LETTER

Detection of Range-Spread Target in Spatially Correlated Weibull Clutter Based on AR Spectral Estimation

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SUMMARY In high range resolution radar systems, the detection of range-spread target under correlated non-Gaussian clutter faces many problems. In this paper, a novel detector employing an autoregressive (AR) model is proposed to improve the detection performance. The algorithm is elaborately designed and analyzed considering the clutter characteristics. Numerical simulations and measurement data verify the effectiveness and advantages of the proposed detector for the range-spread target in spatially correlated non-Gaussian clutter.

key words: *high range resolution, range-spread target, spatially correlated non-Gaussian, AR model, CFAR*

1. Introduction

Due to the superior detecting capability of high range resolution (HRR) radar, the observed target would spread over several range cells which is regarded as a range-spread target [1], [2]. The statistics of such clutter detected by a HRR have been observed to deviate from Rayleigh distribution which is spikier than Gaussian. The false-alarm rate (FAR) would be increased if processing the spikes as targets [3].

In many practical situations, the ground clutter also exhibits significant spatial correlation [4], resulting in non-negligible effects on detection performance. Obviously, under correlated non-Gaussian clutter, the detection of range-spread target faces many problems that are difficult to solve with existing methods which is applied to the point target under uncorrelated Gaussian clutter.

Previous work in the field of radar signal processing employing an autoregressive (AR) model concerns mainly about spectrum estimation, clutter-whitening processing and so on [5], [6]. Inspired by the idea of previous work, in this paper, high range resolution profile (HRRP) based on AR algorithm is used to detect range-spread target rather than inverse Fourier transform approach. The AR model can not only keep high range resolution but also whiten and suppress correlated and uncorrelated clutter, therefore, improving the detection performance for the range-spread target in spatially correlated and uncorrelated non-Gaussian clutter.

The remainder of this letter is organized as follows. In Sect. 2, the proposed AR-OS detection algorithm and clutter characteristic are derived and illustrated, together with the performance evaluations. Then, the effectiveness of the proposed detector is verified by simulations and the measured data in Sect. 3. Finally, Sect. 4 presents our conclusions.

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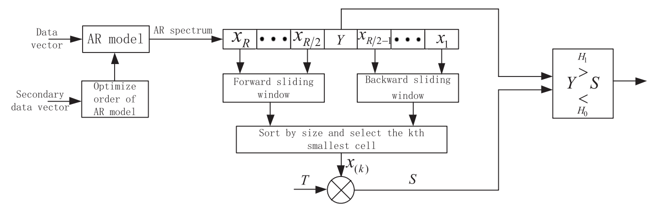


Fig. 1 Flowchart of AR-OS detector.

2. Proposed Detecting Algorithm

The detection problem can be described as the following binary hypothesis,

$$\begin{cases} H_0 : Z = w \\ H_1 : Z = x + w \end{cases} \tag{1}$$

where H_0 is the clutter-only hypothesis, H_1 is the signal-plus-clutter hypothesis, $x = \{x_i \,|i = 0, 1, \ldots, N-1\}$ is a N dimensional vector that represents the target's HRRP, N is the number of range cells, and $w = \{w_i \,|i = 0, 1, \ldots, N-1\}$ is the clutter which is assumed to be uncorrelated or spatially correlated Weibull clutter. In Fig. 1, the proposed detection is conducted in a two-step scheme: 1) establishment of HRRP based on AR model using secondary data; and 2) detection using the ordered statistics (OS) method on HRRP of AR spectrum.

2.1 HRRP Based on AR Algorthm

Non-parametric fourier transform technique is not the only method for estimating the target locations with high resolution. Parametric approaches, such as AR algorithm, can also be extensively employed in the filed of HRRP estimation. The AR model of order m is defined as [7]:

$$x[n] = -\sum_{k=1}^{m} a_k x[n-k] + e[n] \tag{2}$$

where $a_k (k = 1, 2, \ldots, m)$ are AR coefficients and $e[n]$ is forward prediction error. From Eq. (2) the information contained in HRRP is split into two parts: 1) the global frequency-evolving information represented by a_k, reflecting the HRRP structure and can be utilized for detection;

2) the reflectivity of HRRP return and local variations contained in $e[n]$, which can be ignored due to its insignificance for detection.

