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Design and Modeling CFAR Algorithms Detecting Target on a Curvilinear Trajectory

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***Abstract* — This study explores the design and modeling of Constant False Alarm Rate (CFAR) algorithms for detecting targets along curvilinear trajectories in cluttered environments. By focusing solely on primary signal processing, the research introduces a robust approach tailored for nonlinear target motion without post-detection filtering. Using a generalized radar signal processing model and leveraging advanced statistical simulations, the performance of traditional, ordinal, and locally optimal rank-based CFAR algorithms is evaluated. The findings highlight the efficacy of rank-based algorithms under complex clutter conditions, offering significant improvements in detection accuracy and operational reliability.**

***Keywords* — CFAR algorithms, clutter environments, curvilinear trajectories, radar signal processing, target detection.**

I. Introduction

The detection of targets in complex environments remains a critical challenge in modern radar. This study addresses the problem of detecting a target against the background of various interferences, using CFAR algorithms [1], [2]. A distinguishing characteristic of this research lies in its focus on the detection of targets moving along curvilinear trajectories. Unlike conventional approaches that incorporate trajectory processing through filtering techniques [3], the detection here is based solely on primary processing, without any post-detection filtering. Of course, to improve trajectory information and reliable target tracking a postprocessing can be applied after the primary processing, however in this paper we are limited by primary processing only.

CFAR algorithms are integral to radar systems due to their capability to stabilize the false alarm rate under varying clutter conditions. They dynamically adjust the detection threshold based on local clutter characteristics, ensuring robust target detection. However, the complexity increases significantly when the target follows a non-linear trajectory, as traditional CFAR techniques are optimized for scenarios with linear or stationary targets. This study addresses this gap by design and modeling the detection process specifically for curvilinear target motion, taking into account characteristic challenges.

The study compares the performance of various CFAR algorithms, including an approach proposed by the authors, to evaluate their effectiveness in maintaining a constant false alarm rate and detecting targets on curvilinear paths. By leveraging statistical simulations, this work provides a comprehensive analysis of detection performance in complex operational scenarios. This research contributes to the field by offering insights into the design and modeling CFAR algorithms tailored for target detection at their non-linear motion. The findings have implications for improving the accuracy and reliability of target detection, especially in environments where clutter and target dynamics are highly variable.

II. General Structure of Primary Processing

Primary signal processing includes matched filter and extractor, while trajectory (secondary) processing is fulfilled in following tracking unit. Note that primary processing treats only one sample (for instance, a set of n pulses collected within a single radar beam pass through the target), while secondary processing deals with multiple samples, separated by time. In this paper we are limited by primary processing which is nevertheless implemented over a target in movement.

A feature of the model architecture presented in this paper is the modeling of the spatial distribution of clutter situations and target routes. The spatial distribution of clutter along the target path is an important factor in the design and optimization of radar systems, especially in real-world operations, where there are heterogeneous sources of interferences. The model considers a two-dimensional space consisting of N range cells and M azimuth cells. Clutter zones and target trajectories are formed in the observation space.

III. Cluter Model

Clutter model on the base of compound K-distribution [4] was used. It allows the physical interpretations unlike the Weibull or the Log-Normal statistics. For example, in case of sea clutter, the K-distribution describes two components of clutter fluctuations: one from distributed elementary scatterers with comparatively small decorrelation time and other one from a slow varying mean component that corresponds to the sea swell structure. Such model can represent the Rayleigh process, whose mean power is averaged by the Gamma distribution.

Following [5], here the resulting expression for K-distribution is used:

$$f(E) = \frac{4b^{(\nu+1)/2} E^{\nu}}{\Gamma(\nu)} K_{\nu-1}\left(2E\sqrt{b}\right),\ 0 \le E \le \infty \qquad (1)$$

with $K_{\nu-1}(\cdot)$ as the modified Bessel function, ν and b correspondingly as shape and scale parameters.

