Advanced Sea Clutter Models and their Usefulness for Target Detection

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ADVANCED SEA CLUTTER MODELS AND THEIR USEFULNESS FOR TARGET DETECTION

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***Abstract**: Robust naval target detection is of significant importance to national security, to navigation safety, and to environmental monitoring. Here we consider the particular case of high resolution coastal radars, working at low grazing angles. The robustness of detection heavily relies on the appropriate knowledge of two classes of backscattered signals: the target echo, and the sea echo. The latter, usually regarded as a noise, is known as the sea clutter. This particular combination, of high resolution and low grazing angles, raises considerable challenges to radar processing algorithms. Specifically, the probability density function governing the sea clutter amplitude is no more Gaussian and a lot of effort has been aimed at characterizing it. Three approaches are reviewed here: the stochastic, texture and chaotic models. While the stochastic models represent an essay to extend classical detection theory to radars operating in marine environment, the other two models represent entirely new paradigms. Since each model has its strengths and weaknesses and more testing on real data is required to credibly validate any of the proposed models, a definitive conclusion is far from reach. However, critical comments, as well as experimentally supported conclusions are presented in the paper.*

***Keywords**: clutter, stochastic process, detection algorithms, chaotic model.*

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1. Introduction

The exact knowledge of the sea clutter properties is of great importance for a modern maritime surveillance radar because they are directly involved in the optimization of the detection process, mainly through the CFAR processor design. Gaussian models are the most used as they arise from the central limit theorem and lead to simple processing architectures. Indeed, these models are a good match for the sea clutter when the radar resolution is poor and the grazing angle is large enough, but they become inadequate when any of these two requirements is no more fulfilled.

In the latter case, the sea clutter becomes spikier, which results in a false alarm rate much more important than those predicted by a Gaussian model. Therefore, other models, able to take into account this different behavior, have to be considered.

This is typically illustrated by the case of high-resolution radars, which allow to reduce the intensity of sea clutter (by reducing the extent of analyzed cell resolution) and, thus, to improve the signal on noise report. Thus, target detection probability should increase. However, in the real world, at high frequencies, classic models of target radar echo and of reflected sea clutter are no more valid. This penalizes the detection rate. Therefore, one needs better fitted models in high frequency.

Here we critically review some sea clutter models, revealing both their strengths and weaknesses.

2. Sea Clutter as a One-Dimensional Stochastic Process

Although large consensus stands behind the phenomenological model explaining the scattering of electromagnetic waves at the encounter of sea surface, there are different ways to model the outcome of such interaction. Among the simplest ones is the one-dimensional stochastic approach, detailed below.

First, let us present a short introduction to the phenomenological model.

The dynamics of the sea could be, at least at a coarse level, characterized by the sea state and the direction of the sea waves. The sea state synthesizes the amplitude of the waves and the distance between them (their wavelength). Two kinds of waves are encountered at the surface of the sea, generated by two different mechanisms: the capillarity waves and the gravity waves [5].

The first kind of waves is mainly generated by the influence of the wind and expresses the superficial tension of the water. These waves are of small amplitude (we do not discuss here extreme meteorological conditions) and in very large number, having a short wavelength (less than 2 centimeters). In fact, even in almost completely still weather, they are seen at the surface of the sea as a continuous, almost random motion. They are almost ubiquitous, but their properties are, generally, very localized. Additionally, they do not carry much (impact) energy. This will reflect in the properties of their electromagnetic echo. The capillarity waves are superposed onto the second kind of waves, discussed below: the gravity waves.

The second kind of waves is mainly generated by the accumulation of gravitational forces. At the origin, they may be also triggered by the wind or by a storm or by some other meteorological phenomena, including difference of temperature. Unlike the capillarity waves, the gravity waves have larger amplitudes and larger wavelengths (more than 2 centimeters). Their properties are spread over a larger area of the sea (so they have a greater distance of correlation) and are the main energy carrying factor, greatly impacting on naval targets. Eventually, it is their properties which determine the state of the sea.

