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Article

Radar Detection of Fluctuating Target in Heavy-tailed Clutter Using TBD

Jie Gao [1,2,*], Jinsong Du [1] and Wei Wang [1,2]

[1] Shenyang Institute of Automation, Chinese Academy of Sciences, Shenyang 110016, China; jsdu@sia.cn
[2] University of Chinese Academy of Sciences, Beijing 100049, China; wangwei2@sia.cn
* Correspondence: gaojie@sia.cn; Tel.: +86-24-8360-1084

Abstract: This paper considers the detection of fluctuating target in heavy-tailed clutter through the use of dynamic programming based on track-before-detect (DP-TBD) in radar systems. The clutter is modeled in terms of K-distribution, which can be widely used to describe non-Gaussian clutter received from high-resolution radars and radars working at small grazing angle. Swerling type 1 is considered to describe the target fluctuation between scans. Conventional TBD techniques suffer from significant performance loss in heavy-tailed environments due to the more frequent occurrences of target-like outliers. In this paper, we resort to DP-TBD algorithm based on prior information, which can enhance the detection performance by using the environment and target fluctuating information during the integration process of TBD. Under non-Gaussian background, the expressions of the likelihood ratio merit function for Swerling type 1 target are derived first. However, the closed analytical form of the merit function is difficult to be obtained. In order to reduce the complexity of evaluating the merit function and the computational load, an efficient approximation method as well as a two-stage detection approach is proposed and used in the integration process. Finally, several numerical simulations of the new strategy and the comparisons are presented to verify that the proposed algorithm can improve the detection performance, especially for fluctuating target in heavy-tailed clutter.

Keywords: target detection; radar systems; K-distributed clutter; heavy-tailed; Swerling target; track-before-detect (TBD)

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1. Introduction

The detection of fluctuating target with low signal-to-clutter ratio (SCR) is of significant importance in radar systems. Conventional detecting and tracking algorithms use thresholded detection as input. Target with low signal-to-clutter ratio is often lost due to the information is irreversibly discarded after thresholding. Multi-frame integration is an effective strategy used in radar applications to detect dim target by integrating signal returns over multiple consecutive scans. In the presence of moving target, multi-frame integration requires track-before-detect (TBD) techniques to correctly correlate data over time.

Dynamic programming based on TBD (DP-TBD) is one of the TBD techniques [1,2], which has attracted extensive attention for the advantages of simplicity and needing less information. It transforms the integration into an optimal estimation of the physically admissible trajectory by maximal integration value of the merit function, which is a kind of multi-frame test statistic. DP-TBD can detect target of arbitrary motion form and has been widely applied to several kinds of sensors [3,4]. In order to solve the problem of high-dimensional maximization under multi-target environment, a novel partition method to cluster targets into well separate groups was proposed in[5]. In [6,7], the track formation procedure with successive track cancellation (STC) was described to overcome the performance loss when targets are closely-spaced. Meanwhile, research on the merit function of DP-TBD has also been widely carried out in recent years. In [8-10], the expressions for the log-likelihood ratio (LLR), which can better discriminate clutter-plus-target measurements from clutter only measurements, were derived and used. In addition, a low-complexity power-efficient TBD procedure, where the generalized likelihood ratio test (GLRT) was solved using a Viterbi-like tracking algorithm, was proposed in [11]. To reduce the big computational burden of DP-TBD, computationally efficient DP-TBD algorithms were derived in [12] and [13] respectively.

The above quoted papers on DP-TBD techniques always assumed that the background is Gaussian distributed with known power. However, for high resolution radars and radars at small grazing angle, the Gaussian assumption may or may not be adequate. In this case, more heavy-tailed background models should be considered in the real world. Weibull distribution, log-normal distribution and K-distribution are the commonly Compound-Gaussian background models used in radar communities. This paper is mainly concerned with K-distribution, which is widely used in high resolution radar detection systems. K-distribution [14,15]was derived from a paper by Eric Jakeman and Peter Pusey (1978) who used it to model microwave sea echo. It has been found to be a suitable model for heavy-tailed background in radar systems [16], since it provides an excellent agreement between theoretical and experimental data. K-distribution also arised as the consequence of a statistical or probabilistic model used in Synthetic Aperture Radar (SAR) imagery.

