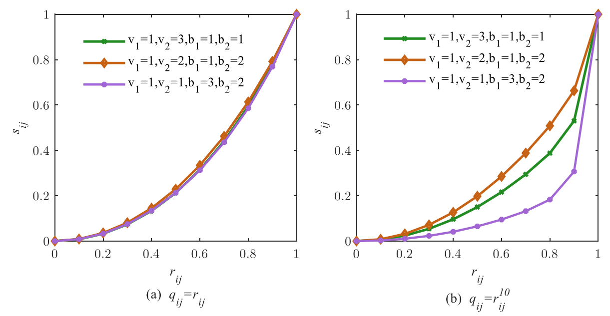


**Fig. 3** Relationship curve between the autocorrelation coefficient $s_{ij}$ of the Generalized compound distributed sequences $r_{ij}$ and $q_{ij}$.

where $k$ and $l$ are the order, $\Lambda$ is given by the next Eq. (8) and ${}_2F_1$ is the hypergeometric function defined by Eq. (9).

$$\Lambda = \frac{\Gamma(v_1)\Gamma(v_2)\Gamma\left(\frac{2}{b_1}+v_1\right)\Gamma\left(\frac{2}{b_2}+v_2\right)}{\Gamma^2\left(\frac{1}{b_1}+v_1\right)\Gamma^2\left(\frac{1}{b_2}+v_2\right)} \tag{8}$$

$${}_2F_1(a,b,c,d) = \sum_{n=0}^{+\infty}\frac{(a)_n(b)_n}{(c)_n}\cdot\frac{d^n}{n!} \tag{9}$$

where $(a)_n$ etc. means Pochhammer's symbol defined by $(a)_n = \Gamma(a+n)/\Gamma(a)$. The right side of Eq. (9) converges only when $|d| < 1$.

Due to the autocorrelation coefficients $r_{ij}$ and $q_{ij}$ cannot be determined directly according to $s_{ij}$, it needs to be determined based on different shape parameters $v_1$, $v_2$ and power parameters $b_1$, $b_2$. In actual simulation process, it is often assumed that $q_{ij} = r_{ij}$ or $q_{ij} = r_{ij}^{10}$, and the relationship curves between the autocorrelation coefficient $s_{ij}$ and $r_{ij}$, $q_{ij}$ are shown in Fig. 3. Observing the Fig. 3, it can be observed that when $q_{ij} = r_{ij}$, the changes of the shape parameters and power parameters have little effect on the values of $r_{ij}$ and $q_{ij}$, which can simplify the calculation to a certain extent. When $q_{ij} = r_{ij}^{10}$, taking different values of the shape parameters and power parameters results in a significant change in the values of $r_{ij}$ and $q_{ij}$. Considering reducing the computational complexity of clutter simulation, this paper selects $q_{ij} = r_{ij}$ in the clutter simulation experiment.

## 3. Improved Correlated Generalized Compound Distributed Clutter Simulation Method

The traditional ZMNL method shown in Fig. 2 requires the shape parameters to be integer or semi-integer, which cannot effectively simulate Generalized compound distributed clutter with non-integral or non-semi-integral shape parameters. Due to the fact that the shape parameters of the simulated clutter are determined by the intermediate $G\Gamma$ distribution variables, in order to extend the shape parameters of the simulated $G\Gamma$ distributed clutter from integers or semi-integers to general real numbers, it is necessary to improve the generation method of the $G\Gamma$ distribution variables in Fig. 2. We would like to propose to use the specific nonlinear transformation relationship between the GΓ distribution and the Gamma distribution to generate the GΓ distributed random sequences. The specific process is as follows:

Assuming that $V$ follows the GΓ distribution, i.e., $V \sim \mathrm{G}\Gamma(a, v, b, u = 0)$, if $T$ follows the scale parameter of 1 and the shape parameter of $v$, i.e., $T \sim \Gamma(1, v)$, then we have Eq. (10) [20]:

$$V = aT^{\frac{1}{b}} \sim G\Gamma(a, v, b, 0) \tag{10}$$

For the Generalized compound distribution, $X$ and $Y$ are mutually independent GΓ distributions, where $X \sim \mathrm{G}\Gamma(X_i; a_1, v_1, b_1, 0)$ and $Y \sim \mathrm{G}\Gamma(Y_i; a_2, v_2, b_2, 0)$. Combining with Eq. (10), it can be obtained that:

$$X = a_1 x^{\frac{1}{b_1}} \tag{11}$$

$$Y = a_2 y^{\frac{1}{b_2}} \tag{12}$$

where $a_1 = 1$, $x \sim \Gamma(x; 1, v_1)$, $y \sim \Gamma(y; 1, v_2)$, due to the fact that the GΓ distribution does not have the additivity, but through the nonlinear transformation relationship between the GΓ distribution and the Gamma distribution in Eq. (10), it can be obtained that the shape parameters of the GΓ distributed random sequences $X$ and $Y$ are determined by the shape parameters of the Gamma distributed random sequences $x$ and $y$.