There are several issues employing AR model for HRRP should be addressed. For instance, it is a vital problem of determining a proper order. If the order of the model is too low, the resolution would be lost; if it is too high, the spurious peaks would be observed. In this paper, the order is optimized from $N/3$ to $N/2$ to satisfy the minimum order criterion [12]. The order meeting the requirement of range resolution is obtained from secondary data. Moreover, there are many methods available for AR model parameters estimation including Yule-Walker method, Burg method, covariance approach and modified covariance approach. Among these, the modified covariance (MCOV) approach, that is minimizing the sum of squares of the forward and backward prediction errors, which is also called forward-backward or least square method is adopted in this parer. It has the advantages of higher spectrum resolution with short data length and gives less dependence on sine signal's initial phase.

Notably, the coefficients a_k in the MCOV method could be solved from a set of linear equations as in equation [8],

$$\begin{bmatrix} r_{xx}[1,1], & r_{xx}[1,2], \ldots & r_{xx}[1,m] \\ r_{xx}[2,1], & r_{xx}[2,2], \ldots & r_{xx}[2,m] \\ \vdots & \vdots & \vdots \\ r_{xx}[m,1], & r_{xx}[m,2], \ldots & r_{xx}[m,m] \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_m \end{bmatrix} = - \begin{bmatrix} r_{xx}[1,0] \\ r_{xx}[2,0] \\ \vdots \\ r_{xx}[m,1] \end{bmatrix} \tag{3}$$

where $r_{xx}[l,k]$ is as follow:

$$r_{xx}[l,k] = \frac{1}{2(N-m)} \sum_{n=m}^{N-1} \left(\begin{array}{l} x^*[n-l]\,x[n-k] \\ +x^*[n-p+k]\,x[n-p+l] \end{array} \right) \tag{4}$$

The resulting residual least-squares error ε_p is

$$\varepsilon_p = r_{xx}[0,0] + \sum_{k=1}^{m} a_k r_{xx}[0,k] \tag{5}$$

2.2 Clutter Characteristics

Since Weibull distribution can fit the experimental data of the ground clutter well in a wide range, it is used as the assumption of amplitude model of the clutter [3]. The Weibull Probability Density Function (PDF) $f(x)$ is given by

$$f(x) = \frac{q}{p}\left(\frac{x}{p}\right)^{q-1} \exp\left(-\left(\frac{x}{p}\right)^q\right), x \geq 0 \tag{6}$$

where p is scale parameter and q is shape parameter.

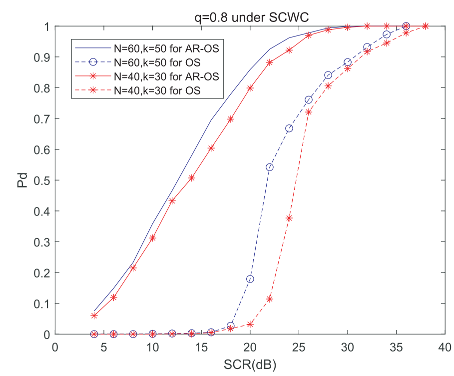
Based on the survey of the experimental data of the ground clutter [9], it is considered that the spatial correlation function includes two components: fast fluctuation and slow fluctuation. The expression of the normalized spatial correlation function $R(d)$ is

$$R(d) = ae^{-d^2/b^2} + (1-a)e^{-d/c} \tag{7}$$

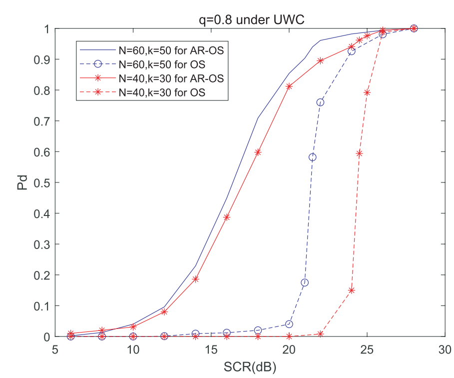
where $0 \leq a \leq 1$ represents the proportion of fast fluctuation component in the total energy, and b and c are the decorrelation distances of fast fluctuation and slow fluctuation components respectively, d is space distance between clutter units.

Table 1 Simulation parameters.