As the signal strength may change from scan to scan, these fluctuations should be taken into account when building the measurement models. Swerling family of target amplitude fluctuation models are commonly used to capture the RCS changes over time [17]. Swerling target of types 0 can be used to model a target with constant RCS, while Swerling target of types 1 is used to model a target whose RCS fluctuates according to the exponential density in radar systems.

Target detection in K-distributed background is more challenging than in Gaussian or Rayleigh distributed background due to the higher likelihood of target-like outliers, especially for fluctuating target. Besides, it is inefficient and computational costly to carry out accurate search for all the discrete states, as the surveillance region is much larger than the size of a target, such as radar target detection. In this paper, attention is devoted to the detection of Swerling target of type 1 in a surveillance region characterized by K-distributed background through the use of DP-TBD. Moreover, by employing two-stage detection approach, the proposed algorithm is able to achieve further computational reduction. The main contributions of this paper are given as below:

1. In order to limit complexity while still retain the benefits of DP-TBD, we resort to two-stage detection process with different resolution cells.
2. For typical non-Gaussian distributed clutter (K-distribution) and typical target amplitude fluctuation model (Swerling 1), the DP-TBD algorithm based on prior information is proposed. By using the likelihood ratio merit function in DP integration, the performance loss produced by the “heavy-tailed” clutter measurements can be reduced.
3. An efficient but accurate approximation method is proposed to reduce the complexity of evaluating the merit function.

The remainder of this paper is organized as follows: Section 2 presents the notations and system models. In Section 3, two-stage detection approach is proposed at first, the expressions of the likelihood ratio merit function are derived in K-distributed clutter background for Swerling target of types 1, the implementation issues of the merit function are also discussed. Simulation results are showed by comparing different DP-TBD strategies in Section 4 and Section 5 provides some conclusions.

2. Models and Notations

2.1. Kinematic Model

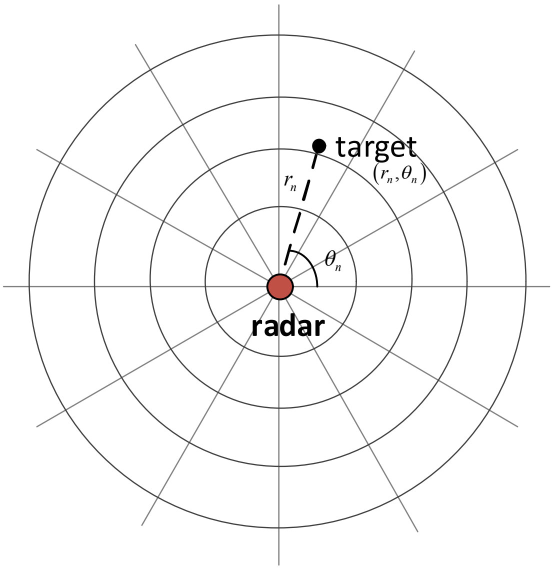

Figure 1. Radar surveillance region illustration.

As shown in Figure 1, we assume that there is only one target in the surveillance region, whose kinematic state at scan n is denoted by the vector s_n. The kinematic vector s_n is specified by

$$s_n = [r_n, \theta_n]' \in \mathcal{R}^2, \quad 1 \le n \le N \tag{1}$$

where $'$ denotes matrix transpose, r_n and θ_n denote the range and azimuth measurement respectively, $\mathcal{R}^2$ denotes the two-dimensional state space and N denotes the number of consecutive frames processed in a DP-TBD integration batch. The evolution of the target state is modeled by the linear process as

$$s_n = Fs_{n-1} + w_n \tag{2}$$

The term w_n is the process noise, F is the transition matrix.

Every real target must comply with some physical constrains on its kinematics, such as the maximum target velocity considered in this paper. The radial and tangential velocity can be calculated by two successive scans, which are given by

$$\begin{aligned} v_{n-radial} &= \frac{r_n - [r_{n-1} \times \cos(\theta_n - \theta_{n-1})]}{T} \\ v_{n-\tan gential} &= \frac{r_{n-1} \times \sin(\theta_n - \theta_{n-1})}{T} \end{aligned} \tag{3}$$

where T denotes the time interval between successive scans.

