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Vessel Target Detection in Sea Clutter via SSA-CFAR Detector

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Abstract

The target detection in sea clutter has long been studied since sea clutter is nonstationary and hardly modeled by statistical models. For effectively finding the vessel covered by sea clutter, we propose a distribution-free method, i.e., the range bins are firstly checked if a target exists by seeking the number of principal components in radar returns, then the singular spectrum analysis (SSA) is applied on the radar returns to enhance the target echo and suppress the sea clutter. Thereafter a vessel target is successfully detected by CA-CFAR and OS-CFAR detectors. The test of vessel target detection is performed on a dataset from Council for Scientific and Industrial Research (CSIR) and comparisons between the proposed SSA-CFAR detector and Pareto distribution based CFAR detectors illustrate the effectiveness of the proposed method.

Keywords: Target detection, Sea clutter, SSA-CFAR detector

1 Introduction

Sea clutter is the radar echo from the footprint on sea surface while radar surveying sea. The correct description on sea clutter is important for carrying out suitable approaches to detecting targets in sea clutter, and therefore the performance of radar could be guaranteed. The early studies on fitting sea clutter distributions are based on various probability models. The reason of adopting the statistical methods is due to the random behavior of the sea clutter waveform [10]. The normally-used models for sea clutter include Weibull [6], log-normal [22] and K distributions [16], [26]. Recent investigations suggest that Pareto distribution could be a better candidate to describe the 'spiky' property of sea clutter [28]. Unfortunately, it is not effective to fit such distributions to the measured sea clutter and the features extracted from these distributions hardly distinguish sea clutter with targets from those without targets [13]. The reason may be due to that sea clutter behaves in manner of the non-stationarity or cyclo-stationarity [9] and the conventional models require the stationary data under test [10].

The nature of sea clutter is nonstationary and nonlinear, since the radar echoes caused by the irregular sea surface consists of two fundamental types of waves, namely, the gravity wave with wavelengths covering the range of hundreds of meters to a fraction of a meter, another one is of the tiny capillary waves with shorter wavelengths in degree of centimeters. The dominant restoring forces for these waves are respectively the gravity and the sea surface tension [10]. Usually, sea clutter is considered as the nonstationary nonlinear dynamic process because its nonlinearity is changing with the "sea states" [7]. The practical tests have shown that sea clutter is heterogeneous when a sea surveillance radar operates with a long coherent integration time (CIT) [28]. Thereby, sea clutter cannot be described with the homogeneous models in theory [17].

The conventional target detection methods include the various kinds of constant false alarm rate (CFAR) detectors which require (1) target is independent, and (2) the interfering targets and clutter in reference cells are uniformly distributed, i.e., they should be independent identically distributed (i.i.d) [24]. Unfortunately, the real-world radar returns are usually not satisfactory to the aforementioned preconditions. For solving this problem, many efforts have been carried out, e.g., K distribution-based methods are widely used to model sea clutter [1], [25], [29]. In those probability distribution function (PDF)-based methods the sea clutter is treated as a stationary random process, hence the non-stationarity of sea clutter is not taken into account. Therefore, these approaches are appropriate for processing sea clutter when radar's CIT is shorter (e.g., shorter than 0.01s [14]). When radar detecting the small and dim targets in sea, the longer coherent processing time is required to enhance the strength of target echoes. Meanwhile, the strength and non-stationarity of sea clutter also rise up. So that those methods hardly find out the small and dim targets within sea clutter [28]. In order to solve this problem, some effective measures have been taken into sea clutter suppression, such as the short-time fractional Fourier transform (STFFT) analysis technique [4], the bi-window nonlinear shrinkage map-based method [32], neural network-based approaches [2-3], [18], the wavelet transform based approach and wavelet-neural network combined approaches [20], fractal analysis-based methods [8], [15], [23],[27], and the chaotic feature-based methods [5], [11-12],[19],[31], etc. Besides the methods above, the nowadays researches pursue the non-parametric or distribution-free CFAR based methods, which can process the non-stationary and heterogeneous sea clatter and easily detect targets within sea clutter. Therefore, in this letter, based on the singular spectrum analysis (SSA) [21], a new non-parametric CFAR detector, i.e., SSA-CFAR is proposed to realize the slow-moving target detection in measured sea clutter. Compared with the methods above, SSA-CFAR detector is designed on the idea of distribution-free and has the ability of enhancing target echo and suppressing sea clutter. This detector can distinguish the backscattering difference between the sea surface and the slow-moving target. So that, the vessel target within sea clutter can be easily found out.