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Supposing the adequate determination of shape and scale parameters for the different clutter conditions, such as sea, land, and atmosphere, expression (1) represents the generalized model of clutter returns. Parametrization of the clutter model was done in the previous paper [5] for different types (sea, land and rain) and intensities of clutter.

IV. Primary Signal-Processing Algorithms

A. Traditional CFAR Algorithms

Several CFAR schemes have been developed. In this study, we will test the most typical ones. The first is Cell Averaging (CA) CFAR [1]. Its structure is shown in Fig. 1 in the form convenient for our consideration. Here T is time delay corresponding to a range bin; C means comparator; α is a weighting factor, which can be used to control detection characteristics. Such CA CFAR implements the algorithm for adaptive quantization of signals from the output of the amplitude detector of a radar receiver. The sample x_{i-m} is a signal sample to be checked, and samples $x_i,..x_{i-m+1}$ and $x_{i-m-1},..x_{i-2m}$ are reference or training samples. This algorithm produces two estimates V and U as the average values of samples $x_i,..x_{i-m+1}$ and $x_{i-m-1},..x_{i-2m}$ respectively received from m previous and m subsequent range bins relative to the signal sample x_{i-m}. In case of homogeneous clutter situation in the vicinity of the signal cell, V and U are practically equal. The classical CA CFAR use arithmetic mean of them. Another approach is using the Greatest Of them (GO) that leads to CAGO CFAR. A binary unit “1” at the output is formed when the signal sample x_{i-m} exceeds both thresholds V and U. This is equivalent to the formation of the quantization threshold as the maximum value $V_q = \max(V,U)$. Thus, the algorithm in Fig. 1 is exactly CAGO CFAR.

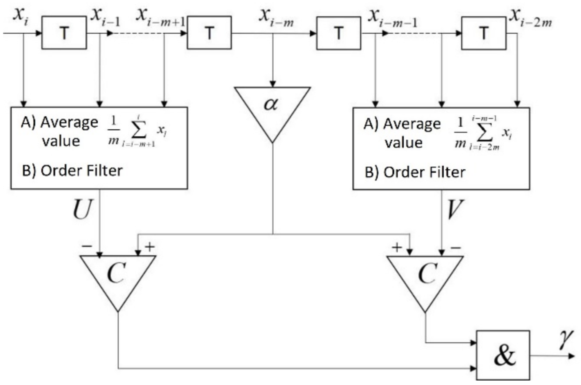

Fig. 1. Cell Averaging CFAR (CA CFAR) and Order Statistic CFAR (OS CFAR). When calculating thresholds U and V, the case A) corresponds to CA CFAR, and the case B) corresponds to OS CFAR.

A. Order CFAR Algorithm

Described above traditional CFAR algorithms well adapt detection procedures under the assumption of homogeneous clutter situation around resolution volume under the consideration. However, such forming the quantization threshold may not provide stability of false alarm probability F, when this assumption is not true or at any deviation of the clutter distribution from Gauss law. Such a deviation may occur, for example, when the sources of clutter are rough sea surface or turbulent meteorological formations. The density distributions of such reflections have "long tails", which may lead to the presence of large outliers in the sample and increase in F. The Order Statistic (OS) CFAR algorithm, which was proposed in [1] and independently in [7], has better properties in this aspect. The structure of OS CFAR is the same (Fig. 1), but here the left and right thresholds are formed not as average values, but as ordinal statistic (case B in Fig.1). For example, these could be medians that cut off rare outliers from the tails.

The detection characteristics of two – CA and OS – CFAR algorithms are compared in Fig. 2. They were obtained by Monte-Carlo simulation based on a single pulse (period of modulation). In this modelling, the probability of a chaotic impulse interference (spike) was accounted in addition to the clutter. Such spike can reduce the uniformity of the clutter situation in the vicinity of the range bin to be checked.