From this conclusion, by combining with the Gamma distributed random sequences generation method and using the additivity of the Gamma distribution, $v_1$ is separated into the integral or semi-integral part $v_{11}$ and the non-integral or non-semi-integral part $v_{12}$, and $v_2$ is separated into the integral or semi-integral part $v_{21}$ and the non-integral or non-semi-integral part $v_{22}$, i.e., $v_1 = v_{11} + v_{12}$, $v_2 = v_{21} + v_{22}$. The non-integral or non-semi-integral part $v_{12}$ and $v_{22}$ are generated by increasing the Gamma distribution generation branches. By converting the PDF of Gamma function into a second-order nonlinear ordinary differential equation [21], [22], the Gamma distribution with arbitrary parameters is generated by power series expansion method. Then the GΓ distributed random sequences with arbitrary parameters can be obtained by the nonlinear transformation Eq. (10).

We are considering the Γ distribution with the scale parameter 1 whose PDF is shown in Eq. (13):

$$f(y) = \frac{y^{v-1}}{\Gamma(v)} \exp(-y) \tag{13}$$

where $\Gamma(v)$ is the Gamma function, $v$ is the shape parameter.

Convert the PDF of the Eq. (13) to the following form:

$$\frac{1}{f(y)} = \frac{dy}{dt} = \Gamma(v) y(t)^{1-v} e^{y(t)} \tag{14}$$

where $y$ is a function of $t$, and $t$ is a random number with distributions of $[0, 1]$, differentiating Eq. (14) with respect to $t$ yields:

$$\frac{d^2 y}{dt^2} = \Gamma(v) \left[ y^{1-v}(t) e^{y(t)} + (1 - v) y^{-v}(t) e^{y(t)} \right] \frac{dy}{dt} \tag{15}$$

Substituting of Eq. (14) into Eq. (15) yields, after simplification:

$$\frac{d^2 y}{dt^2} = \frac{1 - v}{y} \left( \frac{dy}{dt} \right)^2 \tag{16}$$

$$y \frac{d^2 y}{dt^2} - [y + 1 - v] \left( \frac{dy}{dt} \right)^2 = 0 \tag{17}$$

and the following boundary conditions are assumed:

$$y(0) = 0, \quad y(t) \sim [t\Gamma(v + 1)]^{\frac{1}{v}} \;\; as \;\; t \to 0 \tag{18}$$

Applying the transformation:

$$z = [t\Gamma(v + 1)]^{\frac{1}{v}} \tag{19}$$

Substituting Eq. (19) into Eq. (17), we obtain:

$$y \left( \frac{d^2 y}{dz^2} + \frac{1 - v}{z} \frac{dy}{dz} \right) - (y + 1 - v) \left( \frac{dy}{dz} \right)^2 = 0 \tag{20}$$

Assume that the solution of Eq. (20) is given by the infinite power series:

$$y(z) = \sum_{n=1}^{\infty} c_n z^n \;\; \text{with} \;\; c_1 = 1 \tag{21}$$

Substituting the series solution into (20), we find:

$$\begin{aligned} n(n + v) c_{n+1} &= \sum_{k=1}^{n} \sum_{l=1}^{n-k+1} c_k c_l c_{n-k-l+2} l(n - k - l + 2) \\ &-\Delta(n) \sum_{k=2}^{n} c_k c_{n-k+2} k[k - v - (1 - v)(n + 2 - v)] \end{aligned} \tag{22}$$

where $\Delta(n) = 0$ if $n < 2$ and $\Delta(n) = 1$ if $n \geq 2$. In the following we list some $c_n$:

$$\begin{aligned} c_1 &= 1 \\ c_2 &= \frac{1}{1 + v} \\ c_3 &= \frac{1}{2} \frac{5 + 3v}{(1 + v)^2 (2 + v)} \\ c_4 &= \frac{1}{3} \frac{31 + 33v + 8v^2}{(1 + v)^3 (2 + v)(3 + v)} \end{aligned} \tag{23}$$

These solutions are reported in [23]. In summary, the approximate solution of the differential equation function can be obtained as follows:

$$y(t) = \sum_{n=1}^{\infty} c_n \left( [t\Gamma(v + 1)]^{\frac{1}{v}} \right)^n \tag{24}$$

where the coefficients $c_n$ are given by Eq. (23). By using the additivity of the Gamma distribution, we add the Gamma distribution branches with shape parameters $v_{12}$ and $v_{22}$ in the flow diagram of the traditional Generalized compound

