REFERENCES


II. Fractal Properties of Sea Clutter

A. Real-Life IPIX OHGR Datasets

In this study the real-life IPIX OHGR datasets are used to uncover fundamental fractal features of sea cutter and evaluate the performances of DFA in detecting low observable targets. The McMaster IPIX radar is an instrumentation-quality, coherent, dual-polarized X-band (9.39 GHz) radar system. The OHGR database was collected in November 1993 from Osborne Head Gunnery Range (OHGR) on the east coast of Canada. The database has been utilized to identify the radar features that are the most useful in detecting low observable targets within sea clutter. The target is a small spherical block of styrofoam wrapped with wire mesh, and the average target-to-clutter ratio varies in the range of 0–6 dB.

Fourteen sea clutter datasets of the IPIX OHGR database are available from a website maintained by Simon Haykin [10]. Four datasets have been discarded because their amplitude data are affected by clipping. The rest ten datasets are operated by the staring mode, with the antenna dwelling in a fixed direction, illuminating a patch of ocean surface. Each dataset contains 14 spatial range bins, and each range bin has $2^{11}$ samples and the sampling rate is 1000 Hz. Each range bin includes coherent data for four transmitted/received polarization configurations, which include like-polarized (VV, HH) and cross-polarized (VH, HV) data. Here our study only focuses on the amplitude data and does not involve the coherent analysis. In these datasets the wave height of the ocean varies from 0.8 m to 3.8 m (peak height up to 5.5 m). The wind conditions vary from 0 to 60 km/hr (gusts up to 90 km/hr). The grazing angle varies from less than $15^\circ$ to a few degrees [11], [12].

B. Detrended Fluctuation Analysis of Sea Clutter

DFA has been successfully applied to a wide variety of disciplines. Given a time series $x(i)$ ($i = 1, 2, \ldots, N$), the DFA method consists of the following five steps [13].
Step 1: Determine the profile of sea clutter time series
\[ Y(i) = \sum_{k=1}^{N} [x(k) - \langle x \rangle], \quad i = 1, 2, \ldots, N. \] (1)

Here \( \langle x \rangle \) is the mean value of time series \( x(i) \).

Step 2: Divide the profile \( Y(i) \) into \( N_m = \lfloor N/m \rfloor \) nonoverlapping segments with the equal length \( m \), where \( \lfloor . \rfloor \) denotes the integer floor of a variable. If the length of the time series is not a multiple of the time scale \( m \), the same procedure is repeated starting from the opposite end. Altogether we obtain \( 2N_m \) segments data.

Step 3: Calculate the local trend \( y_s(i) \) for each of the \( 2N_m \) segments by the least squares fitting method. Here, \( y_s(i) \) is obtained by linear polynomial fitting in the \( s \)th segment, \( s = 1, 2, \ldots, N_m \). Then calculate the variance \( Y_v(s, m) \) of each segment \( s \)
\[ Y_v(s, m) = \frac{1}{m} \sum_{i=1}^{m} [Y[(s-1)m + i] - y_s(i)]^2 \] (2)
and for \( s = N_m + 1, \ldots, 2N_m \)
\[ Y_v(s, m) = \frac{1}{m} \sum_{i=1}^{m} [Y[N - (s - N_m)m + i] - y_s(i)]^2. \] (3)

Step 4: Average over the variance \( Y_v(s, m) \) of all segments and take the square root to obtain the fluctuation function
\[ F(m) = \left[ \frac{1}{2N_m} \sum_{s=1}^{2N_m} Y_v(s, m) \right]^{1/2}. \] (4)

If the data has long range correlation, \( F(m) \) will increase with \( m \) in a power law form
\[ F(m) \propto m^H \] (5)
where \( H \) is the Hurst exponent.

Step 5: Determine the Hurst exponent from the log-log plot of \( F(m) \) versus \( m \) within the range of fractal scales
\[ H = \frac{\log_2 F(m)}{\log_2 m}. \] (6)

Hurst exponent characterizes the correlation property of time series. If \( H = 0.5 \), there is no correlation and the time series \( x(i) \) (i.e., the derivative of \( Y(i) \)) is uncorrelated; if \( H < 0.5 \), \( x(i) \) is anti-correlated; if \( H > 0.5 \), \( x(i) \) is correlated. For signals with correlation properties, we can obtain their Hurst exponents at various scales through the above steps.