Parameter	Value
Pulse number	64
Frequency step	15 MHz
Range cell number	2880
range resolution	0.15 m
Target	lorry and corner reflector
P_{fa}	10^{-4}
p	1
a	0.054 m
b	0.52 m
c	20.69 m



(a)

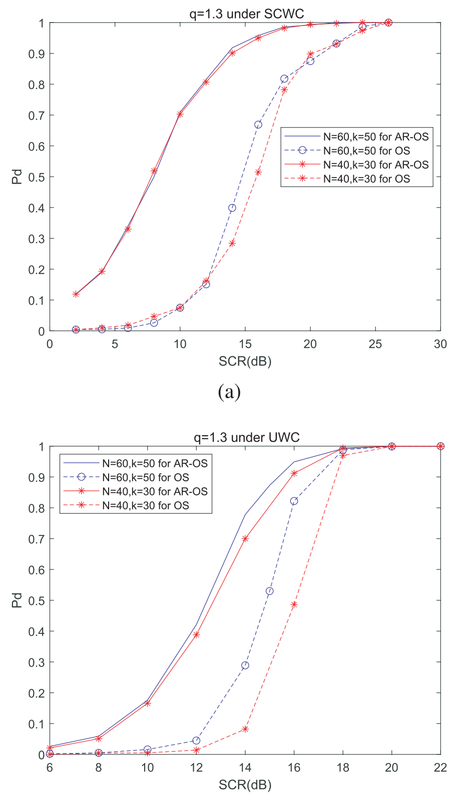


(b)

Fig. 2 Detection performances of AR-OS detector and OS detector with shape parameter $q = 0.8$. (a) P_d versus SCR using $R = 60$, $k = 50$ and $R = 40$, $k = 30$ under SCWC. (b) P_d versus SCR using $R = 60$, $k = 50$ and $R = 40$, $k = 30$ under UWC.

2.3 Detection Algorgthm

Due to the fact that OS method has good resolution in the



(a)

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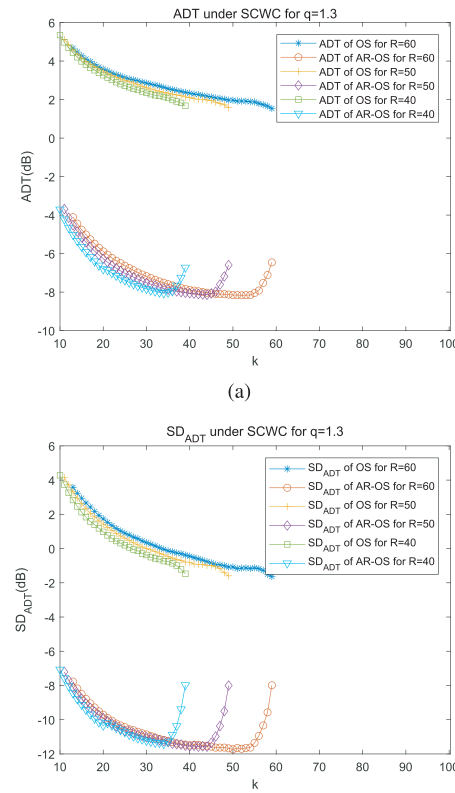
Fig. 3 Detection performances of AR-OS detector and OS detector with shape parameter $q = 1.3$. (a) P_d versus SCR using $R = 60$, $k = 50$ and $R = 40$, $k = 30$ under SCWC. (b) P_d versus SCR using $R = 60$, $k = 50$ and $R = 40$, $k = 30$ under UWC.



(a)

(b)

Fig. 4 ADT and SD_{ADT} under SCWC ($q = 1.3$) for AR-OS detector and OS detector. (a) ADT under SCWC ($q = 1.3$) for AR-OS detector and OS detector with different reference uints R (60, 50 and 40). (b) SD_{ADT} under SCWC ($q = 1.3$) for AR-OS detector and OS detector with different reference uints R (60, 50 and 40).

case of range-spread target detection, it is adopted here for target detection. In AR-OS method, the reference units R of AR spectrum are sorted according to their magnitude. The k-th sample $x_{(k)}$ in order is selected as the estimation of clutter power level, and the detection threshold S is obtained by multiplying $x_{(k)}$ with the threshold factor T which is determined by the designed false alarm probability P_{fa}. By comparing the detection unit Y with the threshold S, the target could be observed if the threshold is exceeded.