Given the different nature of the two kinds of waves, one could easily foresee that the nature of their electromagnetic echo is also different. Indeed, this is the case, as it is also confirmed by the analysis of real data, and most of the stochastic models are based on this assumption.

Generally, the two kinds of waves are superimposed, with the gravity waves having their surface modulated by the capillarity waves. This is illustrated in **Figure 1**.

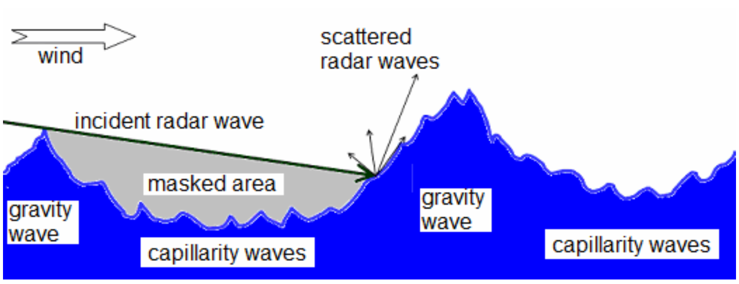


Figure 1. *The phenomenological model of sea surface and interaction with electromagnetic waves*

The figure also illustrates the specific hydrodynamic modulation, as emphasized by [1], i.e. the amplitude of capillarity waves is larger on the advancing front of gravity sea waves (on the figure, the right versant). This is important, by example, in adjusting radar processor parameters with respect to the meteorological conditions.

Figure 1 also illustrated the scattering of electromagnetic waves at the sea surface. Obviously, the irregular surface of the sea will scatter the incident electromagnetic wave in almost every direction. On the other hand, some masked areas are invisible to the radar system, at least under direct sight, since they are masked by other sea waves (the shadowed region in the **Figure 1**).

The electromagnetic waves scattered by the two kinds of sea waves will exhibit different statistic and correlation (or, equivalently, spectral) properties. It is their combined effect that allows us to characterize the properties of the sea clutter. The statistics of sea clutter are important in the detection algorithm, while their spectral properties are very valuable for implementing Doppler filtering. The latter will allow improved signal on noise ratios (SNR), thus increasing the visibility of the target on radar screen (and, obviously, allowing better detection performances). Additionally, for each kind of waves, their respective statistic and spectral properties vary in function of the incidence angle, the frequency range, the regime the radar is working in (e.g. fixed frequency or agility in frequency), and even the type of the mission the radar is performing (aerial patrolling, surveillance etc.) [21, 22].

Since the statistic behavior of the clutter is very important to target detection algorithms, many works have been dedicated to this issue, e.g.: [24, 15, 8, 4, 29, 16, 17, 18, 28, 3, 9].

In the one-dimensional stochastic clutter model, the combined effect of capillarity and gravity waves over the scattered electromagnetic waves translates in a composed echo. The latter is the product of two components: one having a Gamma pdf, corresponding to a large-scale, slow-varying physical structure (the gravity waves), further referred to as “underlying” component, and the other having a Rayleigh pdf, corresponding to a small-scale, rapid varying physical structure, representing the contribution of isolated scatterers (the capillarity waves), further referred to as “speckle” component [20] (**Figure 2**).

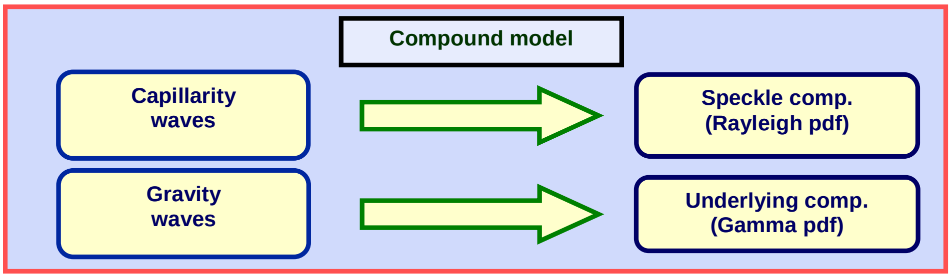


Figure 2. *The compound model of the sea clutter*

The global pdf of sea clutter is a direct description of this physical and phenomenological model:

$$p(x) = \frac{2 \cdot b}{\Gamma(\nu)} \cdot \left(\frac{b \cdot x}{2}\right)^{\nu} \cdot K_{\nu-1}(b \cdot x), \qquad \textbf{(1)}$$

where $K_{\nu}(x)$ is the modified Bessel function of order ν, b is the scale parameter and ν is the shape parameter.

