

A Modified Method for Radar Clutter Recognition Based on a Truncation Set

Gao Yanzhao, Wan Jianwei, Zhan Ronghui, Wen Xiaoyang

School of Electronic Science and Technology

National University of Defense Technology,

Changsha Hunan, P. R. China, 410073

Abstract-his paper is concerned with the recognition of radar clutter. First a recognition method based on α truncation set is introduced. The method is efficient but inconvenient in practical application for the optimal α is difficult to choose. Then a modified method is presented. It makes use of more information of clutter distribution PDFs by defining another kind of α truncation set. As a result, the optimal α is a certain value, making it more convenient for practical application. The simulation and comparisons made at the end show that the modified method has good performance.

Keywords-adar clutter recognition, α truncation set

I. INTRODUCTION

Radar always works in varieties of clutter backgrounds, especially for SAR system. A typical airborne SAR system is capable of providing wide area search coverage (approximately 100 km² area per minute) at medium 1.0m×1.0m resolution [1]. With the complexity of the radar backgrounds, different clutter models are required for different regions. These models have to fulfill certain constraints in both amplitude distribution and correlation properties, i.e., spectral characteristics [2]. As a result, the conventional assumption of clutter amplitude's Rayleigh distribution has become difficult to correctly describe the real clutter distribution, and more other distribution models were presented. Among them, Log-Normal, K and Weibull distributions have been paid most attention.

In order to implement the optimal radar signal processing, especially in the target detection step, the processing strategy should be changed according to the different clutter backgrounds. This may be called the adaptation between the signal processor and clutter background, in which the radar clutter recognition is naturally an indispensable step [3]. It could considerably improve radar detection performance [6].

Many recognition techniques are used for the classification purposes: the spectrum analysis, autoregressive simulation, amplitude distribution analysis, neural network and methods based on α truncation set and multi- α truncation set [2-6], etc, among which the α truncation set like method can overcome the drawbacks of long samples requirement, and has high recognition rate with low computational complexity. However, this kind of method has the common drawbacks, i.e., the optimal value of α have to be properly decided to maximize the recognition rate. Although an adaptive optimization criterion has been presented in [7], the optimal α must be

computed repeatedly in different backgrounds. This absolutely increases the computational burden. In this paper, a modified method based on α truncation set is presented. By defining another kind of α truncation set, more information of the different clutter models is used in the presented method, which leading to a certain value of optimal α and makes it more convenient to use.

This paper is organized as follows. The clutter recognition method based on α truncation set is introduced in section 2, and then the modified method is presented in section 3. The simulation results are given In section 4, followed by the conclusions in section 5.

II. TRUNCATION SET BASED METHOD

A. Processing Flow of the Method [3]

The signal processing flow of the designed radar clutter recognition system is shown in

Figure . Assume that the possible distributions form a set $C: (f_1, f_2, \dots, f_M)$. For $f_i (1 \leq i \leq M)$ and a given constant $\alpha (0 \leq \alpha \leq 1)$, the threshold of α truncation set x_i is defined as:

$$\int_{x_i}^{\infty} f_i(t) dt = \alpha \quad (1)$$

The calculation of x_i and the method flow can be summarized as follows:

1) Estimate the PDF f_0 of the given clutter data to be recognized with TKE method [9];

Calculate the parameters of every kind distribution in set C from the clutter data with maximum likelihood method or moments method to obtain the PDFs which can be noted as: f_1, f_2, \dots, f_M ;

Given α , calculate the thresholds x_0 of α truncation set of the input samples.

Calculate the thresholds x_1, x_2, \dots, x_M of α truncation set of every possible distribution.

Recognize the clutter distributions with distance-deciding method, i.e., the solution i of the equation $\min_{1 \leq k \leq M} (|x_0 - x_k|) = |x_0 - x_i|$ is the kind of recognition result.

B. The Optimal Value of α

The method in A is of excellent performance when is appropriately selected [3]. However, when the environment in which radar works changes, the same α may incur in unacceptable performance degradation. In order to adjust α adaptively according to current clutter data, some optimization criterion has to be adopted.