With H_1 hypothesis, the false alarm probability under Weibull distribution [11] is

$$P_{fa} = \frac{R!\Gamma(R-k+1+T^q)}{(R-k)!\Gamma(R+1+T^q)} \tag{8}$$

where Γ is gamma function.

The averaging decision threshold (ADT) and its standard deviation (SD_{ADT}), compared with OS algorithm, are used here to evaluate the AR-OS algorithm [10], [11], which can be expressed by

$$ADT = \frac{E(S)}{p} \tag{9}$$

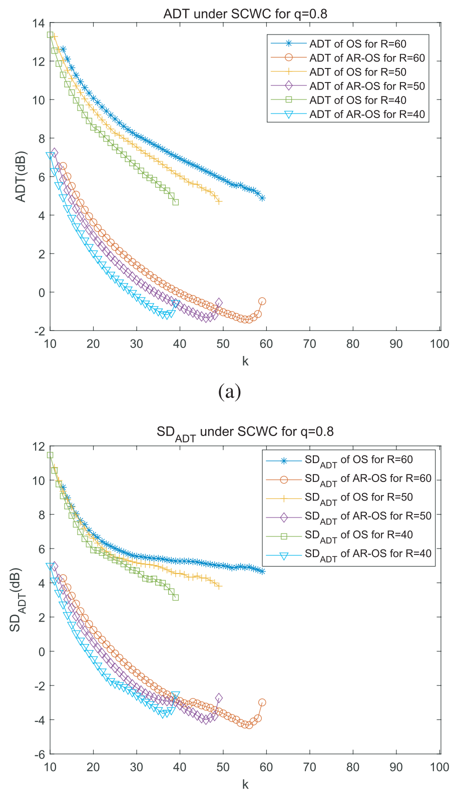
$$SD_{ADT} = \frac{[\mathrm{var}(S)]^{1/2}}{p} \tag{10}$$

Performance analysis reveals that the detection probability depends not only on ADT, but also on SD_{ADT} with the fixed parameters k, R and signal clutter power ratio (SCR). In other words, for parameter k, a smaller ADT value does not always correspond to a higher detection probability P_d. Threshold S estimation is optimal only when the ADT and SD_{ADT} values reach the minimum at the same time, and the parameter k of minimum value is the optimal for fixed clutter parameter. This feature does not depend either on the shape parameter q of clutter background distribution or the predetermined false alarm rate P_{fa}. Moreover, another advantage of the ADT and SADT is that they avoids the complicated evaluations with density functions that are usually required in the situation of nonlinear clutter processing.

3. Performance Evaluation

Here, simulation data and measured data are provided to evaluate the performances of the proposed AR-OS algorithm under spatially correlated weibull clutter (SCWC) and uncorrelated weibull clutter (UWC). It would be compared with the OS detector using fourier transform technique, in terms of different clutter parameters, reference uints R and parameter k.

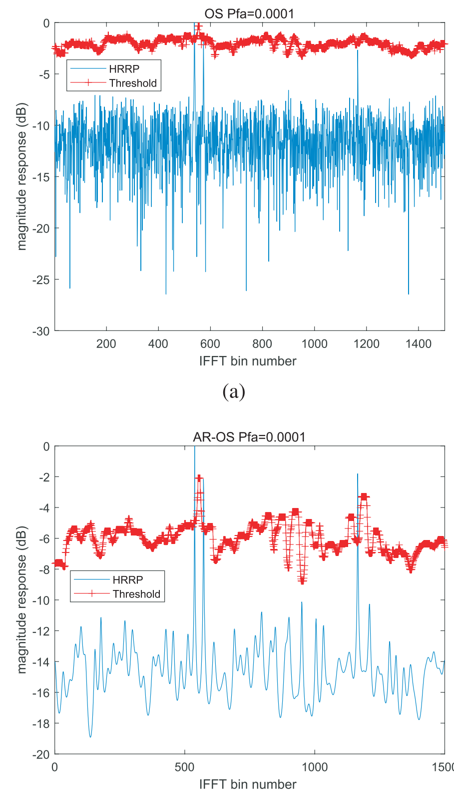
In the experiments, P_{fa} is assumed to be 10^{-4} and the



(a)

(b)

Fig. 5 ADT and SD_{ADT} under SCWC ($q = 0.8$) for AR-OS detector and OS detector. (a) ADT under SCWC ($q = 0.8$) for AR-OS detector and OS detector with different reference uints R (60, 50 and 40). (b) SD_{ADT} under SCWC ($q = 0.8$) for AR-OS detector and OS detector with different reference uints R (60, 50 and 40).