The pdf given by equation (**1**) is known as the K-compound probability law, somewhat accepted as one of the best candidates in describing sea clutter behavior (along with the Weibull probability law). Its scale parameter is linked with the power of the clutter, while its shape parameter gives an indication of how "peaked" the clutter is. As such, for little values of ν, the clutter will have large-amplitude peaks, while for large values of ν, it will be relatively smoothed. In the latter case itself, the K-compound probability law will approach Rayleigh law (which is a particular case and is also used to describe sea clutter distribution, but usually at larger grazing angles).

The differences between the two components of the sea clutter will count for different outcomes when signal processing techniques are applied. By example, the speckle component becomes completely uncorrelated when agility in frequency is used [23]. However, the underlying component remains correlated. The former exhibit very little spatial correlation (between one resolution cell and the surrounding ones), while the latter may be correlated for distances up to 20 or 40 meters [30].

An example of real data [23] is presented in **Figure 3**, where the amplitude of sea clutter in a single resolution cell is depicted. The data has been acquired with fixed frequency (the upper part) and, then, with agility in frequency (the lower part). The moving average (i.e. the underlying component) is depicted in the right side of the figure, for each set of data.

While real data analysis confirm that speckle component becomes uncorrelated when agility in frequency is used, as well as other theoretically predicted properties of sea clutter, it also shows up some difficulties that the researchers may face. By example, data analyzed in [23] show unusual high dispersion of correlation times around the average value. This is quite difficult to interpret and it is possible to be linked with the non-stationary character of sea electromagnetic echo. This incoherence between theory and practice will have negative impact on detection performances, and is foreseeable as one important limitation of the assumed phenomenological model. However, [23] validates the K-compound stochastic model for data used therein.

However, even if one-dimensional statistical model is assumed, a few more difficulties have to be overcome to usefully exploit measured data. For the K-compound model, this has been achieved with standard methods, such as Raghavan and Watts [32], since no analytical relation allowing parameters from measured data exists for this pdf [31].

Note that the K-compound stochastic model is validated (and, thus, useful) for independent simulation of the sea clutter in resolution cells only. As such, samples will be generated according to the K-compound pdf alone, while correlation properties will be enforced using additional filters.

Usually, since the area covered by the radar system during a specified amount of time is a two-dimensional map (expressed as the product between range and an angular interval), the amplitudes for all range resolutions cells are generated at one time. This will give the complete view of the clutter surrounding the radar system. This is the principle of the classic models, such as ones presented in [7].

