Two Methods for Simulating Non-Gaussian Highly Correlated Sea Clutter Maps

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Abstract – **Sea clutter features change significantly when measured by high resolution radars, at low grazing angles. The recorded data may be highly correlated and are characterized by long tail probability density functions, which are in the most cases very different compared to the classical Rayleigh distribution. In this paper we propose two methods for simulating this type of clutter. The former is based on the statistical model of the sea clutter, which can be seen as a combination of two random processes, which are Gamma and Rayleigh distributed. The second makes use of the 2D MA analysis of real sea clutter maps to generate synthetic data having very similar statistic and correlation properties.**

I. INTRODUCTION

The capability to provide accurate simulations of the sea clutter becomes very important whenever the performance assessment of a naval surveillance radar system is required. Simulated sea clutter data can be used to test the conceived detection and classification algorithms, allowing for important resource savings compared to the case when real data acquisition is performed.

When the spatial resolution is low and the grazing angle large enough a Gaussian model is generally considered for the sea clutter. This choice is motivated by the central limit theorem and leads to a good fitting of the real data. However, for high resolution and low grazing angles this model is not valid anymore because the sea clutter turns into non-Gaussian and correlated both in time and space [1]. Simulating sea clutter data becomes a quite difficult task because a generally accepted model for this context still does not exist.

Two innovative approaches are described in the paper for simulating non-Gaussian and highly correlated sea clutter maps. The first method is based on the phenomenological model of the K-compound probability density function (pdf). Our original contribution is that a 3D structure is proposed for generating the sea clutter, while the common approach is to consider a two-dimensional one. The second method is based on the 2D MA analysis of real sea clutter maps, recorded by THALES NAVAL France. The MA kernel obtained by the phase recovering technique is then used to generate synthetic maps having very similar statistical and correlation properties.

The paper is organized as follows. The principles of the two methods are briefly described in Section II and Section III. Their capabilities are also demonstrated through computer simulations. Some concluding remarks are drawn in Section IV together with the main directions for the future work considered.

II. SEA CLUTTER SIMULATION USING THE K-COMPOUND MODEL

The sea surface can be seen as a superposition of capillary waves and gravity waves. Consequently, the radar returns will also have two components.

The former accounts for the reflection from a very large number of independent, identically distributed elementary scatterers. It is fast varying and exhibits a decorrelation time of about 10 ms when the radar operates at fixed frequency and is fully decorrelated with frequency agility.

The second is a spatially varying mean level associated with the sea swell structure. It slowly varies, decorrelates on a much longer scale and is unaffected by frequency agility

So, the echo signal is obtained by the product of a modulating component associated to a large scale structure, slowly varying and Gamma distributed (gravity waves), by an underlying fast varying and Rayleigh distributed component, representing the sum of the contributions of many isolated scatterers (capillarity waves, sea foam, etc.) [1].

The significance of this model is that the non-Rayleigh amplitude distribution of sea clutter may be separated into 2 components which, because of their statistical, spatial and temporal correlation properties, need to be introduced at different stages in the evaluation of signal processing performance.

This phenomenological model leads to the K-compound pdf given bellow:

$$p(x)=\int_0^\infty p(x\mid y)p(y)dy=\frac{2b}{\Gamma(\nu)}\left(\frac{b\cdot x}{2}\right)^{\nu}K_{\nu-1}\left(bx\right) \qquad (2.1)$$

where b and ν represent the scale and the shape parameters,

$$p\left(x\middle|y\right)=\frac{2\cdot x}{y^2}\cdot\exp\left(-\frac{x^2}{y^2}\right) \qquad (2.2)$$

is the Rayleigh pdf of the underlying component and

$$p\left(y\right)=\frac{2\cdot b^{2\nu}\cdot y^{2\nu-1}}{\Gamma\left(\nu\right)}\cdot\exp\left(-b^2\cdot y^2\right) \qquad (2.3)$$

is the Gamma pdf of the modulating component.

In order to validate this model the goodness-of-fit between the real data distribution and 4 pdfs (Rayleigh, Weibull, Gamma and K) has been evaluated by means of the Kolmogorov test, for 42 sea clutter data files.

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Figure 1 shows the obtained results in terms of rejection rate. It is obvious that the K-compound model is the most appropriate to describe the real data distribution among the 4 pdfs considered for comparison.