2.2. Measurement Model

The measurement data consists of M_r cells in the range-dimension and M_θ cells in the azimuth-dimension. If no target exists (hypothesis H_0), the (i,j)th recorded resolution cell, $z_n(i,j)$ $1 \le i \le M_r, 1 \le j \le M_\theta$, at scan n can be expressed as

$$z_n(i,j) = c_n(i,j) \tag{4}$$

while in the presence of a target (hypothesis H_1), the recorded resolution cell $z_n(i,j)$ can be expressed as

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$$z_n(i,j) = A_n + c_n(i,j) \quad (5)$$

where A_n denotes a complex fluctuated amplitude measurement from the target, and $c_n(i,j)$ denotes the K-distributed clutter, which is assumed in this paper.

Swerling 1 fluctuation model supposes that returned signal power per pulse is to be constant during a single scan, but to fluctuate independently from scan to scan. The probability density function (PDF) of the Swerling 1 target amplitude A_n is given by

$$p(A_n) = \frac{2A_n}{\bar{\sigma}} \exp\left(-\frac{A_n^2}{\bar{\sigma}}\right) \quad (6)$$

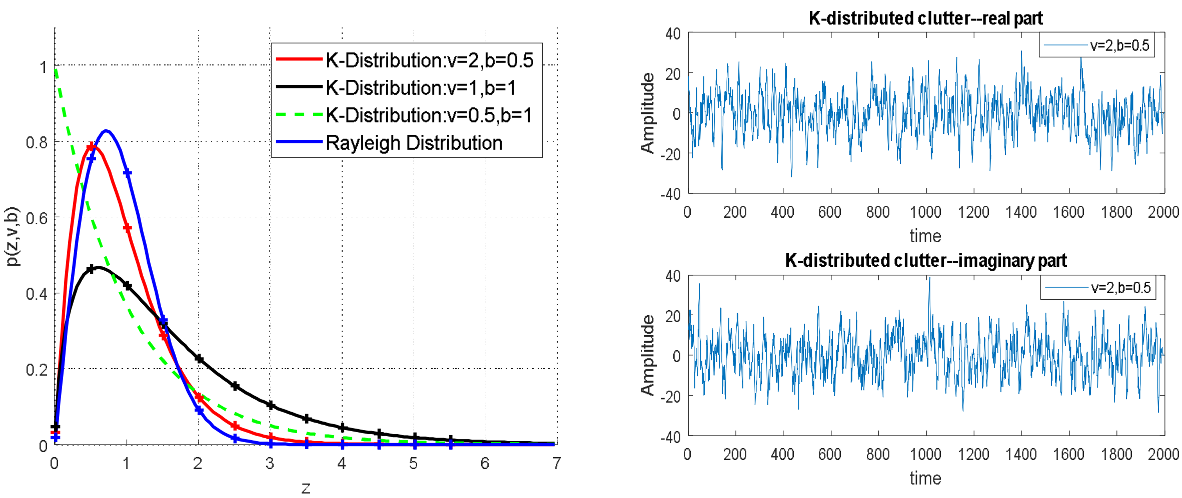
with $\bar{\sigma}$ being the mean squared target amplitude.

2.3. K-distributed Clutter Model

The K-distributed model is proposed as a model for radar clutter in this paper, which has the probability density function as

$$p(z,v,b) = \frac{2}{b\,\Gamma(v)}\left(\frac{z}{2b}\right)^{v} K_{v-1}\left(\frac{z}{b}\right) \quad (7)$$

In formula, $\Gamma(\cdot)$ denotes the Gamma function and $K_{v-1}(\cdot)$ denotes the modified Bessel function of the second kind, z is the clutter amplitude, b is scale parameter which describes the intensity of the clutter, v is the shape parameter which determines the shape of the distribution function. For $v \to \infty$, the K-distribution turns into the Rayleigh distribution. PDFs of K- and Rayleigh-distributions are shown in Figure2 (a) while the K-distributed clutter ($v = 2, b = 0.5$)is shown in Figure2 (b).



(**a**) (**b**)

Figure 2. K-distribution (**a**).PDFs of K- and Rayleigh- distribution for various shape and scale parameters; (**b**).K-distributed clutter including real part and imaginary part.