The remainder of this letter is organized as follows. In Section 2, the steps of target detection within sea clutter are introduced. Meanwhile the principles of SSA as well as the window length selection method are briefly introduced [30] In Section 3, For detecting the slow-moving vessel within the measured sea clutter, the proposed detector is tested by using the Council for Scientific and Industrial Research (CSIR) dataset. A short discussion on the detector performance is then given. Finally, conclusions are drawn in Section 4.

2 Section Principle of SSA-CFAR detector

The SSA-CFAR detector contains following steps.

Step 1. In the process of radar surveillance, the echo of each range bin is preprocessed in radar receiver and converted into I-Q form which can be viewed as a complex time series $\{y_i=v_i+ju_i\}$, i=1,2,…N, where N is the length of data. Calculate the echo amplitude

$$x_i = \sqrt{v_i^2 + u_i^2} \tag{1}$$

Step 2. Choose a window length L for the time series $X=\{x_i\}$ i=1,2,…N, and calculate its autocorrelation

$$R_{xx}(l) = \sum_{i=1}^{N-L+1}(x_{i+l} - \bar{x})(x_i - \bar{x}),\ (l = 0, \cdots L - 1) \tag{2}$$

where $\bar{x}$is the Mean value of time series$\{x_i\}$, and then build up Toeplitz matrix C = Toeplitz (R_{xx}).

Step 3. Apply Singular Value Decomposition (SVD) on this Toeplitz matrix, i.e., [V, D] = eig(C). Extract the eigenvalues σ_i (i =1,2,…L) from the diagonal of D, rearrange them in descending order and adjust the eigenvectors in V accordingly, and then determine the number of principal components σ_p,

$$R_i = \frac{\sigma_i}{\sum_{i=1}^{L}\sigma_i} \tag{3}$$

The ratio R_i is called singular spectrum which can be used to estimate the number of principal components σ_p, i.e., by accumulating R_i one by one and checking if the result is greater than or equal to 95%, if so, stop accumulation and record the times of accumulation that are the number of principal components.

Step 4. Judge if the range bin includes a target

$$P = num(\sigma_p) \gtrless E_T \tag{4}$$

where E_T is threshold, if $P>E_T$, it is case H_1, otherwise it is case H_0. Mark the range bins where targets involved.

Step 5. Apply SSA decomposition on the echo amplitude data $X=\{x_i\}$ $i=1,2, \ldots, N$ in every range bin, i.e., convert time series into Hankel matrix, namely rearrange the time series by the technique of delay coordinate phase space reconstruction on $X=\{x_i\} i=1,2,\ldots N$. The corresponding embedding dimension $m = L$ and time delay $\tau= 1$, therefore, $M\times L$ $(M = N-L+1)$ Hankel matrix are constructed,

$$H = \begin{bmatrix} x_1 & x_2 & \cdots & x_{1+L-1} \\ x_2 & x_3 & \cdots & x_{2+L-1} \\ \vdots & \vdots & \ddots & \vdots \\ x_M & x_{M+1} & \cdots & x_{M+L-1} \end{bmatrix} \tag{5}$$

Then, project H on the subspaces spanned by the eigenvectors in rearranged matrix V

$$W = HV \tag{6}$$

If we denote $W_j = V_j V_j^T H^T, (j = 1, \cdots L)$ as the projection on subspace V_j, then, the trajectory matrix W can be written as

$$W = W_1 + W_2 \cdots + W_L \tag{7}$$

Step 6. Divide W_j in (7) into two groups according to the partition in *step 3,* that is, $W^{I_k}, (k = 1,2)$ which are relevant to the principal and minor components of Hankel matrix H. Apply the inverse Hankelization process on W^{I_k}. This procedure is conducted via averaging the elements of W^{I_k}, that are located on the same anti-diagonal, i.e., the elements $w_{ij}^{I_k}$ with the indices sum $i + j =$ constant. Set X^{I_k} to be the reconstructed time series via W^{I_k}. Then, the j-*th* component of W^{I_k} is obtained by: $x_j^{I_k}=$ Mean {elements of W^{I_k} are placed on the j-*th* anti-diagonal}. Thus, the time series $X=\{x_i\}$ $i=1,2, \ldots N$, is decomposed into ensemble of time series $X_p=\{x_{pj}\}$, j $=1, 2\ldots P$, and $X_m=\{x_{mk}\}$, $k=1, 2\ldots L-P$, which are respectively corresponding to the target echo plus sea clutter ($P> E_T$) or sea clutter ($P< E_T$) and noise.