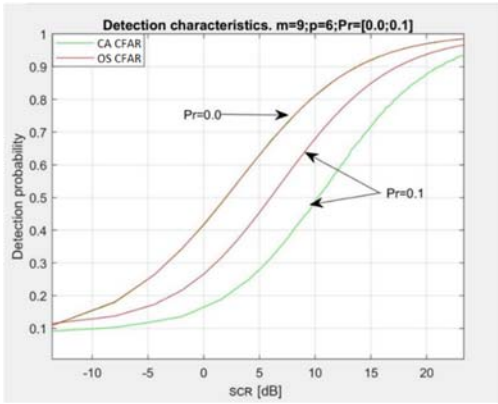

Fig. 2. Detection characteristics CA CFAR and OS CFAR algorithms. Pr is probability of the chaotic impulse interference.

One can see that in case of uniform clutter and absence of spike (Pr=0) the curves for CA CFAR and OS CFAR coincide practically, while when Pr=0.1, that is, a spike is possible, the detection characteristic for OS CFAR is much better.

B. Rank locally-optimal algorithm

Robust algorithms, invariant with respect to the probabilistic characteristics of signals and interference, are of great interest. The idea of rank detector was suggested earlier and analysed in [8], and [9]. The generalized structure of a Locally-Optimal Rank (LOR) CFAR is shown in Fig. 3.

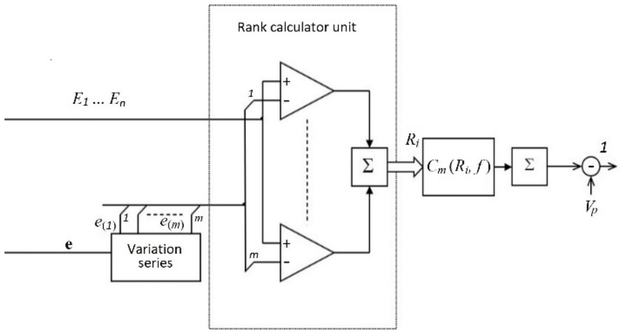

Fig. 3. Locally-Optimal Rank detector structure (LOR CFAR).

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Two samples act at the input: 1) $E_1, E_2, ..., E_n$ that is n reflected signals from the resolution volume (range bin) being tested, and 2) the clutter matrix, which represents reference samples $\mathbf{e} = \{e_{ij}\}$, $i=\overline{1,m}$; $j=\overline{1,n}$. Sample $E_1,..,E_n$ is a signal $\overline{s} = s_1,..,s_n$ and clutter mixture envelope, described by equation $E_i = \sqrt{(as_i + \upsilon_i)^2 + \varsigma_i^2}$ with υ_i and ς_i as normalized Gaussian samples (quadrature) with random scale parameter Gamma distributed; s_i is a signal shape parameter; a is a signal scale parameter. The clutter values, presented in the above matrix $\mathbf{e}$, are obtained from the neighboring resolution volumes of E_i and distributed as (1). An envelope sample E_i is fed to the (+) input of the Rank calculator unit, which consists of m Comparators and the Adder (Fig. 3). The negative (-) inputs of the comparators are fed with m clutter samples, for example, the i-th column of clutter matrix $\mathbf{e}$, (reflections from adjacent range bins), which are ranked previously in the Variation series unit. Thus, each signal reading is compared to m clutter samples. The outputs of the comparators are summed in the 1st Adder (Σ), forming the reference rank R of the envelope. The next unit $C_m(R_i, f)$ calculates a value of the rank function from the ranks accumulated in the 1st adder. The calculated values can be integrated over the whole signal sample in the 2nd Adder and then compared with the decision threshold V_p.

The rank function $C_m(R_i, f)$ provides LOR CFAR weight coefficients for K-distributed clutter (1). If signal samples are present, the E_i is distributed as Rice with random scale parameter distributed by Gamma law: $f_{a\neq 0}(E_i)$. Concerning sample $E_1, E_2, ..., E_n$, we check the hypothesis H_1 : signal is present $(a \neq 0)$, against the hypothesis H_0 : signal is absent $(a = 0)$. The sample $\{e_{ij}\}$, $i = \overline{1,m}$; $j = \overline{1,n}$ is a training sample and contains the clutter only. The algorithm is based on rank statistics $\overline{R} = (R_1, R_2, ..., R_n)$, where ranks of sample values E_i are R_i, $i = \overline{1,n}$ and should be calculated by the formula

$$R_i = \sum_{j=1}^{m} U(E_i - e_{ji}); \qquad U(E_i - e_{ji}) = \begin{cases} 1, \ E_i > e_{ji}; \\ 0, E_i < e_{ji}. \end{cases} \tag{2}$$

