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Research on Clutter Modeling of Marine Microbes

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Marine microbes are tiny organisms that live in marine environments. They include cellular life forms: bacteria, algae and plankton along with the viruses that freeload on the cellular life forms. They can only be seen under a microscope. The influence of them can be viewed as Lognormal distribution. In this paper, we use ZMNL method to model clutter. After making a detailed analysis of ZMNL, we use this method to generate Lognormal distribution clutter based on the characteristics of Lognormal distribution. Simulation results show that the generated clutter approaches the theoretical value and the method is effective. Finally, the whole paper is summarized.

Key words: Marine Microbes, Clutter Modeling, ZMNL, Lognormal Distribution.

The term 'marine microbes', also knows as 'marine microorganisms', encompasses all microscopic organisms generally found in seawater. Most microorganisms are cellular and can be classified into groups of viruses, bacteria, and protists. They differ considerably in biological characteristics. They play nearly every ecological role imaginable. Their most important function is that they form the base of the food chain in marine ecosystems. There are more than a billion microorganisms living in each liter of seawater, and it is well known that microbes dominate the abundance, diversity and metabolic activity in the ocean. Marine microbes comprise 98 percent of the biomass of the world's oceans and supply more than half of the world's oxygen. They are the major processors of the world's greenhouse gases and have the potential to mitigate the influences of climate change.

The influence of marine microbes in seawater can be viewed as Lognormal distribution. It is becoming a hot topic in the research field. A statistically non-Gaussian, space-time clutter model in varying biostatic geometrical scenarios is presented to validate the potential space-time adaptive processing algorithms for airborne biostatic radar clutter suppression under non-stationary and non-Gaussian clutter environments (Duan, *et al*., 2009). A sample of results from a statistical and spectral analysis of a set of sea spikes

selected from the radar returns are shown, focusing on their Doppler properties, the spike duration and the temporal interval among spikes (Greco, *et al*., 2010). An improved empirical model is proposed for radar sea clutter reflectivity (Gregers, *et al*., 2012). Using data-sets with different characteristics, the effects of quantization error, measurement noise, generalization of the neural net over ranges and sampling rate on the RBF clutter model is investigated (Hennessey, *et al*., 2001). A model for generating low-frequency synthetic aperture radar clutter is proposed, which relates model parameters to physical characteristics of the scene (Jackson, *et al*., 2009). Using curved wave spectral estimation that yields reliable results

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for any refractivity profile is suggested, in contrast to plane wave spectral estimation (Karimian, *et al.*, 2012). Three sets of high-resolution, coherent, and polarimetric radar sea clutter data are analyzed and compared with radar sea clutter models (Melief, *et al.*, 2006). A clutter model for such scanning radar applications is proposed, taking the effect of scanning on the clutter correlation into consideration (Roy, *et al.*, 2010). Based on the weighted norm in discrete complex linear space and a simple matrix transformation, a new method of modelling and simulation of temporal-spatial-correlated clutter is proposed (Teng, *et al.*, 2011).

In this paper, we use ZMNL method to model clutter. After making a detailed analysis of ZMNL, we use this method to generate Lognormal distribution clutter. In the simulation, we will compare the generated clutter with the theoretical value and verify the performance of our method.

Principle analysis of ZMNL

There are more than a billion micro-organisms living in each liter of seawater, and it is now known that microbes dominate the abundance, diversity and metabolic activity of the ocean. Figure 1 is a picture of marine microbe. The influence of them can be viewed as Lognormal distribution. Lognormal distribution can be applied in the sea clutter when resolution is high and grazing angle is low.

The simulation of clutter data should not only meet a certain probability distribution in amplitude, but should also meet the requirements in correlation properties. That means the first-order and second-order characteristics of the data have to be produced to meet the requirements of the clutter.

Sometimes it is required to produce coherent and incoherent signal, so that there is also a coherent related sequence and incoherent related sequence division in corresponding clutter signal in system simulation.