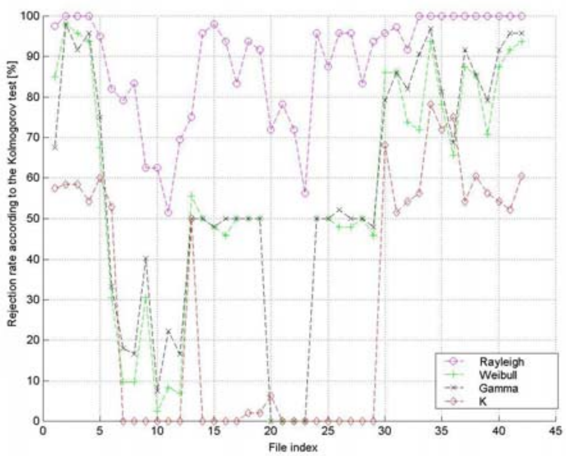

Fig. 1 Measured data pdf matching using the Kolmogorov test

The correlation properties must be also taken into account. The behavior of the two components is again very different. For instance, the underlying component is decorrelated in the frequency agility mode, whereas the modulating component is not. Otherwise, the underlying component is not spatially correlated, whereas the modulating component can be correlated on several meters. In fact, the data are correlated in time, range and azimuth, the autocorrelation function support depending mainly on the radar operating mode and the sea state.

The 3D approach proposed on figure 2 allows the integration in the structure of the generated signal of all the 3 types of correlation:

- time correlation (within a range/azimuth resolution cell);
- range correlation (within an azimuth resolution cell or during a burst);
- angular correlation (within a range resolution cell).

The underlying idea is that the backscattered signal is sampled at the same rate (PRF) in both time and azimuth.

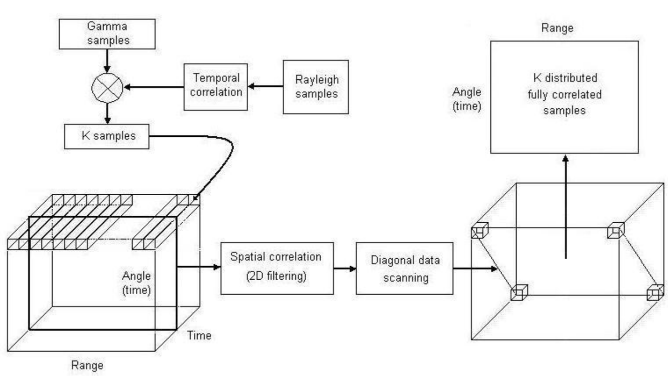

Fig. 2 3D approach for simulating sea clutter using the compound model of the K pdf

The spatial correlation is introduced by running a two-dimensional sliding window of appropriate size over the 2D Gamma distributed data.

The Rayleigh samples are correlated in time if the clutter recorded at fixed frequency has to be simulated and fully decorrelated for the frequency agility mode.

The clutter power is set by means of a coefficient related to its RCS, which can be predicted by using different models (Nathanson, Katzin, Dariccau or Reilly/Dockery).

The simulated clutter should have the correct single-point statistics and the correct temporal and spatial correlation properties. An example of simulated sea clutter map using this technique is given on figure 3.

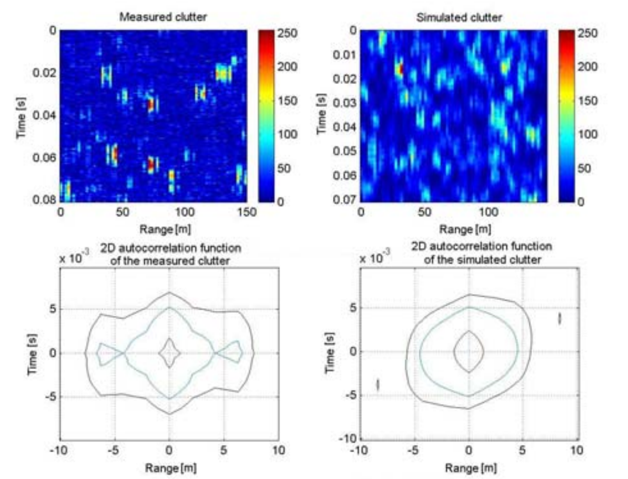

Fig. 3 Simulated sea clutter using the compound model of the K pdf

III. SEA CLUTTER SIMULATION USING THE 2D MA ANALYSIS

The sea clutter is generally analyzed from a one-dimensional point of view, as a random process associated to a given resolution cell. The azimuth/range two-dimensional clutter maps are then obtained by extension, as a series of such individual random processes.