Synthesis of the locally optimal free distribution rank algorithm for signal detection is based on the study of the distribution of ranks' vector $\overline{R} = (R_1, R_2, ..., R_n)$, for the hypothesis H_1 , when the sample contains a signal, $w_m(\overline{R} \mid a \neq 0)$, and constructing a locally optimal decision rule $\lambda(\overline{R}) = \frac{\partial w_m(\overline{R} \mid a)}{\partial a}|_{a=0} > V_d$. To construct the distribution $w_m(\overline{R} \mid a \neq 0)$, we need to know the distribution of the signal sample for an alternative hypothesis H_1 . Let $f\,(y,a)$ is one-dimensional probability distribution for H_1 , and $f\,(y,0)$ is a probability density for the hypothesis H_0 . Then probabilities of ranks can be calculated as:

$$w_m(R_i = l, f) = \mathrm{m}\binom{m-1}{l-1}\int_{-\infty}^{\infty} f\,(y,a)[F(y)]^{l-1}[1-F(y)]^{m-l}\,dy \tag{3}$$

where $F(y)$ is cumulative distribution function (CDF) of K-distribution.

The dependence of the values of the function on the rank l is calculated as

$$C_m(l, f) = m\binom{m-1}{l-1}\int_{-\infty}^{\infty} J(E,a)[F(E)]^{l-1}[1-F(E)]^{m-l}\,dE, \tag{4}$$

where $J(\mathrm{E}) = \frac{\partial f\,(y,a)}{\partial a}|_{a=0}$ is the derivative of a one-dimensional probability distribution $f\,(E,a)$ over a signal parameter a at the point $a = 0$; $F(E)$ is one-dimensional CDF of the clutter.

V. Detection Probability Estimation

A. *Estimating the quality of detection*

For assessing the probability of detection at sufficiently low level of false alarm probability F, a large enough number of simulation cycles is necessary, at least an order of magnitude larger than the value of F^{-1} . Actually, this concerns also the result presented in above Fig. 2, however, the level of F was rather high over there. A simulation session consists of K frames, each of which has a size of $n \cdot m = S$ resolution cells, where n and m are numbers of independent radar bins over azimuth and range correspondingly. The probability F is calculated as the ratio of the sum of target-like blips M, received in each frame in all K frames of the session, to the product of the number of resolution cells S in the frame by the number of frames K under the condition of target absence $F = M / (SK)$. The probability of detection D is calculated as the ratio of the number of frames C, in which the target blip is registered, to the number of frames in the session K under the condition of target presence $D = C / K$.

B. *Comparison of two processing algorithms*

The results of estimating the quality of detection using Rank LO algorithm and CA GO algorithm are presented in Fig. 4. Here both algorithms are implemented with integration over the whole signal sample while simulation shown in Fig. 2 was done for the detection over a single pulse. Both algorithms were investigated under the similar clutter conditions. In the graphs, v is shape parameter, N is sample size, m is size of training (or reference) sample, and F=10^{-5}.

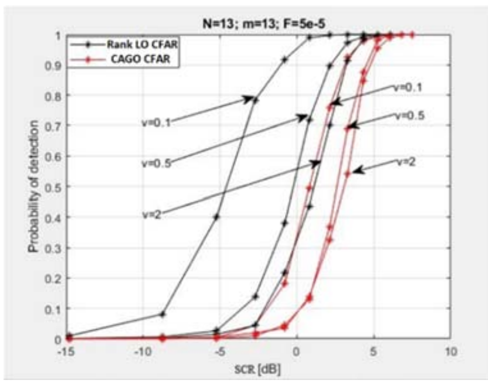

Fig. 4. Comparison of the detection characteristics in cases of rank local-optimal algorithm (Rank LO CFAR) and Cell Averaging CFAR algorithms.