The signal to clutter ratio (SCR) could be estimated by the ratio

$$SCR = \frac{\sigma_{p1}}{\sum_{i=2}^{P} \sigma_{pi}} \tag{8}$$

The signal to noise ratio

$$SNR = \frac{\sigma_{p1}}{\sum_{k=1}^{L-P} \sigma_{mk}} \tag{9}$$

In case that only sea clutter exists, the clutter to noise ratio could be

$$CNR = \frac{\sum_{i=1}^{P} \sigma_{pi}}{\sum_{k=1}^{L-P} \sigma_{mk}} \tag{10}$$

Step 7. Extract the first time series x_{p1} from $X_p=\{x_{pj}\}$, $j=1, 2\ldots P$, where the target may exist in the range bin, and the last time series x_{ml} from $X_m=\{x_{mk}\}$, $k=1, 2\ldots L-P$ where only sea clutter exists in range bins. Apply the conventional CFAR detectors on the target and calculate the detecting probability P_d and the false alarm probability P_{fa}. In case of the multi-targets, the targets will be processed in sequence, i.e., when one target is processed the others are taken out from the reference cells to avoid producing the interference effects.

In *Step 2* the selection of window length is critical since the accuracy of SSA-CFAR detector is mainly relied on this parameter. When the window length L is appropriately selected, the lagged vectors X_k and X_l ($k \neq l$) in reconstructed Hankel matrix H, can be treated as linearly independent. In the case of target detection in sea clutter, for an echo $X=\{x_i\}$ (i=1, 2…N) in certain range bin, the window length L is selected to be the counting of the first zero crossing point of autocorrelation function R_{xx} to its origin, i.e., because the autocorrelation R_{xx} is an even function, we choose the positive part of R_{xx} to determine the window length L. Firstly, we choose a relative large time lag (e.g. 30 to N/2), and then find the global extrema and their indexes (R_{max}, I_{max}, R_{min}, I_{min}) from the half of R_{xx}, sort these extrema in descending order and find out indexes $I_{max}(2)$ and $I_{min}(2)$(i.e. the first pair of extrema of R_{xx}). When $I_{min}(2)$ is following $I_{max}(2)$, let $L = I_{min}(2)$, otherwise, let $L = floor((I_{max}(2)+I_{min}(2))/2)$. Therefore, the columns of H are mutually independent.

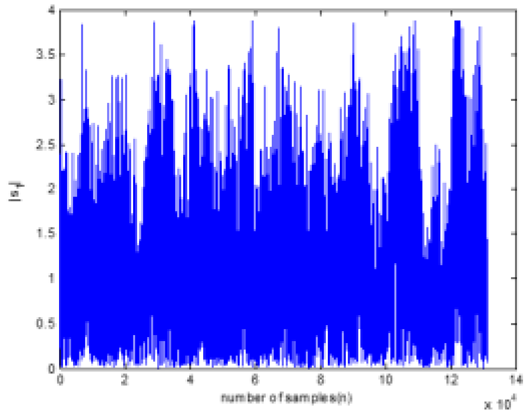

Fig. 1. IPIX radar echoes in low sea state (The lo.dat from http://soma.ece.mcmaster.ca/ ipix /Dartmouth /datasets.html). |s1| is the magnitude of the complex envelope of radar returns.