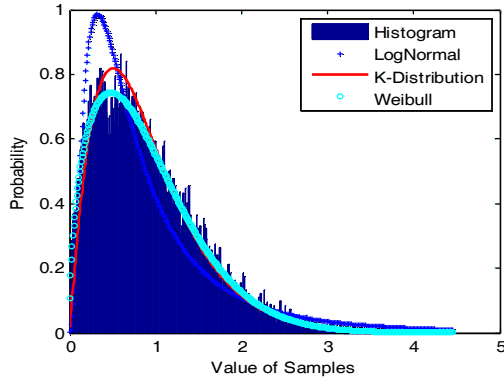


Figure 2. Histogram and possible PDFs of the input samples generated from Weibull distribution

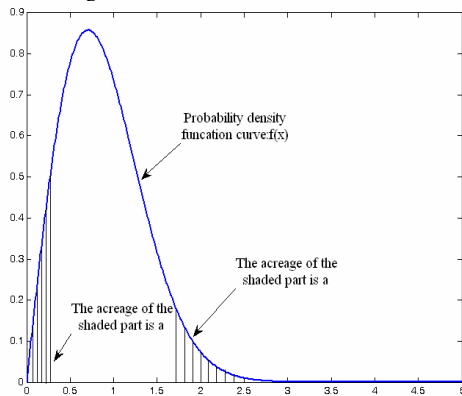


Figure 3. Schematic diagram of the two kinds of α truncation set

In the literature [7], an adaptive optimization criterion has been presented. This criterion is mainly due to the consideration that whether the selected value of α is appropriate or not determines the degree of differences of the possible distribution models, thereby determines the separability of the input samples. So it's reasonable to some extent to consider "maximize the degree of differences between the thresholds of different α truncation sets" as the adaptive optimization criterion to select the optimal α . Define the degree of differences between the thresholds of different α truncation sets as:

$$Error(\alpha) = \sum_{i=1}^M \sum_{j=1}^i |x_i - x_j| \tag{2}$$

Apparently, the optimal α is the one maximize (2) according to the optimization criterion. In practice, however, there are at least two drawbacks about this criterion. Firstly, it's very hard to solve the optimal α directly from the

complex nonlinear equation [7]; secondly, the "optimal α " determined by this criterion is not correct in some situation.

Consider the problem of three kinds of typical clutter distribution models in this paper (the PDFs are given in Table I), and assume the input samples are generated from Weibull distribution. Figure 2 shows the histogram of the input samples and the estimated possible distributions.

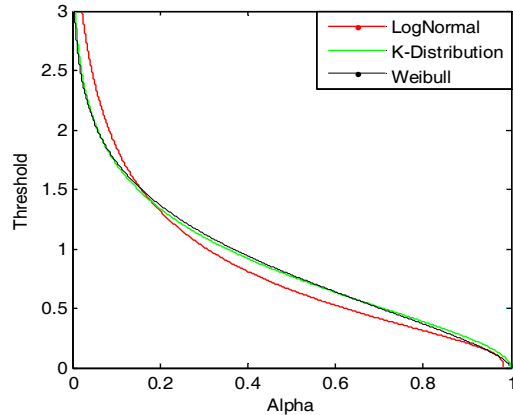


Figure 4. Threshold versus α for $\alpha \in (0,1)$

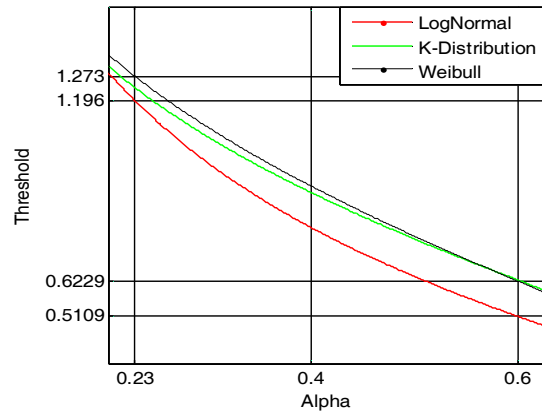


Figure 5. Local enlargement of Figure 4

Figure 4 shows the relationship between threshold and α when α changes from 0 to 1, and Figure 5 shows some special part of Figure 4. It can be seen that $Error(\alpha)$ when $\alpha=0.6$ is larger than the one when $\alpha=0.23$, but the separability of the three possible distributions is apparently worse. Actually, the recognition rate is 95% when $\alpha=0.23$, which is much higher than 15.75% when $\alpha=0.6$. Therefore, it is very important to select an appropriate α in this method. Unfortunately, the optimal α is hard to selected, especially when radar works in changing environment.

III. THE MODIFIED METHOD

The method introduced in A has excellent performance if α is selected appropriately [3]. But it's inconvenient to repeatedly compute the optimal α in practice when radar works in complex environment.

The presentation of the α truncation set method is mainly due to the consideration that the most serious influence of clutter to radar signal processing is its tail [7]. However, the diversity of different clutter distribution PDFs at their beginning is also remarkable and can also provide useful information in the clutter recognition.