If we want to simulate single point statistics, there are many methods which are also quite mature, but the method of producing relevant random sequence which has a certain probability is under investigation. There are three relatively representative related radar clutter simulation methods at present: the method of spherically invariant random process (SIRP), the method of zero memory nonlinearity transformation method

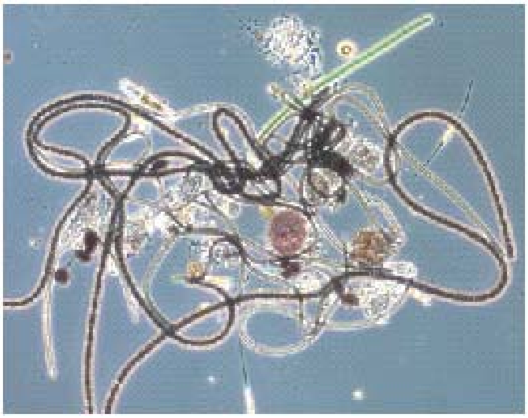

Fig. 1. A picture of marine microbe

(ZMNL) and stochastic differential equation method (SDE). ZMNL is a commonly used method, and it can realize the simulation of several common distribution clutters. This paper mainly uses ZMNL method.

For inputting Gaussian random process, any ZMNL dose continuate its output spectrum smoothly. In the actual derivation process, the expression is so complex that it can not be dealt with, so we have to make necessary approximation to make it easier, thus it will cause certain differences in the results. But if the given related function attenuates quickly or before and after nonlinear transformation, the relation of input/output correlation function is close to linear, such difference is very small. For some kinds of common amplitude model, the relation of input/output correlation function of ZMNL transform is close to linear, so that the errors caused by approximation are generally very small. Many people also pointed out that we must keep the balance between correlation and PDF.

ZMNL method developed earlier, and applied widely, its basic method is to transfer the relevant Gaussian random sequence process to the required relevant random process by a kind of nonlinear transformation. During the transformation between Gaussian process and non-Gaussian process, nonlinear transform will make change in related characteristics before and after the transformation. So nonlinear transformation is not perfect. We should find out the transformation relationship between the correlation function before and after the transformation according to the concrete transformation method, so that we can derive correlation function of Gaussian process before the transformation by the given non-Gaussian process related function, which is the key to this method.

In addition, the reason why we choose relevant Gaussian to process nonlinear transform, is decided by the particularity of Gaussian process. It means that only Gaussian process do not change its characteristic after getting through the linear filter.

The basic way of clutter modeling with the method of ZMNL is:

(1) Produce white Gaussian noise sequence $w(k)$ and make it get through a linear filter $H(z)$, so that we can get relevant Gaussian sequence $y(k)$;

(2). After making nonlinear transformation in relevant Gaussian noise sequence , we can get related sequence with certain probability distribution.

The concrete block diagram of the clutter modeling of ZMNL method is as follows:

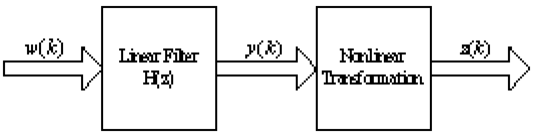

Fig. 2. Block diagram of the clutter modeling of ZMNL method

As is shown in the figure 2, white Gaussian random process change into relevant Gaussian process after getting through the filter . After the nonlinear transformation, this process can get the required clutter sequence $z(k)$. Assume that $w(k)$ is a unit power white Gaussian random process whose mean value is zero, and the coefficient of the filter is normalized, so should have unit variance.

Getting the nonlinear relationship between the input and output of correlation function in nonlinear transformation is the premise of the application of this method. However, the nonlinear transformation will make the spectral broadening, which will make autocorrelation function between and has a very complex transformation relationship. For some distribution model of the clutter simulation, such as Weibull distribution clutter and K distribution clutter, it is not easy to get the autocorrelation function of from the autocorrelation function of .