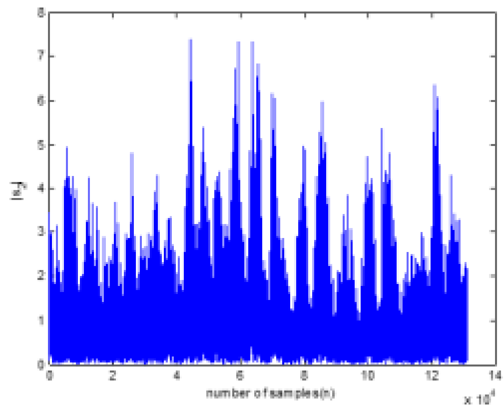

Fig. 2. IPIX radar echoes in high sea state (The hi.dat from http://soma.ece.mcmaster.ca/ ipix /Dartmouth /datasets.html). $|s_2|$ is the magnitude of the complex envelope of radar returns.

The threshold E_T in (4) is an integer which is determined by the trials of measured sea clutters. We have obtained two datasets of sea clutter (*lo.dat*, *hi.dat*) measured by IPIX radar (http://soma.ece.mcmaster.ca/ipix/Dartmouth /datasets.html). IPIX radar was situated at a place with height of c.a. 30m above the sea level in Dartmouth, Nova Scotia, on the east coast of Canada. IPIX radar was operating in a dwelling manner and the grazing angle 0.4 Deg, the carrier frequency was 9.3

GHz and pulse repetition frequency (PRF) 1 KHz (pulse width 200ns). Thereby, IPIX radar would entirely catch the dynamics of the sea clutter since the wavelength of IPIX radar is c.a. 3cm. Dataset *lo.dat* (1.0 MB) is the radar echoes in range bin 5 (VV polarization), which was pre-processed in analytical form, namely the in-phase component (I) in column 1 and the quadrature component (Q) in column 2 (see Figure 1, the absolute amplitude waveform of sea clutter). Dataset *hi.dat* (0.9 MB, refers to Figure 2) consists of the sea clutter in range bin 3 with the same polarization and data form as *lo.dat*. We apply the PCA algorithm on both datasets and find out the number of principal components is all equal to 2, which accord with the fact that sea clutter reflected from the irregular sea surface is caused by two fundamental types of waves, i.e., the gravity waves, and the smaller capillary waves. It is also true with the CSIR dataset used for slow moving target detection in Section 3. Therefore, let $E_T=2$ for judging the target existence is a rational choice.

3 Tests on the measured sea clutter

In order to validate the proposed detector, we carry out tests with the measured sea clutter data, CSIR dataset (TFC15_023.01). Details on this dataset can be found in [33]. The range bins involved in this dataset is 31, samples of each range bin is 33001, therefore, it is a 33001×31 complex matrix. A slow-moving vessel is in range bin 11 and interaction range bins are 9~13. Range resolution is 15m. Range Window is 3360~3810m. Radar height is 56m. The pulse repetition frequency (PRF) is 2.5 KHz. The grazing angle is 1.187 Deg and the significant wave height is 2.88m.

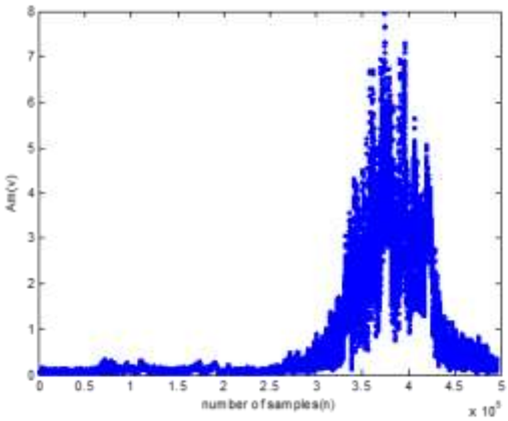

Fig. 3. Echo amplitude of vessel in range bin 11 after SSA

This dataset is processed step by step as what mentioned in Section 2. The window length L = 5 is calculated with the echo data in range bin 11 where the slow-moving vessel is located. After *Step 3*, the singular spectrum is obtained, σ_i={ 0.8978, 0.0728, 0.0256, 0.0031, 0.0007 }. The first three values are principal components; the first one is corresponding to the power of target echo, and the second and third are the power of sea clutter in this range bin. Two minor components are the power of noise. Therefore, SCR=9.6014 dB and SNR=23.7717dB. After *Step 5*, the echo data is decomposed into 5 time series. Fig.

3 illustrates the first time series, i.e. the target echo and Fig.4 depicts the sea clutter waveforms.