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One can see from the curves at Fig. 4 that, in all simulated cases, the Rank LO CFAR algorithm is more efficient than CA CFAR algorithm. At small values of the shape parameter v the advantage is greater. Note that under conditions of uniform clutter, the CA and OS algorithms give identical results (see Fig. 2). This leads to the conclusion that the rank algorithm is also superior to the OS algorithm.

C. Curve trajectories with complicated clutter conditions

During this research, the original software was developed. It allows to form certain space distributions of various types of clutter, simulate target trajectories and test target detection algorithms. This makes possible to study the operation of detection algorithms during target movement through areas with various clutter situations. Various scenarios were modeled and investigated, including sea, land, and rain clutter of different intensity. Moreover, it was possible to add manually some zones of very intensive 'secondary' clutter. As an example, Fig. 5, 6 and 7 show the detection of a moving target against a background of rain clutter. For the simulation, a heavy rain regime with a rain rate of about 40 mm/h was used and a fairly small target RCS of 3 m^2 was selected. Three CFAR algorithms were compared at $F \approx 2 \cdot 10^{-6}$.

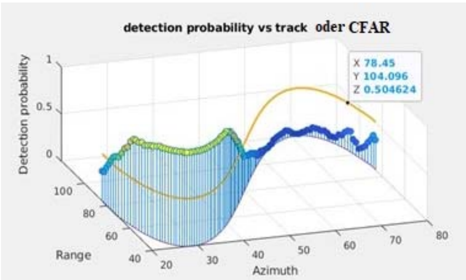

Fig. 5. CA CFAR detector.

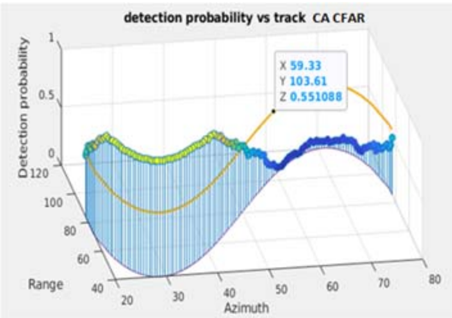

Fig. 6. Order CFAR detector.

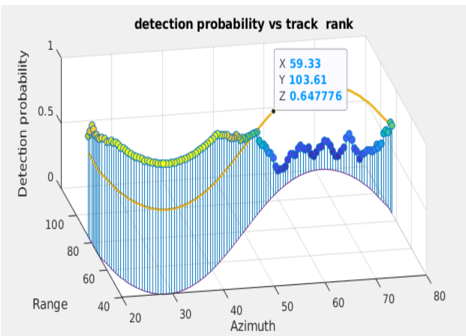

Fig. 7. Rank LO CFAR.

The graphs show how the detection probability changes during movement along the trajectory. The clutter situation also changes, with the strongest shower corresponding to the right side of the graphs. The numbers X, Y, Z show the values of the detection probability (Z) at specific points of the trajectory (X, Y). All the studied algorithms demonstrate a decrease in the detection quality in extremely complex conditions, but the LO CFA still gives the best result.

VI. Conclusion

The robust CFAR algorithms for primary processing of radar signal, including the developed by authors rank local-optimal algorithm, have been investigated.

The study has shown that rank-based CFAR algorithms essentially outperform traditional and order-statistic CFAR techniques, particularly under challenging clutter conditions.

The foundational role of primary processing has been shown for achieving reliable target detection even without the computational overhead of secondary filtering techniques, which will obviously be more effective on this reliable basis.

The research findings underline the practical advantages of the proposed methods for modern radar systems, especially in dynamic environments requiring high accuracy in detecting targets with nonlinear motion.

While here we were focused on primary processing, future studies could integrate trajectory tracking and secondary signal processing to further enhance detection precision and system robustness.

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