Generation of lognormal clutter

Relevant Gaussian clutter can be viewed as the response which Gaussian noise whose mean value is zero makes effect on the filter. The process of simulating correlation Gaussian clutter, is actually the request of designing the digital filter that has the needed power spectrum correlation characteristics. Suppose white Gaussian noise is generalized stationary stochastic process, and its sample of one moment is $W(k)$, the response after getting through the filter $H(z)$ is

$$Y(k) = h(k) * W(k) \qquad ...(1)$$

where $h(k)$ is the unit sequence response of $H(z)$, *means convolution, $Y(k)$ is the simulation for the relevant Gaussian clutter sequence. According to some properties of Fourier transformation, we can get

$H(z)$

$$P_Y(w) = |H(w)|^2 P_W(w) \qquad ...(2)$$

Where $P_Y(w)$ and $P_W(w)$ are power spectrum density function of relevant Gaussian noise and white noise; $H(w)$ is the frequency response function of $H(z)$. As the power spectrum density function of white noise signal is constant, assuming that the variance of white noise is σ_W^2, then

$$P_Y(w) = |H(w)|^2 \sigma_W^2 \qquad ...(3)$$

Therefore, frequency characteristics of filter $H(z)$ is decided by the required related power spectrum characteristic of clutter.

After using the filter design methods to achieve the requirements of related characteristics, then we can simulate the related clutter. This paper uses the frequency domain method to produce relevant Gaussian sequence . Principle diagram is shown in figure 3.

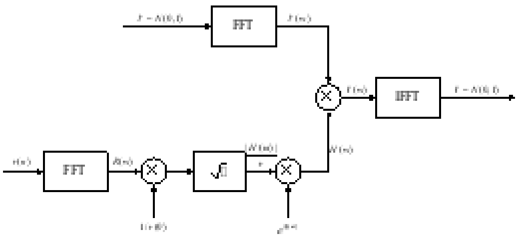

Fig. 3. Principle diagram of generating relevant Gaussian sequence

We can easily produce independent non-relevant Gaussian sequence V. To get the correlation coefficient sequence $r(n)$, we can solve it according to the clutter power spectrum that we want to get. According to the relationship of Fourier transformation between relevant sequence and power spectrum density, making IFFT transformation to the known clutter power spectrum, we can get clutter related sequence. Then through the relationship between two related sequence nonlinear transformation, we can finally get the correlation coefficient $r(n)$ of the correlation Gaussian sequence. In this way, we can easily determine the relevant Gaussian sequence Y according to figure 3. The specific transformation is followed, first transform $r(n)$ into the frequency domain

$$R(w) = FT(r(n)) \quad ...(4)$$

Let

$$|H(w)| = \sqrt{R(w)/r(0)} \quad ...(5)$$

We can get the amplitude of $H(w)$, select an appropriate phase angle function, and make $H(w)$ become physically realizable. At the same time, make the non-related independent standard Gaussian sequence V transform into the frequency domain, then

$$Y(w) = H(w)V(w) \quad ...(6)$$

So the power spectrum density is

$$S_y(w) = S_v(w) * |H(w)|^2 \quad ...(7)$$

is known, so

$$S_y(w) = |H(w)|^2 = R(w)/r(0) \quad ...(8)$$

Make the obtained frequency domain $Y(w)$ change into time domain, then Y sequence is a relevant Gaussian random sequence whose power spectrum is $R(w)/r(0)$.

As is known, we can use random variables $n_i \sim N(0,1)$ to get random variables which obey normal distribution $N(\ln\mu_c, \sigma^2)$ through linear transformation. After w_i getting through nonlinear transformation $x_i = \exp(w_i)$, we can get Lognormal distribution with double parameters.

The block diagram of producing incoherent Lognormal distribution clutter is shown in the figure 4.