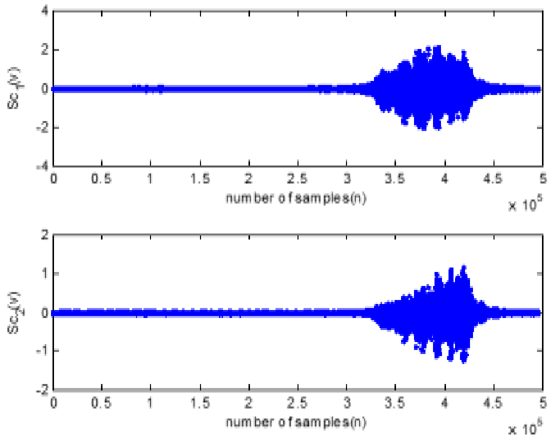

Fig. 4. Waveforms of sea clutter in range bin 11

The multiple peaks of target echo reflect the multiple backscattering centers of vessel. The two waveforms in Fig.4 are respectively caused by Types 1and 2 fundamental sea waves. Here, only the target echo is kept for the further processing.

The ranges bins, where only sea clutter involved, are processed with the window length L=4. After the SSA decomposition only the last time series is taken out for the further CFAR processing. In this way the SSA technique plays as the adaptive filter. The signal decomposition does not rely on the statistical distribution but depend on the difference in signal powers. The only restriction here is the signals involved in radar returns must be independent, which is easily satisfied in practice.

After *Step 6* the radar returns are reassembled, i.e., the target echo in range bin 11 is enhanced and the power of sea clutter in all range bins are suppressed. Then in *Step 7* the CA-CFAR and OS-CFAR detectors are respectively applied on the reassembled dataset. The number of training range bins is 16, the number of guard bins is 2, the goal of P_{fa} is $P_{fa\_goal} = 10^{-3}$ and the target detection is performed by scanning the range bins 9 to 13. The probability of detection $P_d = 0.9876$, $P_{fa} = 3.0302\times10^{-5}$ with CA-CFAR and $P_d = 0.9907$, $P_{fa} = 1.2121\times10^{-4}$ with OS-CFAR.

For the purpose of comparison, we follow the method in [6] to repeat the trial of target detection. The distribution of sea clutter is Pareto intensity distribution and its two parameters, shape parameter k and scale parameter *sigma* are estimated via maximum likelihood estimation. Fig.5 depicts these two parameters in different range bins. It is clear that CSIR dataset is nonstationary and the vessel target is in heterogeneous clutter environment. Therefore, with CA-CFAR detector $P_d = 0.186$, $P_{fa} = 6.06\times10^{-5}$ and with OS-CFAR detector $P_d = 0.33$, $P_{fa} = 1.21\times10^{-4}$.

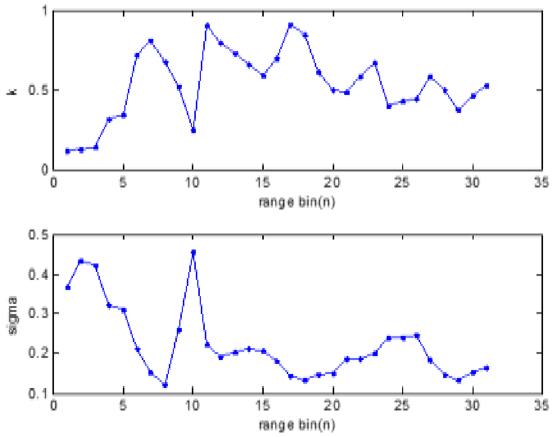

Fig. 5. Model parameters of Pareto distribution of CSIR dataset, the shape parameter *k* is in upper part and the scale parameter *sigma* is in lower part.

4 Conclusion

The detection of multiple targets in sea clutter has been drawing attention for long term in domain of radar signal processing and is still a hot topic which provides many practical and theoretical issues that require being deeply investigated. In this letter, we focus on the non-parametric CFAR detectors since conventional methods are often faced with some difficulties for constructing the statistical models for the nonstationary sea clutter. For solving this bottleneck problem, we combine the SSA technique with the traditional CFAR and realize a new distribution-free detector. Relied on the SSA decomposition, the target echo is enhanced and the sea clutter is suppressed. The proposed SSA-CFAR detector is a powerful implemental technique in radar engineering.

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