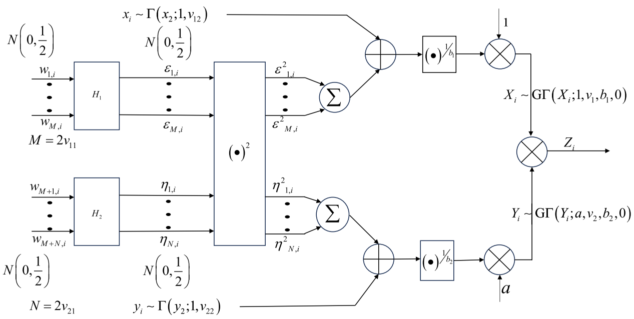


**Fig. 4** Flow diagram for improved generation of generalized compound distributed clutter by ZMNL method.

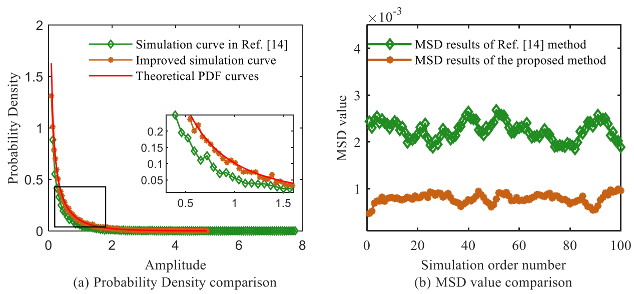


**Fig. 5** Improved Gamma distributed clutter model.

distributed clutter simulation. The improved Generalized compound Gaussian distributed clutter generation ZMNL process is shown in Fig. 4:

## 4. Clutter Simulation Experiment and Analysis

In Ref. [14], according to the additive property of the Gamma distributed shape parameter, Zhu and Tang generated the specific Gamma distribution with non-integral or non-semi-integral shape parameter by the product of Beta distributed random numbers and exponential distributed random numbers, which overcame the shortcoming of the traditional ZMNL. Now, we compare the proposed method with Zhu and Tang's method. In the experiment, we set the shape parameter of the Gamma distribution is $v = 0.15$, $a = 1$, Sampling frequency is set 1,000 Hz and the total simulation number is 20,000. The Gamma branches whose shape parameters $v_{12}$ and $v_{22}$ ($v_{12} = v_{22} = 0.15$) are generated by the method of in Ref. [14] and the proposed method respectively. The comparison of results is shown in Fig. 5(a). Obviously, it can be seen from the locally enlarged curve that the fitting degree between the average histogram of simulated data and the theoretical PDF curve of the proposed method is higher than that of Zhu's method.

To illustrate the performance of the proposed method, the mean squared difference (MSD) technique is used to test the fitting degree of the simulated data. Simulation was done 100 times and a MSD value was obtained in each time. The MSD value comparison is shown in Fig. 5(b). The proposed method has improved the fitting degree on the generation of the GΓ distributed random sequence.

**Table 1** Simulation parameters for amplitude distribution.

| $a$ | $v_1$ | $v_2$ | $b_1$ | $b_2$ | Distribution type |
|---|---|---|---|---|---|
| 2.5 | 1 | 0.5 | 2.5 | 2.5 | Weibull Distribution |
| 2.5 | 1 | 1.65 | 2 | 2 | K-Distribution |
| 2.5 | 1.65 | 1.65 | 2 | 2 | Generalized K-Distribution |
| 2 | 1.65 | 1.65 | 2 | 3 | Generalized compound Distribution |