In the same way, assume that the possible distributions of clutter form a set $C:(f_1, f_2, \dots, f_M)$. For $f_i (1 \leq i \leq M)$, and a given constant $\alpha (0 \leq \alpha \leq 1)$, define two kinds of α truncation-set: the first kind is the one defined above, which is truncated at the tail of the PDF; the other kind is defined almost in the same way but at a different position, which is truncated at the beginning of the PDF. Figure 3 shows how to get the two kinds of α truncation set.

Given the thresholds of the two kinds of α truncation set, and denoted as x_i and y_i :

$$\int_0^{x_i} f_i(t) dt = \alpha$$

$$\int_{y_i}^{\infty} f_i(t) dt = \alpha$$
(3)

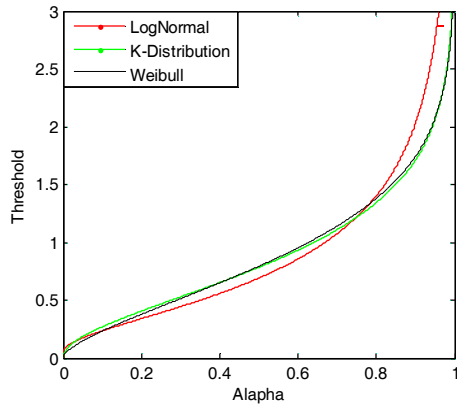


Figure 6. Threshold versus α for $\alpha \in (0,1)$ (the second kind α truncation set)

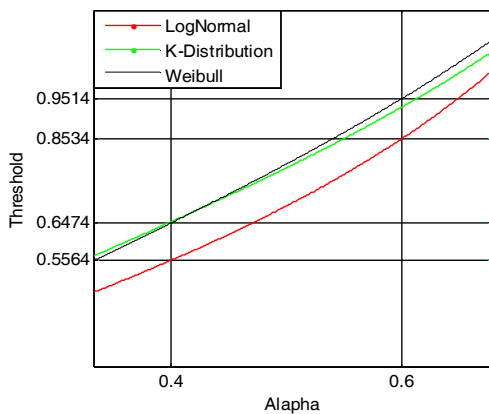


Figure 7. Local enlargement of Figure 6

Figure 6 shows the relationship between threshold of the second kind α truncation set and α . Figure 7 shows some special part truncated in Figure 6.

In the original method, the possible distributions are not distinguishable when α is chosen from some special value, for example $\alpha=0.6$ (Figure 5). However, in the same place, the method has good performance (the recognition rate is 85%) if the second kind α truncation set is used (Figure 7). This result show that these two kinds of α truncation set could be combined together as a new decision basis to recognize radar clutter models, and the new recognition method may have better performance.

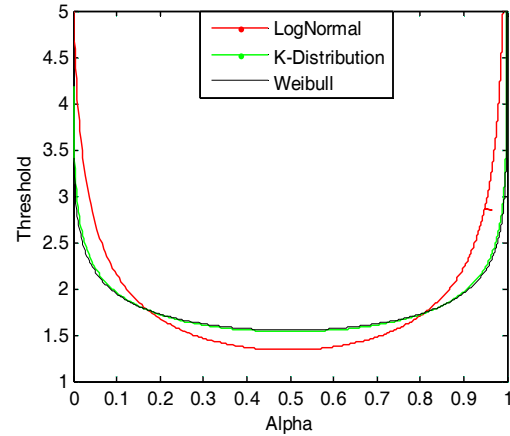


Figure 8 Threshold versus α for $\alpha \in (0,1)$ (Sum of the two kinds α truncation-set)

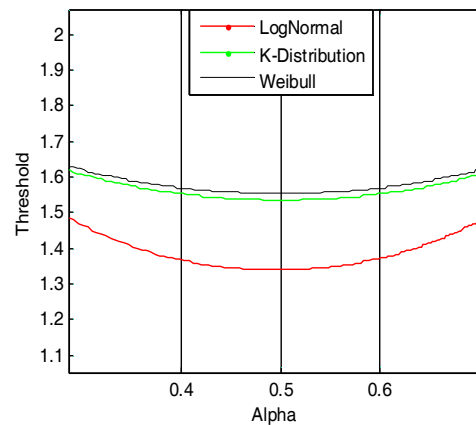


Figure 9 Local enlargement of Figure 8

Based on the above considerations, a modified method is presented. The calculation of x_i and y_i and the method flow are as follows:

Estimate the PDF f_0 based on a group of given clutter data to be recognized with TKE method;

Calculate the parameters of every kind distribution in set C from the clutter data with maximum likelihood method or moments method and get the possible PDFs which can be denoted as: f_1, f_2, \dots, f_M ;

Given α , calculate the threshold x_0 of α truncation set of the input samples.

