DETECTION OF LOW OBSERVABLE TARGETS WITHIN SEA CLUTTER BY STRUCTURE FUNCTION BASED MULTIFRACTAL ANALYSIS

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ABSTRACT

Sea clutter is the backscattered returns from a patch of the sea surface illuminated by a radar pulse. Robust detection of targets within sea clutter is of significant importance to our coastal and national security, to navigation safety, and to environmental monitoring. However, no simple and reliable methods for detecting targets within sea clutter have been proposed. We apply the structure function based multifractal theory to analyze 392 sea clutter datasets measured under various sea conditions. The method developed in this paper is mathematically rigorous, conceptually elegant, computationally fast, and practically easily implementable. Our results demonstrate that the method can robustly detect low observable objects within sea clutter.

1. INTRODUCTION

Sea clutter refers to the radar backscatter from a patch of ocean surface. Robust detection of low observable targets within sea clutter has significant importance to our coastal and national security, since objects within sea clutter may include submarine periscopes, low-flying aircrafts, and missiles. The task is also very important to navigation safety and environmental monitoring, since objects within sea clutter can be small marine vessels, navigation buoys, small pieces of ice, patches of spilled oil, etc. Accurate modelling of sea clutter is an important problem in remote sensing and radar signal processing applications. Sea clutter study may also help understand the propagation of electromagnetic waves so that wireless communication channel characterization and signal detection can be greatly improved.

Traditionally sea clutter is often studied in terms of certain simple statistical features, such as the marginal probability density function. The non-Gaussian feature of sea clutter has motivated researchers to employ Weibull [1], lognormal [2] and K [3] distributions to model sea clutter. Such simple phenomenological modelling of sea clutter does not help one gain much analytical or physical understanding, however. To gain deeper understanding of the nature of sea clutter, the concept of fractal has been employed for the description and modelling of the roughness of sea surface, and investigation of scattering from rough surfaces modelled by fractal processes. Possible chaotic behavior of sea clutter has also been studied [4, 5, 6, 7].

Since the ultimate goal of sea clutter study is to improve detection of targets embedded within clutters, a lot of effort has been made to design innovative methods for target detection within sea clutter. Notable approaches include wavelet based [8], neural network based [9, 10], and wavelet-neural net combined approaches [11], as well as utilizing the concept of fractal dimension [12] and fractal error [13]. However, no simple and reliable methods of detecting targets have been proposed.

Here we adopt advanced signal processing concepts and tools from random fractal theory to study sea clutter. Specifically, we apply structure function technique from multifractal theory to analyze 392 sea clutter data measured under various sea conditions. Our method is mathematically rigorous, conceptually elegant, computationally fast and practically easily implementable. Our results demonstrate that the method developed here can robustly detect low observable objects within sea clutter.

The remainder of the paper is organized as follows. In Sec. 2, we briefly describe the sea clutter data. In Sec. 3, we analyze the sea clutter data by structure function based multifractal analysis. The target detection performance within sea clutter by this type of multifractal technique will be discussed in Sec. 4. Finally we summarize our work in Sec. 5.

2. SEA CLUTTER DATA

We have obtained 392 time series datasets. They comprise 14 sea clutter datasets from a website maintained by Professor Simon Haykin:
http://soma.ece.mcmaster.ca/ipix/dartmouth/datasets.html.
The measurement was made with an IPIX radar of RF 9.39 GHz (and hence a wavelength of $\sim$ 3 cm), with two polarizations, HH (horizontal transmission, horizontal reception) and VV (vertical transmission, vertical reception). The grazing angle varied from less than 1^0 to a few degrees. The wave height in the ocean varied from less than 1 m to a few meters. Each dataset contains 14 spatial range bins of HH

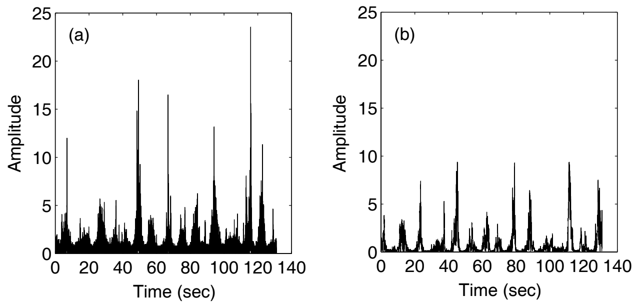

Fig. 1. Examples of sea clutter amplitude data of (a) without and (b) with target.