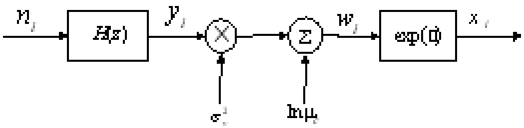

Fig. 4. Generation principle diagram of LogNormal distribution clutter

In the figure 4, $n_i (i = 1,2,3...N)$ is a white Gaussian sequence which obeys the distribution of $N(0,1)$; y_i is a related Gaussian sequence which obeys the distribution of $N(0,1)$, suppose the correlation coefficient is ρ_{ij}; x_i is the incoherent Lognormal distribution clutter whose correlation coefficient is S_{ij}. And we can get the relationship between ρ_{ij} and S_{ij} after deriving

$$S_{ij} = \frac{e^{\sigma_v^2 \rho_{ij}} - 1}{e^{\sigma_v^2} - 1} \quad ....(9)$$

From the formula above we can get

$$\rho_{ij} = \frac{\ln[1 + S_{ij}(e^{\sigma_v^2} - 1)]}{\sigma_v^2} \quad ...(10)$$

We can get $H(w)$ from ρ_{ij}, let

$$S_u = FT(\rho) \quad ...(11)$$

In the formula $FT(\square)$ means Fourier transformation. Define normalization transfer function

$$|H(w)| = \sqrt{S_u(w) / \rho(0)} \qquad ...(12)$$

The amplitude of $H(w)$ is determined by formula (12) .

According to the analysis above, the steps of producing Lognormal distribution clutter are as follows:

1. Select the needed power spectrum density $S(w)$ for clutter, and choose appropriate sampling rate Δw, and after sampling from $S(w)$, we can get sequence $\{S_n\}, n = 1, 2, ..., N$;
2. Make IFFT transformation to the sequence $\{S_n\}$, we can get the required correlation coefficient sequence S_{ij}, $i, j = 1, 2, ..., N$ from non-Gaussian random sequence ;
3. Through formula (10) we can get correlation coefficient sequence $\rho_{ij}, i, j = 1, 2, \ldots, N$ from relevant Gaussian random sequence;
4. Through ρ_{ij}, formula (11) and formula (12) we can produce relevant Gaussian sequence $\{y_n\}, n = 1, 2, ..., N$;
5. Make linear and nonlinear transformation $\exp(\square)$ in y_i through the parameters $\ln \mu_c$ and , and we can get related Logormal distribution sequence $\{x_i\}, n = 1, 2, ..., N$.

In the next section, we will make simulation of Lognormal distribution clutter in a certain condition through the steps we have discussed above, and analyze the results of simulation.

Simulations

Simulation conditions are as follows. The length of the random sequence is 8000 points, power spectrum using Gaussian spectrum model. Sampling frequency $f_s = 1000Hz$, standard deviation of random sequence $\sigma_f = 50Hz$, the center frequency $f_0 = 0Hz$, shape parameter $\sigma_v = 0.9$, scale parameter $\mu_c = 1.7$. Simulation results are in figure 5 to figure 9.

Figure 5 to figure 9 present the results of Lognormal clutter simulation with the metod of