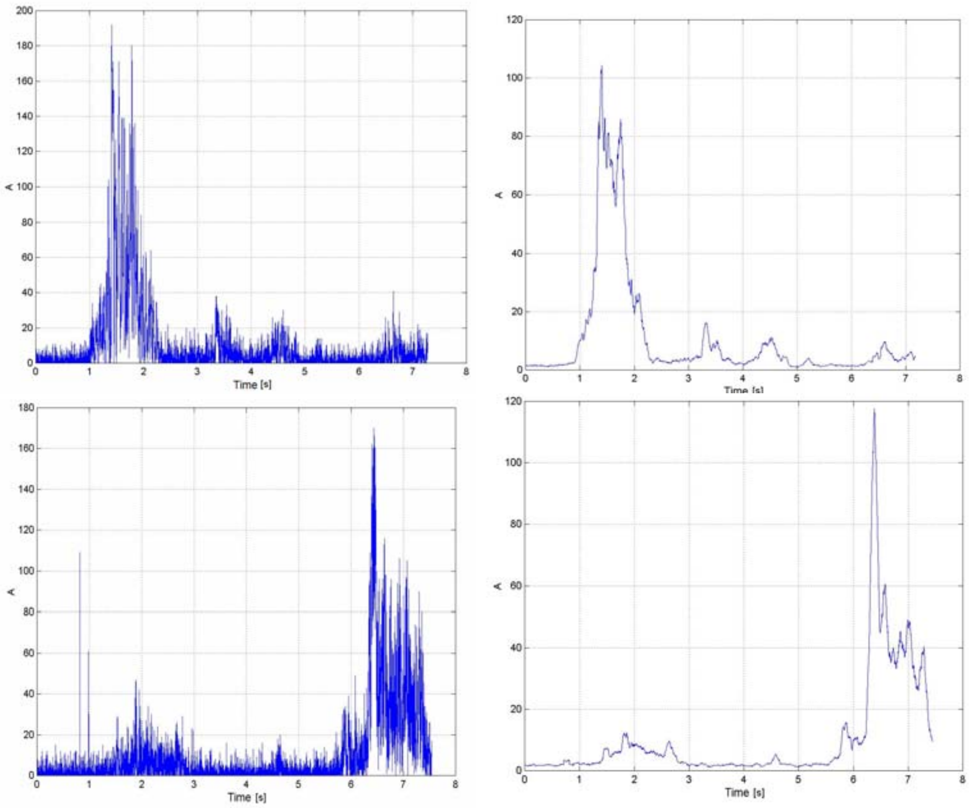
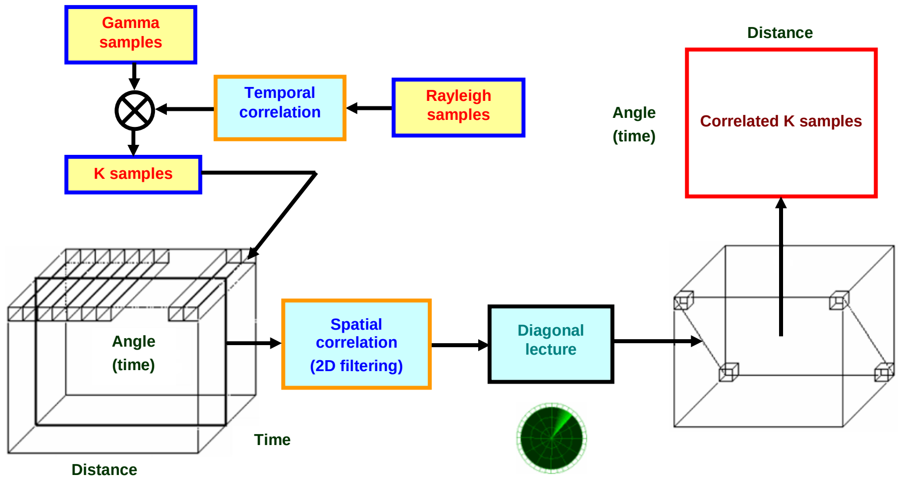


Figure 3. *Amplitude of the clutter in a given resolution cell as acquired by radar (left) and the extracted underlying component (right), at fixed frequency (upper) and with agility in frequency (lower)*