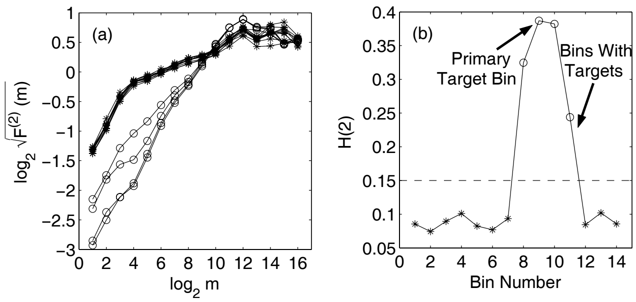

Fig. 2. (a) $\log_2 \sqrt{F^{(2)}(m)}$ vs. $\log_2 m$ for the 14 range bins; (b) The $H(2)$ values for the 14 range bins. Open circles denote bins with target, while * denote bins without targets.

as well as 14 range bins of VV datasets. A few of the range bins hit a target, which was made of a spherical block of styrofoam of diameter 1 m, wrapped with wire mesh. Each range bin data contains 2^{17} complex numbers, with a sampling frequency of 1000 Hz. We analyze the amplitude data. Fig. 1 shows two sea clutter amplitude data without and with target.

3. STRUCTURE FUNCTION BASED MULTIFRACTAL ANALYSIS OF SEA CLUTTER

Our purpose in this section is to show that the $H(q)$ spectrum from structure-function based multifractal formulation may offer a simple and effective solution to the problem of detecting targets within sea clutter. The major results are depicted in Figs. 2 and 3. Let us provide some necessary background for this type of multifractal first.

Many natural or man-made objects and temporal/spatial variations are very irregular, and cannot be adequately described by simple linear mathematics. Fractal is one of the powerful tools and concepts that can help us understand many irregular objects and phenomena. Mathematically, fractals are characterized by power-law relations over a wide range of scales. Such power-law relations are often called scaling laws.

To better understand scaling laws, let us first discuss one of the key concepts from fractal theory — the notion of dimension. A common method of measuring a length, a surface area, or a volume is by covering it with intervals, squares, or cubes whose length, area, or volume is taken as the unit of measurement. These unit intervals, squares, and volumes are called unit boxes. Suppose, for instance, that we have a line whose length is 1. We want to cover it by intervals (boxes) whose length is ϵ. It is clear that we need $N(\epsilon) \sim \epsilon^{-1}$ boxes to completely cover the line. Similarly, if we want to cover an area or volume by boxes with linear length ϵ, we would need $N(\epsilon) \sim \epsilon^{-2}$ to cover the area, or $N(\epsilon) \sim \epsilon^{-3}$ boxes for the volume. Generally, we can write

$$N(\epsilon) \sim \epsilon^{-D}, \ \ \epsilon \to 0 \tag{1}$$

D is called the topological dimension, and takes on a value of one for a line, two for an area, and three for a volume. For isolated points, D is zero. That is why a point, a line, an area, and a volume are called an 0–D, 1–D, 2–D, and 3–D objects, respectively.

For many irregular curves such as a wild and very jagged mountain trail or coastline, Eq. (1) still holds, but the parameter D is no longer an integer — this derives the term “fractal (i.e., fragmented) dimension”. This notion has been applied to study radar images [13, 14].

Quite often, different objects or phenomena have very similar fractal dimensions. Hence, the notion of fractal dimension alone is often not sufficient to fully characterize the object or phenomenon under investigation. One thus resorts to multifractals, which are often characterized by many or infinitely many power-law scaling relations.

The structure-function based multifractal formulation is most useful for the study of the so-called 1/f noise. The power spectral density of 1/f noise decays in a power-law manner. Such type of noise is very ubiquitous. For classic as well as recent examples of such processes, we refer to [15, 16, 17].

Under this framework, let $y(n), n = 1, \cdots$ denote the sea clutter data. We then examine whether the following scaling-law holds or not,

$$F^{(q)}(m) = \langle |y(i+m) - y(i)|^q \rangle \sim m^{\zeta(q)}, \tag{2}$$

where $\zeta(q)$ is a function of real value q, and the average is taken over all possible pairs of $(y(i+m), y(i))$. One often also defines the so-called $H(q)$ spectrum,

$$H(q) = \zeta(q)/q \tag{3}$$

When the scaling laws described by Eq. (2) hold, the process under investigation is said to be a fractal process. Fur-

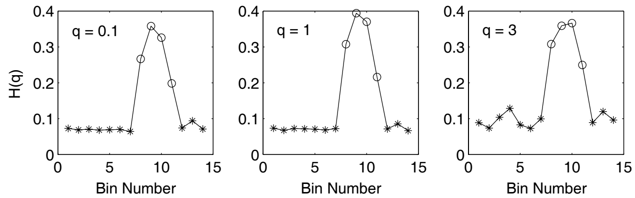

Fig. 3. $H(q),\ q = 0.1, 1, 3$ for the 14 range bins. Circles represent range bins with target, while * represent bins without targets.

thermore, if $H(q)$ is not a constant, the process is a multifractal; otherwise, it is a monofractal [18, 19, 20].The case of $q = 2$ is of special interest. It characterizes the correlation structure of the data set. In fact, when Eq. (2) holds, the autocorrelation for the "increment" process, defined as $x(i) = y(i+1) - y(i)$, decays as a power-law, $r(k) \sim k^{2H(2)-2},\ \ as\ \ k \to \infty$, while the power spectral density (PSD) for $y(n), n = 1, \cdots$ is $E_y(f) \sim 1/f^{2H(2)+1}$. $H(2)$ is often called the Hurst parameter, and simply denoted as H. We have found that sea clutter data can be well described by Eq. (2) in the time scale range of 30 msec to about 1 sec, and that the $H(q)$ spectrum can accurately detect whether a range bin hit a target or not. Fig. 2 shows a representative result for $q = 2$. We observe that $H(2)$ is much larger when the range bins hit a target. Fig. 3 shows that other q values can also robustly detect targets within sea clutter.