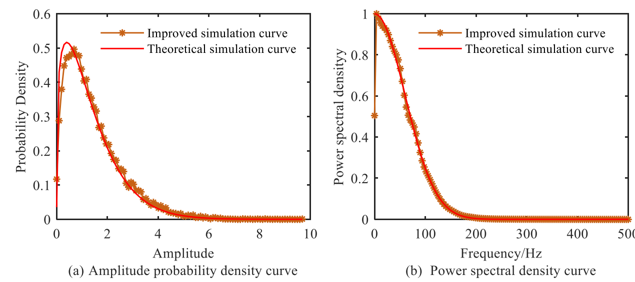


**Fig. 6** Probability density function and power spectral density function of Weibull distributed sequence.

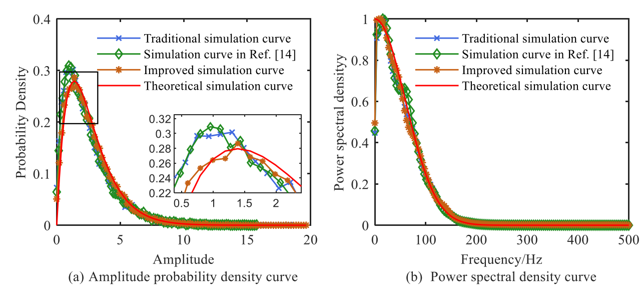


**Fig. 7** Probability density function and power spectral density function of K-distributed sequence.

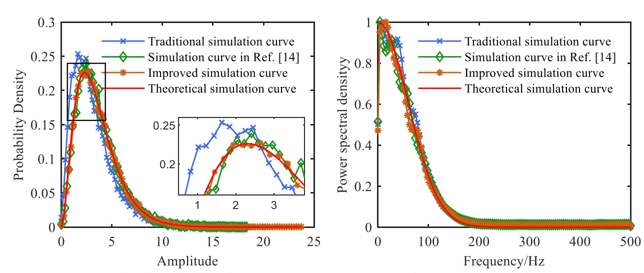


**Fig. 8** Probability density function and power spectral density function of generalized K-distributed sequence.

To further verify the effect of non-integral shape parameters, four sets of Generalized compound distributed sea clutter sequences with the data length of 20,000 and the radar pulse repetition frequency of 1,000 Hz were generated using the method proposed in Sect. 3. The simulated power spectrum is Gaussian spectrum with a bandwidth of 60 Hz. The specific simulation parameters are shown in Table 1. Figures 6, 7, and 8 show the simulation results of the Generalized compound distribution degenerated into Weibull distribution, K-distribution, and Generalized K-distribution, respectively, and Fig. 9 shows the simulation results of the ordinary Generalized compound distribution.

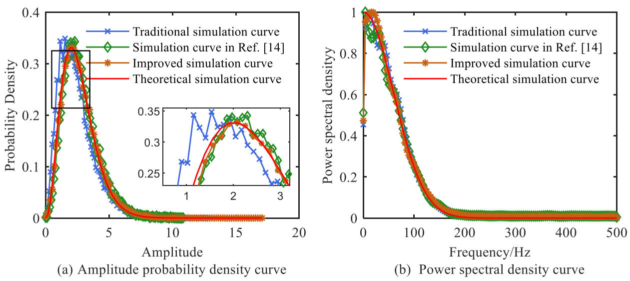


**Fig. 9** Probability density function and power spectral density function of generalized compound distributed sequence.

Among them, Fig. 6(a) shows the comparison between the simulated Weibull distributed clutter and the theoretical amplitude probability density curves. When degenerating to the Weibull distribution, the shape parameter can only be fixed values, i.e., $\upsilon_1 = 1$, $\upsilon_2 = 0.5$, which does not involve the problem of approximating shape parameters. The Weibull distributed clutter sequence simulated by this Generalized compound distribution model fits well with the theoretical values. Figures 7(a)–9(a) show the comparison of amplitude probability density curves for the K-distribution, Generalized K-distribution, and Generalized compound distribution of traditional and improved methods, where the shape parameters of the traditional method are taken down to integers or semi-integers, i.e., $\upsilon = 1.5$. In Figs. 7(a)–9(a), the probability density curves of the K-distributed, Generalized K-distributed, or Generalized compound distributed clutter simulated by the traditional ZMNL method have some deviations from the theoretical values. Compared with the improved Generalized compound distributed clutter simulation method, especially when the amplitude value is small, the proposed method has a higher fitting degree than the traditional method. Figures 7(b)–9(b) show the comparison of the power spectral density curves between traditional and improved methods. In Figs. 7(b)–9(b), the power spectrum characteristics fit well with the ideal Gaussian spectrum curve within the effective bandwidth, and the newly added branch has a negligible impact on the power spectral density of the Generalized compound clutter simulation.

## 5. Conclusion

Traditional Weibull distribution, K-distribution, Generalized K-distribution, etc. are special cases of Generalized compound distribution, and the Generalized compound distribution is more universal, which is the core of radar sea clutter modeling and simulation. This paper analyzes the Generalized compound distributed sea clutter model. Focusing on the problem that the traditional ZMNL method can only simulate random sequences with shape parameters of integers or semi-integers in the GΓ distribution, it is proposed to combine the GΓ distribution with Gamma distribution through the proprietary nonlinear transformation relationship. By using the additivity of the Gamma distribution, the shape parameters of the Generalized compound distributed sea clutter are extended to general real numbers by adding the Gamma distribution generating branches before the nonlinear transformation. The simulation results show that the PDF simulation curves obtained from the simulation of the improved ZMNL method fit the theoretical PDF curves better and improves the performance of the amplitude characteristic simulation of the Generalized compound distributed sea clutter.

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