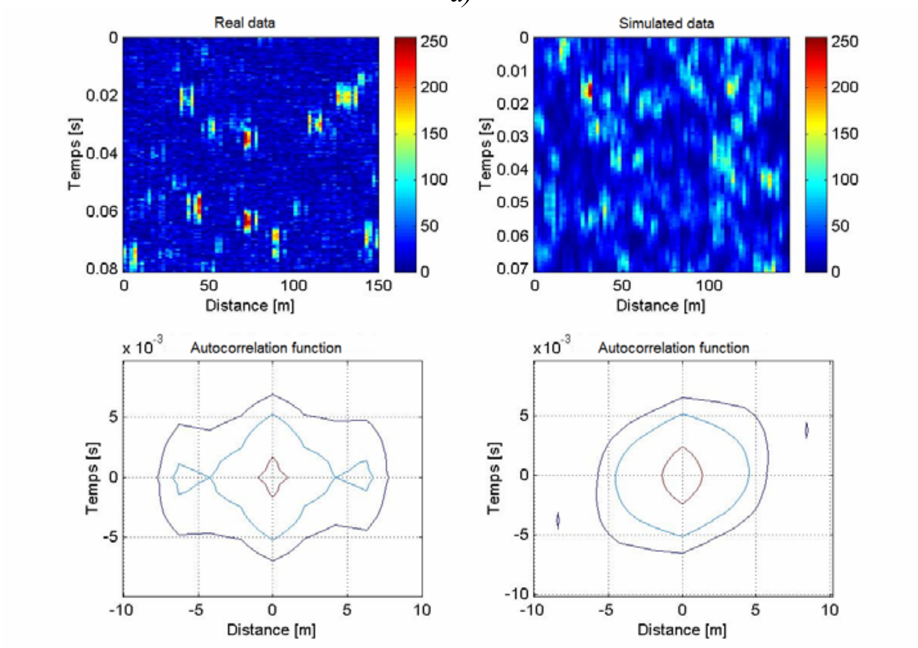
However, these models forget that not all the resolution cells are seen at the same time. As such, time correlation between cells (i.e. the changing of the clutter, in the same cell, with time) is not appropriately accounted for. In fact, while radar antenna turns, it will continuously discover resolution cells whose angular coordinate (with respect to the radar's polar coordinate system) is linearly varying with time. Since the radar turning speed is generally constant, the polar angle will be proportional with the time passed.

In conclusion, sea clutter data should be progressively generated, and the angular coordinate of the resolution cell should also be linked with the observation time. Specifically, the correlation imposed in time and in angle should be coherently applied.

This is achievable by using an additional diagonal lecture of generated sea clutter samples, stepping simultaneously in time and angular coordinate. The implementation of the method is illustrated in **Figure 4a**.



a)



b)

Figure 4. *The one-dimensional stochastic model for sea clutter (upper) and comparison of real and simulated sea clutter (lower)*

Further, to take into account the variation of sea clutter's radar cross-section (RCS), i.e. the exponentially decrease of its power with the increase in range, a multiplication with a coefficient is doable. The RCS of sea clutter may be determined as shown in [5].

However, while simple and appealing, the clutter simulated with this procedure is not entirely similar with the real recordings [23]. This may be seen, by example, in **Figure 4b**. While amplitudes of real and simulated clutter data may look quite similar (the upper subfigures), their correlation functions (and, consequently, their spectral properties) differ significantly.

3. Sea Clutter as a Two and Multi-Dimensional Stochastic Process

These approaches extend the number of correlation dimensions when clutter is generated. This is justified by the generally poor match between the real data sets and the K-compound theoretical distributions. Generalizations have been made, and usually a spherically invariant random process (SIRP) model is assumed for the sea clutter, especially at very low grazing angles and large bandwidths, where the K-compound distribution also fails.

The SIRPs are positive definite quadratic forms. Under this paradigm, sea clutter samples are simultaneously generated in angular and range coordinates, while integrating multi-dimensional statistics (i.e. also, conjoint pdf between clutter samples). This approach has been exposed in [4]. While the generated sea clutter better copes with real measured data, difficulties arise in exploiting this model into a detection algorithm. Indeed, the computation of the generalized likelihood ratio is difficult when multi-dimensional stochastic clutter model are assumed.

4. Sea Clutter as a Texture Realization

These drawbacks of stochastic modeling of sea clutter lead to new approaches, especially in estimating the parameters of the assumed pdf, but also in the appropriateness of the chosen pdf to a given meteorological condition, led to new approaches. The latter are non-parametric, although the information about specific framework (meteorological conditions, radar position and regime, mission) may be coded, recorded and reloaded into the system as needed.

Basically, a set of real data, representing measured sea clutter samples, is recorded. Then, this information is used to extract a "mask" filter of the clutter, which would allow reproducing its stochastic and correlation properties. This is achievable without making narrow and easily erroneous assumptions about the laws governing the distribution of clutter samples, and it s possible to adapt clutter model in real time.