Some research works aim to unify the amplitude statistics and correlation properties by defining a multidimensional probability density function. Such models are known as SIRP (Spherically Invariant Random Process) [2]. However, despite of their optimality, the application of these models has to overcome several difficulties, which may dramatically reduce their effectiveness:

- real time estimation of the K parameters, which is directly involved in the CFAR detector operating, is a difficult task, while the estimation errors may lead to poor detection performances;
- other types of noise, like the receiver thermal noise or the rain clutter, which add to the sea clutter in a real scenario, may deviate even more the model from the real processed signal;

– there are a lot of parameters related to the radar (frequency, range and azimuth resolution, polarization, operating mode etc.), to the environment (sea state, wind speed, season, day time, weather etc.) or to their interaction (grazing angle, angle between the line of sight and the wave direction etc.) which have to be taken into account by a signal model.

We propose an image approach for the sea clutter modelization, based on texture synthesis [3]. The method aims to concentrate the information contained by a two-dimensional sea clutter map, seen as a random field, into a low dimensional kernel, using an optimization or a training procedure. This kernel is nothing else than the pulse response of a two-dimensional MA (Moving Average) filter, which can be afterwards employed to simulate sea clutter maps having the same characteristics as the analyzed clutter, with an uniform white noise as input.

The additive noise effect (receiver thermal noise for example) can be also taken into account by a component added to the simulated clutter.

The model is a moving-average (MA) filter driven by an excitation function, with noise added to the result and followed by histogram specification. The MA filter kernel is computed for a given clutter map using a phase-recovery procedure. The procedure is to iterate between two estimates, one that has the chosen support but an incorrect magnitude spectrum and another that has the correct magnitude spectrum but incorrect support. The phase spectrum is allowed to vary each time through the iteration.

The principle of the simulation method is shown on figure 4. The simulated image I_s is generated using the relationship given bellow, where E and N stand for 2D white noise maps, Φ is the histogram modification operator, while H represents the 2D MA kernel obtained by the phase recovery algorithm.

$$I_s = \Phi\left[H \otimes E + \alpha N\right] \tag{3.1}$$

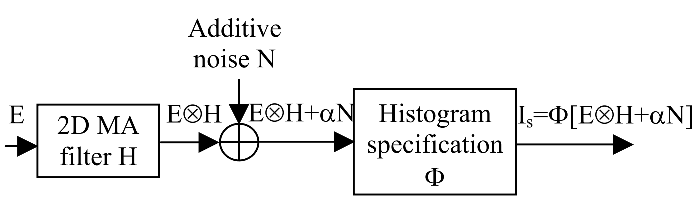

Fig. 4 2D MA filtering based technique for simulating sea clutter data

Figure 5 illustrates an example of simulated sea clutter map obtained by this method.

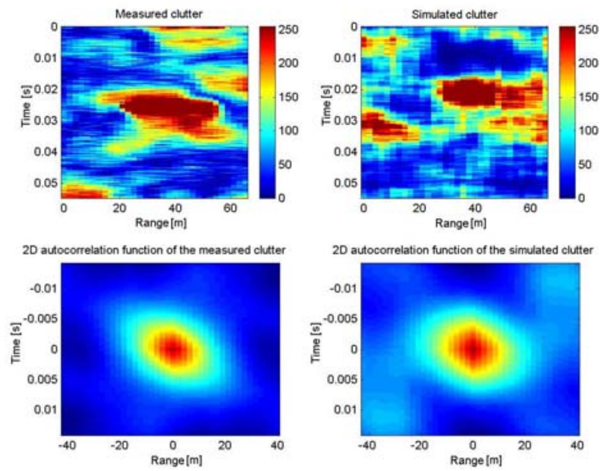

Fig. 5 Simulated sea clutter using the 2D MA kernel based approach

IV. CONCLUSION

Two methods for simulating realistic, non-Gaussian, highly correlated sea clutter maps are presented in the paper. First, a simple and intuitive K-compound based approach has been used. The main drawback is that the synthetic images are not quite similar to the original ones especially when the correlation properties are integrated into the model.

An “image” approach, based on texture synthesis has been finally proposed in order to overcome the shortcomings of the “signal” approach. It is able to generate synthetic clutter maps, different from the original ones, but still having the same visual characteristics, as well as the histogram and the related statistics. The model does not exactly duplicate the spectrum or autocorrelation function of the original sea clutter map, but yields reasonable approximations. It meets in this way the goal of matching the first order statistics (mean and variance) and closely approximating the second order statistics (autocorrelation function).

The proposed method is better suited for simulating sea clutter maps than AR or ARMA models, which tend to be sensitive to the choice of the model order and often produce results visually less faithful to the original clutter map

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