The substitution is used as $a_n = |z_n|$, which denotes the amplitude measurement, so that (7) can be rewritten as

$$p(a_n) = \frac{4a_n^{\alpha}}{\beta^{(\alpha+1)/2}\Gamma(\alpha)} \mathrm{K}_{\alpha-1}\left(\frac{2a_n}{\beta^{1/2}}\right) \quad (8)$$

where $\alpha = v$ denotes the shape parameter, $\beta = 4b^2$ denotes the scale parameter.

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Meanwhile, K-distribution can also be viewed as a Rayleigh distribution modulated by a Gamma distribution for convenience

$$p(a_n) = \int_0^{+\infty} p(a_n|\eta) p(\eta) d\eta \tag{9}$$

where

$$p(a_n|\eta) = \frac{2a_n}{\eta} \exp\left(-\frac{a_n^2}{\eta}\right) \tag{10}$$

$$p(\eta) = \frac{\eta^{\alpha-1}}{\beta^{\alpha}\Gamma(\alpha)} \exp\left(-\frac{\eta}{\beta}\right) \tag{11}$$

3. Development of the Proposed Strategies

DP-TBD algorithm decomposes the integration among N successive scans into N sub-processes. The nth sub-process contains all the measurements up to scan n. Target can be detected and tracked by calculating the maximum of the energy integration value through a recursive model, which could be expressed as:

$$V(s_n) = I(s_n) \nabla \max_{s_{n-1} \in \tau(s_{n-1})} \left[V(s_{n-1})\right] \tag{12}$$

$$\Psi(s_n) = \arg \max_{s_{n-1} \in \tau(s_n)} \left[V(s_{n-1})\right] \tag{13}$$

where $I(s_n)$ is defined as the merit function at scan n; $V(s_{n-1})$ is defined as the maximal integration value of all the admissible trajectories; $\tau(s_n)$ is a collection of states at scan n for which a transition to s_n is possible, and it can be obtained by the location and maximum velocity of the target; ∇ is the operator of integration; $\Psi(s_n)$ is the retracing function, indicating the best state of the previous scan, which makes the integration value reach its maximum.

In summary, DP-TBD implements the equivalent of an exhaustive search in an efficient manner by enumerating and valuing all physical admissible state sequences, finally returning the state sequences whose final maximal integration value $V(s_N)$ exceeds a given detection threshold γ,i.e.

$$V(s_N) > \gamma \tag{14}$$

There are mainly two problems throughout the process. Firstly, the computational complexity of DP-TBD is unaffordable in the presence of high-mobility target when the number of resolution elements is large. The discretization of state space is always based on the sensor's resolution so as to make full use of the measurements and achieve possibly accurate estimates. In this situation, strategies hardly lead to real-time implementable schemes, even resorting to dynamic programming algorithm. In order to reduce the burden of computation, a two-stage detection approach is proposed in this work. Secondly, most of the previous work on DP-TBD assumed that the background model would be Rayleigh or Gaussian distribution with a known power. Such assumptions may or may not be adequate, as in real world, more heavy-tailed background model is often encountered than expected. To improve the detection performance, we propose a novel DP-TBD algorithm based on the prior information to solve the aforementioned problem. In this paper, the merit function is set to be likelihood ratio under both target-present hypothesis and null-target hypothesis in a surveillance region which characterized by K-distributed background, and the simulated data would be tested for presenting the performance.

3.1. Two-stage Detection Approach

Since the surveillance region is much larger than the part of the measurements which are related to the target, it is inefficient and computational costly to carry out accurate search based on all the sensor's resolution for the discrete states. In order to reduce the computational load, while still retain the benefits of TBD, here we resort to a two-stage detection approach which is illustrated in Figure 3.