One similar approach is found in texture generation [2] where new textures, similar to a given model, are simulated. The essential of this technique is to concentrate the information from a bi-dimensional clutter map (a range of resolution cells), into a kernel. The storing space needed for the kernel is greatly reduced compared with the original clutter map.

Once the kernel is extracted, new clutter maps are generated by considering a moving average (MA) 2D filter having the extracted kernel as impulse response. Excited with white noise, the filter will generate clutter maps whose correlation properties are identical with the ones of the original clutter map. Additional noise (e.g. the thermal noise of the receiver) may be easily accounted for, too.

Once the kernel is available, different clutter maps may be generated using the following relation:

$$I_s = H \otimes E \Rightarrow \hat{I}_s = \hat{H} \cdot \hat{E}\,, \qquad \mathbf{(2)}$$

where ^ operator stands for the 2D Fourier transform, H is the 2D kernel, I_s is the simulated clutter map, and E are the different excitations (white noise) applied at the filter's input.

The main issue is to extract the 2D kernel corresponding to a given clutter dataset. A reference clutter map, I_r, is used and its corresponding kernel, of a predefined size ($p \times q$) is extracted, using the algorithm in [2].

If the kernel is correctly extracted, generated clutter maps are very similar to the reference ones, both in terms of amplitude (and visual) characteristics and of correlation properties. The **Figure 5** depicts two situations of this kind.

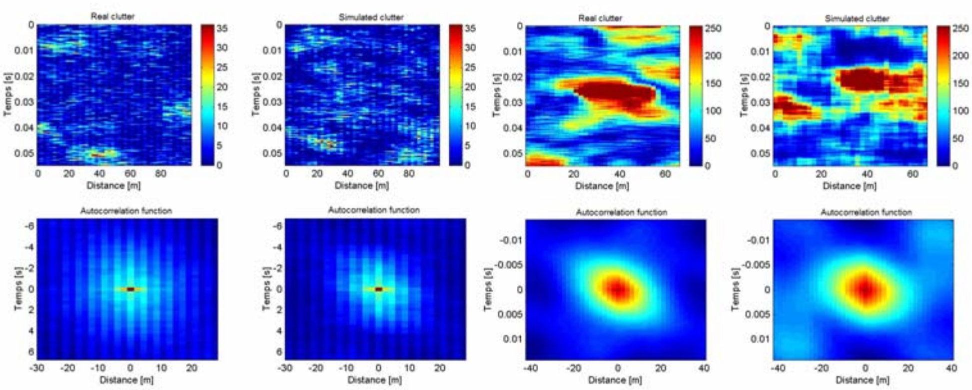


Figure 5. *Reference and simulated clutter maps, compared in terms of amplitude (upper) and correlation (lower)*

5. Sea Clutter as a Chaotic Model

The use of chaotic models for sea clutter was proposed in [11]. By analyzing the IPIX [14] public dataset, it was concluded that the sea clutter may be seen as manifestation of an underlying chaotic system (a subclass of dynamical systems). The IPIX dataset comprises sea real radar echo, measured on the coast of Canada, in different conditions. After some careful thought, the conclusion of a chaotic model in not very surprising, if one accepts that the processes involved in sea clutter generation are, basically, non-random but purely deterministic phenomena (sea wave motion is described by hydrodynamic theory, while electromagnetic scattering is described by electromagnetic, both theories relying on deterministic models only). Thus, one could aim for a deterministic description of the phenomena, the only remaining reason for accepting unpredictable behavior being in the complexity of the model, and in the imperfect knowledge of its initial conditions.

The chaotic modeling challenges the classical detection algorithms, since the latter relies heavily on statistics. As it will be shown, a different approach is needed to make the information extracted by chaotic modeling valuable for target detection.

The classic chaotic model, assumed by [11] is the exponential one, also known as the Exponential Sensitivity to Initial Conditions (ESIC) model. It states that, no matter how close their initial conditions (IC) are, two systems governed by the same laws will have divergent evolutions. This latter property may be mathematically expressed as follows: let $d(0)$ be the small separation between the IC of the two systems (at the time $t=0$). Then, the separation between their states at the time t will be written as:

$$d(t) \sim d(0)\mathrm{e}^{\lambda_1 t}, \tag{3}$$

where λ_1 is a positive quantity, known as the Lyapunov exponent.