Calculate the thresholds $x_1, y_1, \dots, x_M, y_M$ of α truncation set of every kind distribution.

Calculate the modified thresholds $\{z_i | z_i = x_i + y_i\}_{i=0}^M$.

Recognize the clutter models with distance-deciding method, i.e., the solution value i of the equation $\min_{1 \leq k \leq M} (|z_0 - z_k|) = |z_0 - z_i|$ is the kind of recognition result.

The relationship between the threshold $z_i (i=1, 2, \dots, M)$ and α is given in the Figure 8 and Figure 9. It is obvious that the threshold is symmetrical about $\alpha=0.5$, and the axis of the symmetry is the optimal α , i.e., $\alpha_{opt} = 0.5$.

IV. SIMULATION RESULTS

In this paper, three kinds of typical clutter distributions mentioned above are considered: Log-Normal, Weibull and K Distribution. The corresponding PDFs are summarized in Table I. In the recognition process, it is necessary to estimate the parameters of these possible distributions from a group of observation samples, so the parameters calculation formulas are also given in Table I. In this table, $u(\cdot)$ is the unit step function, $\Gamma(\cdot)$ is the Gamma function, $K_\gamma(\cdot)$ is the second modified Bessel function of order γ and $r \approx 0.5764$ is Euler constant. Other parameters in table I are defined as:

$$\delta = \sqrt{\frac{1}{N} \sum_{i=1}^N (\ln x_i - \mu)^2}, \quad \mu = \frac{1}{N} \sum_{i=1}^N \ln x_i \quad (4)$$

$$\beta_p = \frac{\mu_{p+2}}{\mu_p \mu_2}, \quad \mu_p = \frac{1}{N} \sum_{i=1}^N x_i^p, \quad p > 0 \quad (5)$$

The recognition rate is statistically obtained through Monte Carlo method. Three groups of random samples are generated from Lognormal, K and Weibull distribution respectively with the parameters given in Table II and Table III, and the number of samples is 5000. The simulation results are given in Table II and Table III, where L, K and W are the abbreviations for Log-Normal, K and Weibull distribution

Table II shows the recognition rate of the original method introduced in section II with different α and distributions. From the results, it can be seen that the value of α have great effect on the performance of the method. For

instance, the recognition rate is high when $\alpha=0.1$ for all the kinds of distribution, but it decreases evidently when $\alpha=0.3$ for the Log-Normal and K Distribution. This means that it is necessary to select a optimal α in each decision for the original method, and of course this is not convenient for in practical use.

Table III shows the recognition rate of the modified method with different α and distributions. From the results, it also observed that the two factors have effect on the recognition rate, but not so much as the original method does. When $\alpha=0.5$, the recognition rate is high for all the distributions, and it decrease generally as α changes, which is consistent with the above analysis. So the effectiveness of the modified method is verified.

V. CONCLUSIONS

The clutter recognition method based on α truncation set is efficient, but in the traditional method the optimal α is difficult to choose when the clutter background is complex. The modified method presented in this paper makes use of the difference among the possible PDFs at their beginning distributions, and defines a new kind of α truncation set. The optimal α of the presented method is a certain value, which makes it more convenient for practical application.

REFERENCES

- [1] L. M. Novak; G. J. Owirka; A.L. Weaver. Automatic Target Recognition Using Enhanced Resolution SAR data [J], IEEE Trans. on AES, 1999, 35(1) :157-175.
- [2] C. Bouvier; L. Martinet; G. Favier; H. Sedano; M. Artaud. Radar Clutter Classification Using Autoregressive Modeling, K-distribution and Neural Network [C], Proc. of ICASSP, Detroit, USA, 1995, 1820-1823.
- [3] Ma Xiaoyan; Fang Xueli; Radar Clutter Recognition Based on Feature Extraction by α Truncation Set [C], Proc. of ICR, Beijing, China, 2001, 436-439.
- [4] Fang Xueli; Liang Diannong. A New Method of Radar Clutter Recognition Based on Multi- α Truncation set [C], Proc. of IEEE International Conference on Robotics, Intelligent Systems and Signal Processing, Changsha, China, 2003, 858-862.
- [5] Simon Haykin; Wolfgang Stehwien; Cong Deng. Classification of Radar Clutter in an Air Traffic Control Environment [J], Proc. IEEE, 1991, 79(6): 742-771.
- [6] A. Jakubiak. Radar Clutter Classification Using Kohonen Neural Network [C], Proc. Of International Radar Conference, 1997, 185-188.
- [7] Fang Xueli. Target Detection and Discrimination in UWB-SAR Image [D], Doctor Degree Thesis, National University of Defense Technology, 2005.
- [8] Jakubiak A. Signal Detection in Non-Gaussian Clutter [J], IEEE Trans. on AES, 1991, 27(5): 758-760.
- [9] Dan Yao. The Transformation Method of Nonparametric Function Estimation [D], Doctor Degree Thesis, Xidian University, 1991.