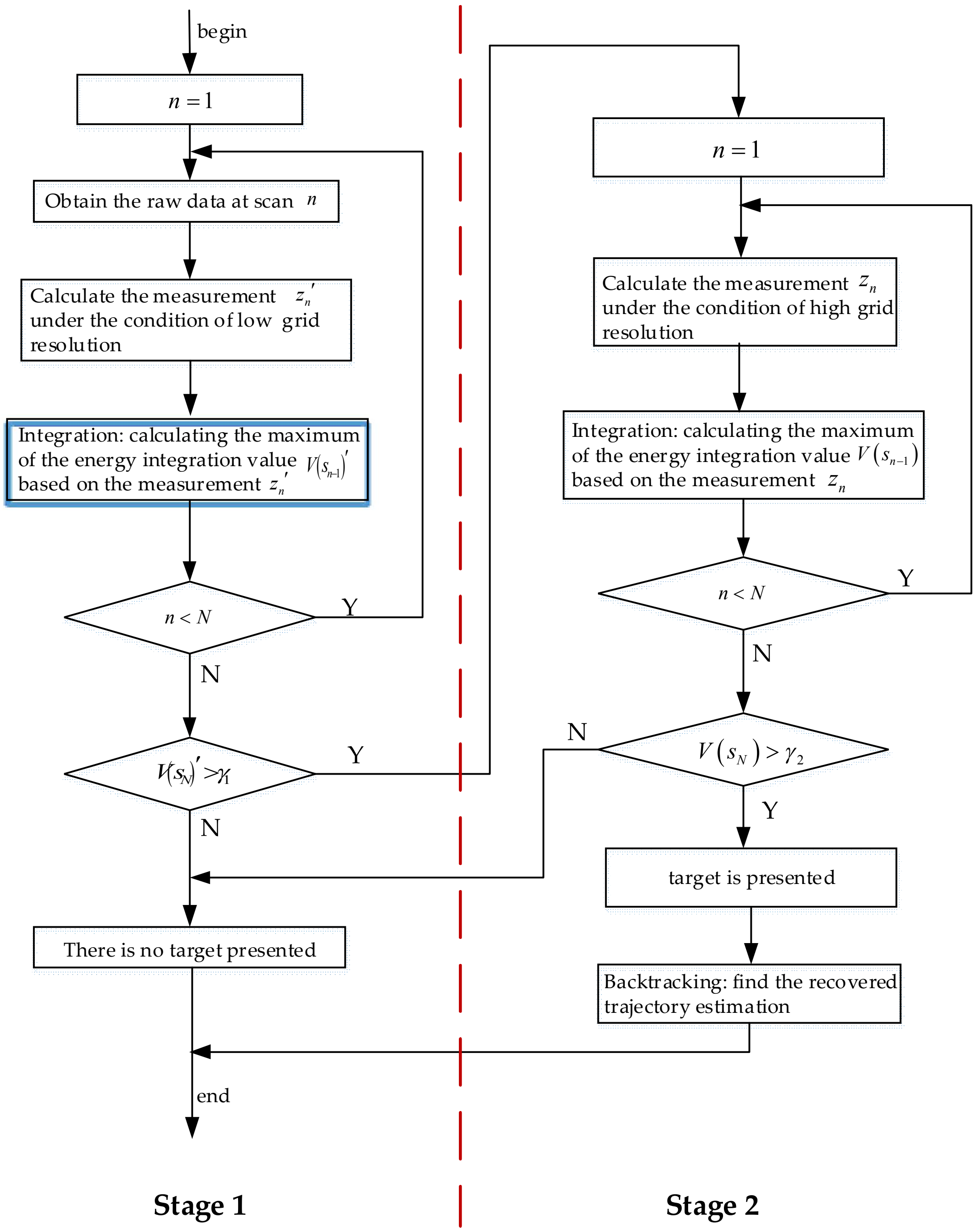

Figure 3. The flowchart of the two-stage detection approach.

At stage 1, we first obtain the raw data at scan n, and roughly calculate the measurement z_n' under the condition of low grid resolution. The target states are estimated by searching discrete grids with larger cell size based on the DP integration. After N times loop, the maximum of the energy integration value $V(s_N)'$ at scan N could be got by the process. For single target model, the maximum integration value $V(s_N)'$ which exceeds detection threshold γ_1 is used to determine the existence of target. If there is a target presented in the surveillance region, we could refine the target trajectory in stage 2.

In order to obtain a more accurate estimate, stage 2 is employed to recalculate the measurements under the high grid resolution condition. Once the maximum integration value $V(s_N)$ exceeds the detection threshold γ_2, the estimation of final target trajectory can be obtained by backtracking. For each estimated the state $\hat{s}_n$, we have :

$$\hat{s}_{n-1} = \psi(\hat{s}_n),\ for\ n = N,\ldots 1 \tag{15}$$

So the recovered trajectory estimate is $\hat{S}_N = \{\hat{s}_1,\ldots,\hat{s}_N\}$.