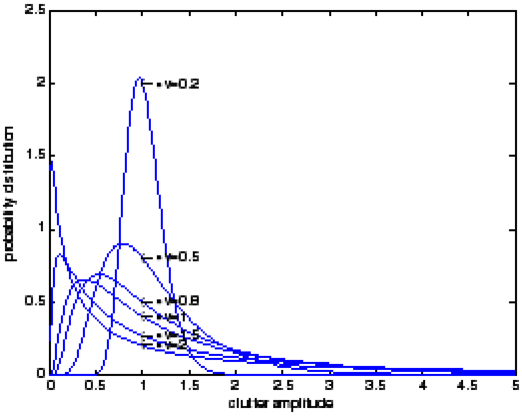

Fig. 5. Probability density distribution of Lognormal distribution clutter

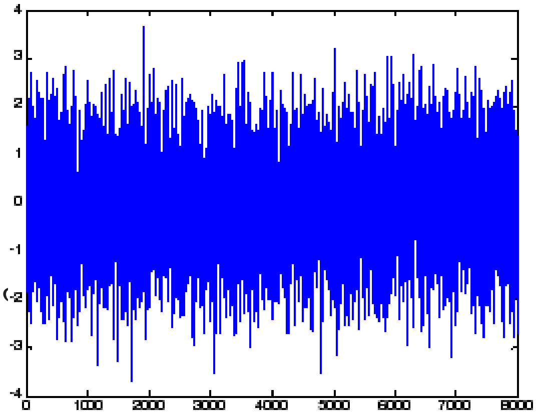

Fig. 6. Independent non-relevant Gaussian random sequence

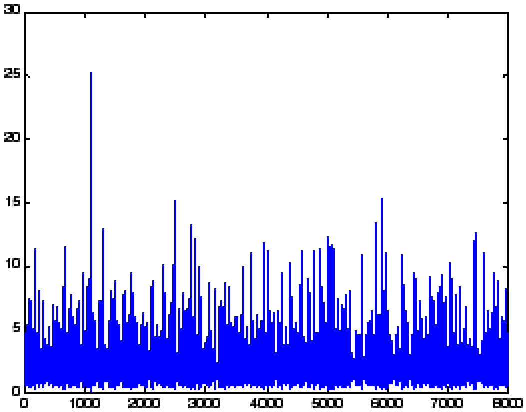

Fig. 7. Lognormal distribution clutter

ZMNL. Figure 5 is probability density distribution of Lognormal distribution clutter, figure 6 is independent non-relevant Gaussian random sequence and figure 7 is Lognormal distribution clutter obtained in simulation. The changes of sequences before and after the simulation can be seen through figure 6 and figure 7.

Figure 8 shows the comparison between actual amplitude distribution of clutter and the theoretical amplitude distribution of clutter. It can be seen that both are consistent with each other. Figure 9 adopts the method of burg to estimate the power spectrum of clutter that has been generated, and giving the comparison with theoretical power distribution, both are consistent with each other. Spectrum broadening is small, the error of high frequency part is existed.

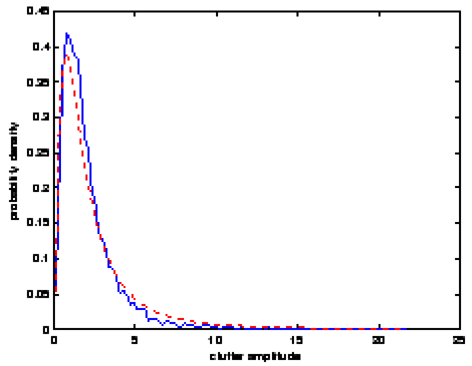

Fig. 8. Distribution of clutter amplitude

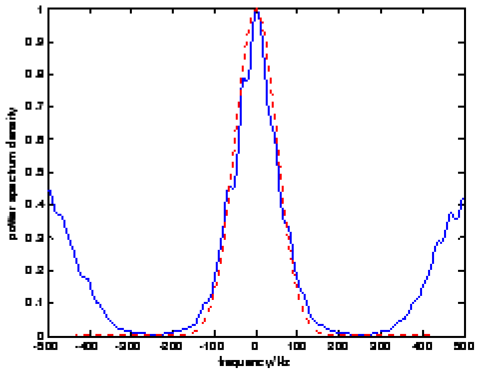

Fig. 9. Clutter spectrum

CONCLUSIONS

In this paper, the influence of marine microbes is viewed as Lognormal distribution. We use ZMNL method to model clutter. After making a detailed analysis of ZMNL, we use this method to generate Lognormal distribution clutter. Simulation results show that the actual amplitude distribution of clutter and the theoretical amplitude distribution of clutter are consistent with each other. The generated power spectrum and the theoretical power distribution are consistent with each other. So the generated clutter approaches the theoretical value and the method is effective.

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