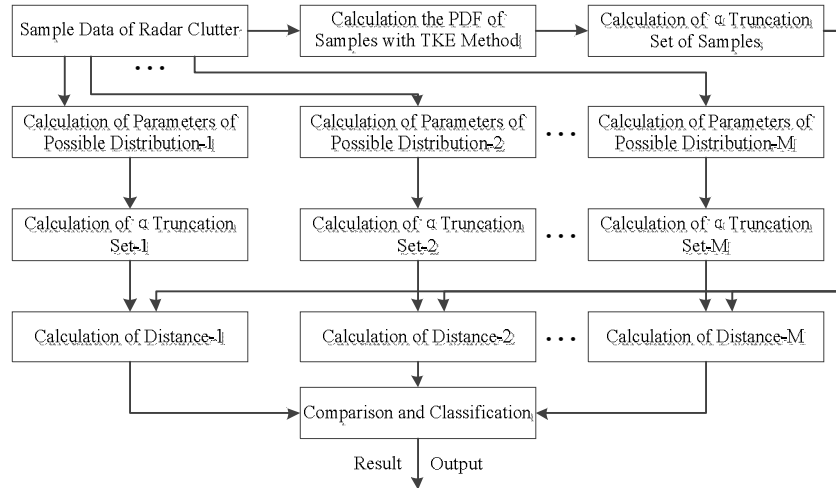


Figure 1. Processing flow of α truncation set-based radar clutter recognition

TABLE I. PDF AND PARAMETER FORMULA OF TYPICAL RADAR CLUTTER DISTRIBUTIONS

Clutter Model	Probability Density Function	Parameter 1	Parameter 2
Log-Normal	$f(x) = \frac{1}{\sqrt{2\pi\sigma x}} e^{-\frac{(\ln x - \mu)^2}{2\sigma^2}} u(x)$	$\hat{\mu} = \frac{1}{N} \sum_{i=1}^N \ln x_i$	$\hat{\sigma}^2 = \frac{1}{N} \sum_{i=1}^N (\ln x_i - \hat{\mu})^2$
Weibull	$f(x) = \frac{m}{\sigma} x^{m-1} e^{-\frac{x^m}{\sigma}} u(x)$	$\hat{m} = \frac{\pi}{\sqrt{6\delta}}$	$\hat{\sigma} = e^{\left(\frac{\pi\mu}{\sqrt{6\delta}} + \gamma\right)}$
K	$f(x) = \frac{2}{a\Gamma(\gamma+1)} \left(\frac{x}{2a}\right)^{\gamma+1} K_{\gamma}\left(\frac{x}{a}\right) u(x)$	$\hat{\gamma} = \frac{(p+2)^2/4 - \beta p}{\beta p - (p+2)/2}$	$\hat{a} = \frac{\mu\Gamma(\gamma+1)}{\sqrt{\pi}\Gamma(\gamma+1.5)}$

TABLE II. RECOGNITION RATE OF THE ORIGINAL METHOD

Clutter Model (Parameters)	Probability of Classifying to Every Distribution (%)								
	$\alpha=0.1$			$\alpha=0.3$			$\alpha=0.5$		
	L	K	W	L	K	W	L	K	W
	100	0	0	2	2	49	61.5	0	3
	0	99.5	0	0	1	81	0	70.5	2
	0	8	91.5	0	0	100	0	2	98

TABLE III. RECOGNITION RATE OF THE MODIFIED METHOD

Clutter Model (Parameters)	Probability of Classifying to Every Distribution (%)								
	$\alpha=0.3$			$\alpha=0.5$			$\alpha=0.7$		
	L	K	W	L	K	W	L	K	W
	61	39	0	94	2	2	94	0	5
	0	66	3	0	94	6	0	72	2
	0	0	100	0	1	99	0	1	99