This exponential divergence, combined with the bounded nature of the region in which it is possible for the system's states to lay, causes complex evolutions for the chaotic systems. The set of all touched states is, generally, fractal, characterized by a non-integer dimensionality. This dimensionality (known as the "box dimension") may be computed as:

$$N(\varepsilon) \sim \varepsilon^{-D},\ \varepsilon \to 0, \tag{4}$$

where N represents the maximal number of boxes, of linear length not larger that ε, needed to cover the attractor, and D is typically a non-integer number, called the fractal dimension of the attractor (the attractor is a set of system states which is invariant with respect to the evolution of the system).

It was assumed that a system having an evolution with an estimated positive largest Lyapunov exponent and a non-integral fractal dimension is a chaotic systems. In fact, it was the very assumption used by [11] when concluded that the sea clutter is chaotic.

However, a number of researchers [6, 26, 27] have questioned this conclusion. The showed that the two main invariants used in [11] and [12], namely the "maximum likelihood of the correlation dimension estimate" and the "false nearest neighbors" are problematic in the analysis of measured sea clutter data. This is because both invariants may interpret stochastic (so, purely random) processes as chaotic. By example, let us consider the following class of stochastic processes (the "pink" noise), having the following power spectral density:

$$s(f) = f^{-(2H+1)}, \qquad \textbf{(5)}$$

where f is the frequency and $H \in]0,1[$ is the Hurst parameter.

The trajectory of such stochastic process has a fractal dimension of $1/H$ [13]. And, with most algorithms of estimating the largest Lyapunov exponent, one obtains a positive number for it, and, thus, the purely random process is wrongly interpreted as being chaotic.

An improved method to asses the chaotic nature of recorded data is the dynamical test for deterministic chaos [10]. This method compares the common envelope of different estimations of largest Lyapunov exponents. For non-chaotic systems, this envelope is absent (see **Figure 6**, in the vicinity of origin). Applied in [13] this method proved that, in fact, none of the datasets analyzed in [11] is chaotic (under the ESIC assumption).

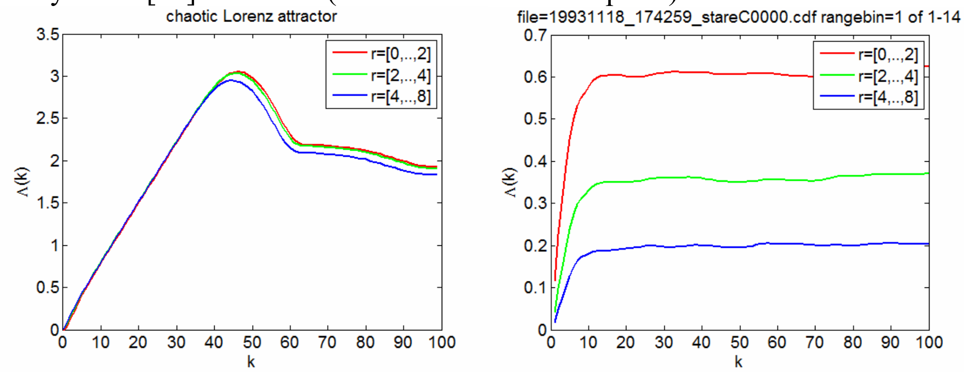


Figure 6. *Different estimated Lyapunov exponents, for a chaotic system (left) and for a stochastic one (right)*