4. TARGET DETECTION PERFORMANCE WITHIN SEA CLUTTER

We have systematically studied the 392 time series of 14 sea clutter datasets measured under various sea conditions by structure-function based multifractal formulation. To better appreciate the detection performance, we have first only focused on bins with primary targets, but omitted those with secondary targets, since sometimes it is hard to assure whether a bin with secondary target really hits a target or not. The PDFs under each hypothesis (the bins without targets and the ones with primary targets) for HH and VV datasets are shown in Figs. 4 and 5, respectively, for the case $q = 2$. We observe that the PDFs completely separate for the HH datasets. This means the detection accuracy can be 100%. The accuracy for the VV datasets is also very good, except for two measurements. Careful examination of the amplitude time series data of those two cases reveals that those data are a lot more noisy than other measurements, and that these two VV datasets correspond to the two HH measurements with the two smallest H values.

Actually, Fig. 6 suggests that a better detector may be designed by using the ratio between the $H(2)$ values of the bins with targets and the ones without targets. This idea will be pursued in the near future.

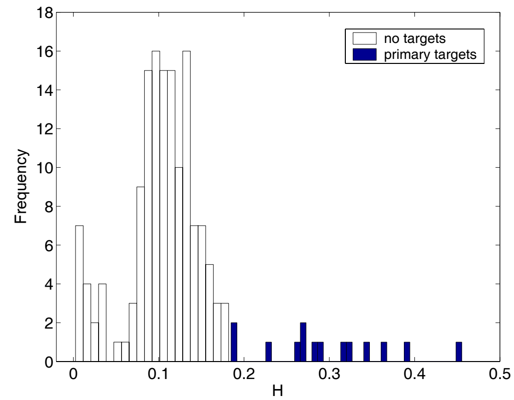

Fig. 4. The PDFs of the bins without targets and the bins with primary targets for HH datasets.

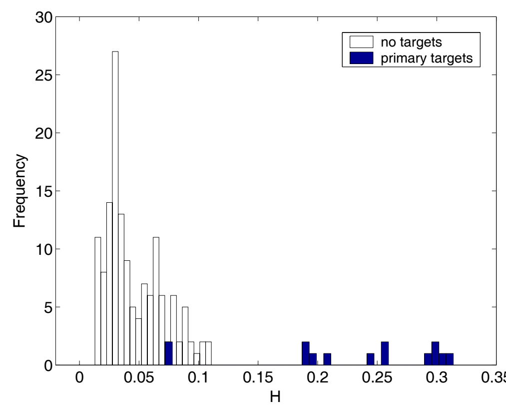

Fig. 5. The PDFs of the bins without targets and the bins with primary targets for VV datasets.

5. CONCLUSION

In this paper, we have introduced the structure function based multifractal technique for detecting small low observable targets within sea clutter. We have found that sea clutter data exhibits multifractal behaviors in the time scale range of 30 msec to about 1 sec, and that the $H(q)$ spectrum can accurately detect whether a range bin hits a target or not. We have systematically studied 392 amplitude time series of 14 sea clutter datasets measured under various sea conditions. It is found that the method is very effective in detecting low observable objects. It should be emphasized that the method developed is mathematically rigorous, conceptually elegant, computationally very fast, and practically easily implementable. These attributes strongly suggest that the method may be developed into an automated target de-

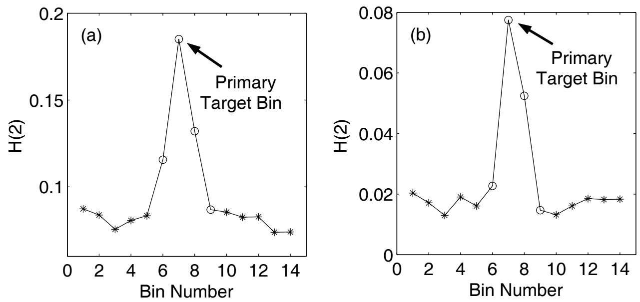

Fig. 6. The $H(2)$ spectrum for the (a) HH and (b) VV datasets where the bins with primary targets are marginally detected and missed. Open circles denote bins with target, while * denote bins without targets.

tector within sea clutter.

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