The surveillance region is divided into $M_r \times M_\theta$ grid cells based on the resolution of the radar system, i.e., Δr and $\Delta\theta$, where M_r and M_θ denote the number of cells in range and azimuth, respectively. To realize the target search with larger cell size, the state space is re-discretized by $\Delta r'$ and $\Delta\theta'$ to obtain $M_r' \times M_\theta'$ grid cells at first. As shown in figure 4, all the measurements and DP integrations are processed in stage 1 based on the new state space, which may get a roughly target trajectory by less computation. Then in stage 2, DP integration concentrates on the part of states which are indicated by stage 1. As calculations of less meaningful states could be avoided, the computational costs will become more reasonable.

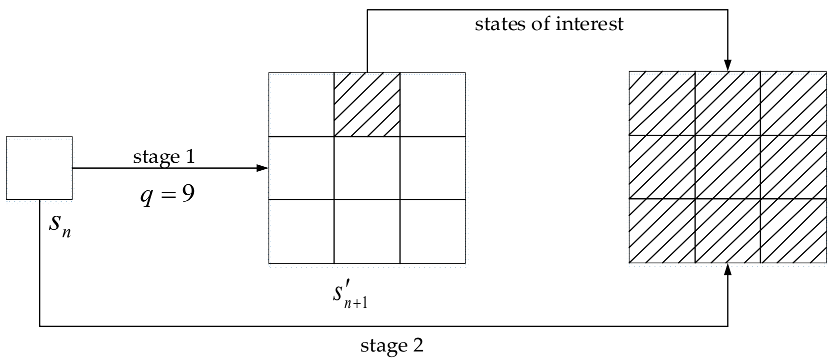

Figure 4. Illustration of possible transition state collection during the two-stage DP integration.

3.2. Derivation and Implementation of the Merit Function

Combined (6), PDF for the Swerling 1 target in K-distributed clutter is given by

$$p(a_n|\eta,s_n) = \frac{2a_n}{\eta+\bar{\sigma}}\exp\left(-\frac{a_n^{\ 2}}{\eta+\bar{\sigma}}\right) \tag{16}$$

and $p(a_n|s_n)$ can be derived by marginalizing over η since η is random, i.e.

$$\begin{aligned} p(a_n|s_n) &= \int_0^\infty p(a_n|\eta,s_n)p(\eta)d\eta \\ &= \int_0^\infty \frac{2a_n}{\eta+\bar{\sigma}}\exp\left(-\frac{a_n^{\ 2}}{\eta+\bar{\sigma}}\right)\frac{\eta^{\alpha-1}}{\beta^\alpha\Gamma(\alpha)}\exp\left(-\frac{\eta}{\beta}\right)d\eta \\ &= \frac{2a_n}{\beta^\alpha\Gamma(\alpha)}\int_0^\infty \frac{\eta^{\alpha-1}}{\eta+\bar{\sigma}}\exp\left(-\frac{a_n^{\ 2}}{\eta+\bar{\sigma}}\right)\exp\left(-\frac{\eta}{\beta}\right)d\eta \\ &= \frac{2a_n}{\beta^\alpha\Gamma(\alpha)}\int_0^\infty f(\eta)d\eta \end{aligned} \tag{17}$$

where the integrand $f(\eta)$ is given by

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$$f\left(\eta\right)=\frac{\eta^{\alpha-1}}{\eta+\bar{\sigma}}\exp\left(-\frac{a_n^{\ 2}}{\eta+\bar{\sigma}}-\frac{\eta}{\beta}\right) \tag{18}$$

Substituting (8) and (17) into the expression of merit function $I\left(s_n\right)$ at scan n, $I\left(s_n\right)$ can be written as