C. Crucial Fractal Scale of Sea Clutter

Given a time series of sea clutter, we can get the fluctuation function \( \log_2 F(m) \) at different scales \( m \) by DFA. If the fractal feature of sea clutter coincides with that of theoretical fractal model, \( \log_2 F(m) \) will increase with \( \log_2 m \) in a linear manner. The typical curves of \( \log_2 F(m) \) versus \( \log_2 m \) for all range bins of sea clutter with four different polarizations are shown in Fig. 1. It is obvious that all the curves of \( \log_2 F(m) \) do not rise with \( \log_2 m \) in a linear way, which indicates the fractal feature of sea clutter varies with the time scale. We find that a crossover of \( \log_2 F(m) \) appears at the time scale of 250 ms (\( m = 2^8 \)), and it is just at this crucial scale that \( \log_2 F(m) \) curve of sea clutter possesses very special property. The standard deviation of \( \log_2 F(m) \) is small, which means the fractal feature of sea clutter at this scale is comparatively stable, although sea clutter is collected over different environments and polarization configurations. The standard deviations of \( \log_2 F(m) \) are found to be much larger both below and above this crucial scale.

It is well known that sea clutter can be described by the compound Gaussian model [14]. The complex envelope of sea clutter \( x(n) \) can be represented by two interactive components:
\[ x(n) = \sqrt{\tau(n)} \cdot y(n). \] (7)
Here, \( y(n) \) is the fast component (speckle) and \( \tau(n) \) is the slow component (texture). The correlation time of the speckle is about 10 ms, and that of the texture is about a few seconds [15]. It is interesting that the crucial scale 250 ms (\( m = 2^8 \)) is in the middle of the two different correlations, which implies that there may exist an equilibrium between the fast and slow components at the crucial scale. The physical mechanism of the fractal scale breaking and crossover of sea clutter at this scale will be investigated further. Actually, Haykin et al. have found that the relationship between the speckle and the texture is much more complicated than (7) [16]. We are only devoted to uncovering this significant fractal feature of sea clutter and applying it to detect low observable targets within sea clutter in this paper.

Compared with sea clutter, the range bins of primary targets show significantly different fractal properties. The curves of \( \log_2 F(m) \) versus \( \log_2 m \) for all range bins of primary targets are shown in Fig. 2, and we find that the curves of \( \log_2 F(m) \) of primary targets have no crossover. Actually, \( \log_2 F(m) \) of primary targets increases approximately linearly with \( \log_2 m \), with its standard deviation decreasing. The \( \log_2 F(m) \) of primary targets at the crucial scale 250 ms (\( m = 2^8 \)) shows a large standard deviation, which is remarkably different from sea clutter whose standard deviation minimizes at this scale.

D. Optimal Fractal Scales of Sea Clutter

In the previous section we have shown that sea clutter exhibits the fractal scaling breaking and crossover phenomena, which means sea clutter possesses the irregular fractal feature at certain scales. Usually the fractal features of real-life data are strongly affected by the presence of noise, especially at small scales. Sea clutter generally can be regarded as a fractal process only at certain scales by approximate fitting. Therefore finding the optimal fractal scale is the most important for describing fractal properties of sea clutter and detecting targets.
Another reason why we select $m = 2^k$ as the lower bound of optimal fractal scales is that this is the crucial scale of sea clutter. Most previous works on fractal features of sea clutter only consider the average difference between sea clutter and targets over all fractal scales as is measured by fractal dimension. The difference between sea clutter and targets at some specific scale, however, is rarely studied. In this paper, we find that sea clutter has a relatively stable fractal feature at the crucial scale, while primary targets do not have this property. The intercepts of $\log_2 F(m)$ at the crucial scale ($m = 2^k$) reveal the specific discrepancy between sea clutter and targets in terms of fractal features, which is extremely useful to detect low observable targets within strong sea clutter.

E. Fractal Features of Sea Clutter and Targets

The Hurst exponent obtained from $\log_2 F(m)$ versus $\log_2 m$ is a significant statistic for fractal features. Analyzing the Hurst exponents at coarse and optimal scales respectively, we find that the Hurst exponent of sea clutter is lower than that of primary targets. Fractal dimension [2] is a very efficient statistic to describe the texture property of rough surface [8]. There is a general relation between Hurst exponent $H$ and fractal dimension $D$ [17]:

$$D = 2 - H$$

(8)

This means that the fractal dimension of sea clutter is higher than targets, according to the formula (8). This result is consistent with the previous works on the fractal dimension of sea clutter [1], [5]. More rough surface corresponds to larger fractal dimension [2]. High-resolution sea clutter at low grazing angles is highly spiky, and the number of scatterers is not enough to satisfy the central limit theorem. These complex interactive scattering signals lead to the high fractal dimension of sea clutter. Conversely, the echo of the target in the primary target range bin is the main component of the scattering signal, which suppresses the scatter of sea clutter and leads to a low fractal dimension.

III. JOINT FRACTAL DETECTION OF LOW OBSERVABLE TARGETS

A. Joint Fractal Detection Method

We have proposed two novel statistics to detect targets: the Hurst exponent of optimal scales and the intercept at the crucial scale in above sections, which uncover the different fractal properties between sea clutter and primary targets. The former reflects the total fractal property difference at suitable multi-scales, and the latter reveals the fractal feature difference at the specific crucial scale. Obviously, a joint fractal detection method combining these useful information is expected to furthermore increase the accuracy of detection.