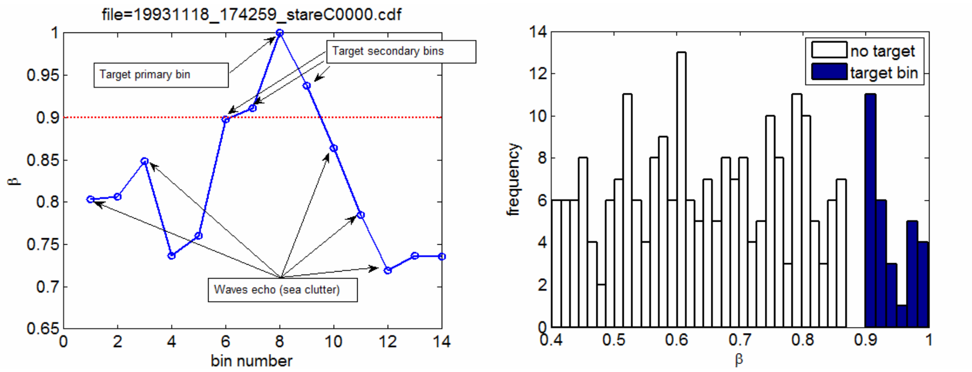
While this conclusion may seem to incline balance in favor of stochastic modeling, this is far from truth. In fact, it has been shown, also in [13], that a generalization of the classical chaotic ESIC model may be used to characterize sea clutter: the PSIC (Power-law Sensitivity to Initial Conditions) model [25, 19].

For 1D state system (i.e. whose state can be described using a scalar), the PSIC is written as:

$$\xi(t) = \lim_{\Delta x(0)\to 0} \frac{\Delta x(t)}{\Delta x(0)} = \left[1 + (1-q)\lambda_q t\right]^{\frac{1}{1-q}}, \quad (6)$$

where $\Delta x(0)$ is the infinitesimal discrepancy of IC, $\Delta x(t)$ is the discrepancy at the current time t, q is the entropic index, and λ_q equals K_q, the generalization of the Kolmogorov-Sinau entropy [25]. Note that for large t, $\xi(t) \sim t^{1/(1-q)}$ and that, when $q \to 1$, $\xi(t) \to e^{\lambda_1 t}$ (the PSIC reduces to ESIC).

Further, the newly-introduced PSIC concept may be applied to target detection as follows: let $\beta = (1-q)^{-1}$ and then compute the values of this parameter for the time series formed by the samples from the same radar resolution cell. It is remarked that β has low values for the resolution cells without targets (consequently, the entropic index q is also low). On the other hand, β has high values when a target is present in the analyzed resolution cell (see **Figure 7a**).



a) *b)*

Figure 7. *a) Values of parameter β for a number of resolution cells)*
b) Histogram of β for a number of resolution cells, without target (white bars) and with targets (dark bars)

The results using this new method, on the IPIX dataset, are strongly encouraging. An ideal, 100% good detection rate has been achieved [13] (see **Figure 7b**).

6. Conclusions and Perspectives

The presented results illustrate different approaches to the sea clutter modeling and target detection: mono or multiple-dimensional stochastic modeling, texture (kernel) modeling, or chaotic modeling.

The first approach is the classic approach, and has the advantage of being compatible with the existing radar processor and the detection algorithms implemented therein. However, this model seemed to have been stretched out to the limit: it is quite difficult to obtain a valid set of parameters for an assumed pdf from recorded (usually, in real time) sea clutter samples. There is no consensus with respect to the most adequate probability law to describe the distribution of sea clutter samples (more exactly, of their envelope). The multi-dimensional stochastic modeling, while more flexible, basically removes the advantage of simplicity: the CFAR detector is far more difficult to implement. Additionally, the increase in flexibility (and modeling power) comes at the cost of an even more difficult estimation of the set of parameters of the underlying pdf (SIRP) process.

The second approach shatters the classic detection algorithms. In fact, a completely new technique must be used, since no stochastic description is given to the sea clutter. Instead, a kernel (coding the intrinsic information) is constructed. Thus, one must presumably rely on automatic classifiers (e.g. neural networks), by turning the detection problem into a two-class classification problem. Details have been given. This approach seems quite promising. However, more work on real data is required before credibly validating it. On the other hand, it depends on the training performance of the neural network.

The third approach also requires new radar processor paradigm. However, this time, the detection threshold may be given a numerical value and the detection function (the parameter β) can be numerically estimated. The obtained results seem among the most promising ones, achieving 100% detection rate. Noise robustness and more real data validation are required for credible validation, though.

Acknowledgments

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