(a)

(b)

Fig. 6 The result of AR-OS detector and OS detector with $R = 60$, $k = 50$ for lorry. (a) OS detector with fourier transform technique. (b) AR-OS detector with AR model.

detection performances of AR-OS and OS are obtained from Monte Carlo simulation where 1000 independent trials are conducted at each SCR level. In this way, the performance of AR-OS and OS algorithms is compared by ADT and SD_{ADT}. Thereafter, the results of measured data obtained by stepped-frequency synthetic broadband radar are used to demonstrate the availability of the proposed detector. The simulation parameters required for generating SCWC [9] and other experimental parameters are given in Table 1.

In Fig. 2 and Fig. 3, performances of AR-OS detector and OS detector using different reference uints R (60 and 40) and different k (50 and 30) with SCWC and UWC ($q = 0.8$ and 1.3) are compared. Whatever SCWC and UWC is, AR-OS detector shows superiority to OS detector. This means that the SCR required to achieve the same P_d is smaller. For UWC, the performance superiority owes to the fact that the filtering effect of AR model greatly reduces the influence of clutter fluctuation on detection while maintaining high range resolution. For SCWC, due to the ability of spatial decorrelation of AR model, it achieves better detection performance than OS detector. The AR model combines decorrelation with spectrum estimation to decrease the influence of spatial correlation on detection and obtain the HRRP of the range-spread target. Furthermore, because of the model stability of parametric approaches, P_d obtained by AR-OS detector varying from 50% to 80% doesn't change dramatically with SCR fluctuated.

The performance of AR-OS and OS for normalized HRRP with different reference units R (40, 50 and 60) under SCWC ($q = 0.8$ and 1.3) assumptions are evaluated based on ADT and SD_{ADT} in Fig. 4 and Fig. 5. The ADT and SD_{ADT} of AR-OS detector reach the minimum at the same time under different reference units. And the value of ADT and SD_{ADT} obtained by AR-OS detector is also smaller than those of OS detector. In other words, compared with OS detector, the estimated k in the AR-OS detector is closer to the optimal value under SCWC assumption.Therefore, with the same clutter parameters, the threshold estimation of AR-OS detector is better and more accurate than that of OS detector.

Furthermore, Because the minimum values of ADT and SD_{ADT} in OS detector curve are all obtained when optimal k is equal to R, these curves are monotonically decreasing. And in AR-OS detector the optimal k are all less than R, those curves of AR-OS detector are parabola. It is notable that the type of these curves, i.e., monotonous or parabolic, is determined by the selected parameters (q and R) in this paper, as is revealed in [10], [11].

Further, measured data is used for comparison, and the performance of AR-OS detector and OS detector with $R = 60$, $k = 50$ in terms of range-spread target are compared in Fig. 6. The range-spread targets are two adjacent points of lorry and one point of corner reflector. The weaker scattering point of lorry and corner reflector are missed for OS detector as depicted in Fig. 6(a), while the AR-OS detector has detected all these points of the range-spread target as depicted in Fig. 6(b). Therefore, the AR-OS detector, to some extent, can reduce the influence where the range-spread target will be shielded by strong scattering point.

4. Conclusion

In this paper, the AR-OS detector has been proposed and demonstrated to be effective for detecting the range-spread target under SCWC and UWC assumptions. The AR model employed in the detector combines spectrum estimation with spatial decorrelation to improve the detection performance, obtaining more accurate optimal estimation of k and reducing the shielding effect in terms of range-spread target. The performance of the AR-OS detector has been analyzed in terms of probability of detection using Monte Carlo simulations. Results of simulations and measured data reveal that compared with OS detector, the AR-OS detector is more adaptable for range-spread target under SCWC assumption while guaranteeing the CFAR property.

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