In order to study the validity of this joint fractal detection method, a two-dimensional feature space (i.e., a plane) of the Hurst exponent optimal fractal scales and the intercept at the crucial scale is adopted. The fluctuation functions of sea clutter $\log_2 F_{\text{sc}}(m)$ and primary targets $\log_2 F_{\text{pt}}(m)$ at the optimal scales ($m = 2^{k}\sim 2^{k+3}$) can be expressed as

$$\begin{align*}
\log_2 F_{\text{sc}}(m) &= H_s + \log_2 m + B_s \\
\log_2 F_{\text{pt}}(m) &= H_t + \log_2 m + B_t
\end{align*}$$

(9)

where the Hurst exponents $H_s$ and $H_t$ are the slopes of the fluctuation functions at the optimal scales for sea clutter and primary targets, respectively, and $B_s$ and $B_t$ are the intercepts at the crucial scale ($m = 2^k$). We use the two statistics $(H, B)$ in a two-dimensional feature space to distinguish sea clutter and primary targets, with the Hurst exponent $H$ indicating the average fractal difference of sea clutter and targets over multiple-scales, and the intercept $B$ at the crucial scale representing the fractal discrepancy at the specific scale.
B. Comparison of Detection Performances

To compare the detection performances of the four methods in quantitative manner, the receiver operation characteristic (ROC) curves for all the methods are calculated and shown in Fig. 4. To demonstrate the effectiveness and robustness of our method, we divide each range bin (originally with $2^{17}$ samples) into several nonoverlapping segments, each with $2^{15}$ samples. As can be seen in Fig. 4, the ROC curve for the Hurst exponent of coarse scales is the lowest among the four, indicating the lowest correct detection probability for the same false alarm probability. If the intercept at the crucial scale and the Hurst exponent of optimal scales are used respectively, their detection performances will exceed that of the Hurst exponent of coarse scales, as their ROC curves are both higher. Obviously, the joint fractal detection method which uses the classical and simple linear boundary with Neyman-Person criterion [18] outperforms the others. It achieves a significantly better detection performance than the methods using the Hurst exponent of optimal scales or the intercept at the crucial scale respectively, which reflects that the latter two methods can extract information complementary to each other, and that our joint fractal detection method adequately fuses useful information to increase the performance of targets detection.

C. Influence of Data Length on Detection Performance

We set the fixed false alarm rate to be 1% for all the detection methods and various data length ($2^{12} \sim 2^{17}$ samples). Comparing the detection results of different methods in Fig. 5, we can see that data length is a significant factor that influences the detection performance: longer data contains more information about targets and sea clutter. Detection results of different length data indicate that to get more accurate results, longer data should be adopted. The intercept at the crucial scale only measures the difference at a specific scale, so it is more sensitive to data length. The Hurst exponents of optimal scales and coarse scales measure the average difference of sea clutter and targets at multi-scales, therefore these two methods are less influenced by the length of data. The Hurst exponent of optimal scales has a better performance because the optimal scales are more suitable than the coarse scales in terms of targets detection. The joint fractal detection method integrates the useful information efficiently, so it can always get the best detection performances for any data length.

IV. CONCLUSION

In summary, we analyze the fractal features of sea clutter by DFA and discuss how to accurately detect low observable targets within sea clutter for a low grazing angle (less than 1° to a few degrees) X-band (9.39 GHz) radar system. We find that the time scales from 250 ms to 4 s can be considered as the optimal fractal scales of sea clutter, as sea clutter at this special time range resembles a fractal process more than any other scales. In particular, the fractal feature of sea clutter at the crucial scale (250 ms) is comparatively stable, which indicates that there may exist an equilibrium between the fast component (speckle, the correlation time is about 10 ms) and slow component (texture, the correlation time is about a few seconds) at this special scale. How the crucial scale changes with the measurement conditions is still difficult to explain, so it is worth proposing a theoretical explanation and extending the current result to a more general sea clutter analysis in the future.

Based on the refined fractal features of sea clutter, a joint fractal detection method is proposed, which simultaneously utilizes the intercept at the crucial scale and the Hurst exponent of optimal scales. This novel method exhibits a robust and accurate detection performance in various sea conditions (wave height: 0.8 m to 3.8 m, and peak height up to 5.5 m), wind conditions (wind speed: 0 to 60 km/hr, and gusts up to 90 km/hr) and polarization configurations (like-polarized data: VV and HH, cross-polarized data: VH and HV) for the IPIX Dartmouth real-life datasets. The new approach has the potential to become a real-time and automatic detector, for it is simple and can be easily realized without any training. Furthermore, our method, like those work in [7], [9], can also be extended to the spatial domain such as remote sensing images [8]. We expect that our method can be more fruitfully applied to a wider range spatial and temporal data in the field of radar and remote sensing.

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References