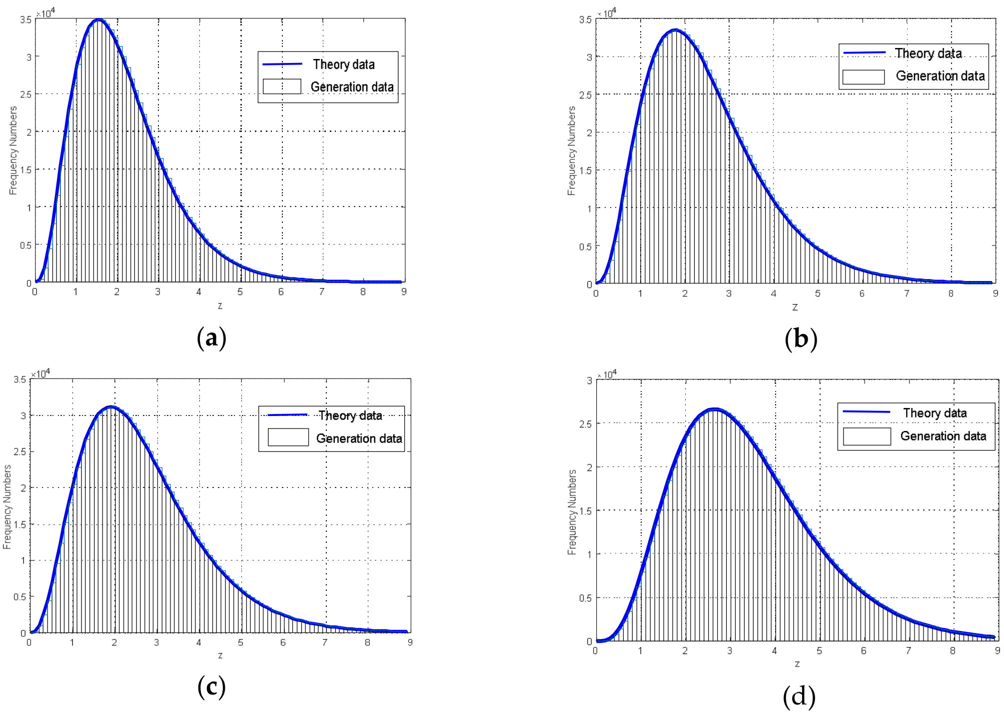
$$\begin{aligned} I\left(s_n\right) &= \ln\left(\frac{p(a_n|s_n)}{p\left(a_n\right)}\right) \\ &= \ln\left(\frac{a_n^{-\alpha+1}\beta^{(-\alpha+1)/2}\int_0^{\infty} f\left(\eta\right)d\eta}{K_{\alpha-1}\left(2a_n/\beta^{1/2}\right)}\right) \end{aligned} \tag{19}$$

Although the integrand $f\left(\eta\right)$ in (18) has no closed-form solution, it can be evaluated with reasonable accuracy by using the trapezoidal rule, i.e.

$$\int_0^{\infty} f\left(\eta\right)=\sum_{i=1}^{N_{sa}}\frac{f\left(\eta_i\right)+f\left(\eta_{i+1}\right)}{2}\delta_i \tag{20}$$

where $f\left(\eta_i\right)$ is sample point drawn from the time interval δ_i, δ_i is a sampling interval which is short enough to cover the effective support of $f\left(\eta\right)$, N_{sa} denotes the number of sample points.

The sample points can be obtained by either deterministic sampling with a uniform grid or stochastic importance sampling. Since the integrand $f\left(\eta\right)$ may tend quickly towards ∞ when $\eta\rightarrow 0$, while tend slowly towards 0 when $\eta\rightarrow\infty$. A reasonable approximation obtained by deterministic uniform grid sampling or stochastic importance sampling is difficult to carry out. A grid with variable resolution method was proposed in[18] to approximate merit function which also leads to high computational complexity.



(a) (b) (c) (d)

Figure 5. Histogram of generation data and theory PDF data with SCR=15dB (**a**). α=2 and β=1; (**b**). α=3 and β=2; (**c**). α=5 and β=2; (**d**). α=10 and β=5;

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In order to reduce the complexity of approximation, we could possibly circumvent these problems by generating a lookup table offline with sample points using a uniform grid. The number of sample points with uniform grid is large enough to approximate the integrand $f(\eta)$ accurately. Based on the lookup table, this calculating method trades little cost of precision and memory space to a great improve on running speed in calculation. Histogram of generation data and theory PDF are shown in Figure 5 for Swerling targets types 1 with different parameters. According to Figure 5, we conclude that the approximation error is negligible.

Note that the K-distribution shape parameter α, the scale parameter β are supposed to be known in the derivation of merit function. In the case where the background is significantly heavy-tailed and the parameters are unknown, we should estimate the parameters first, which can be obtained through a numerical maximization of the likelihood function. Since the maximum likelihood techniques require numerical optimization routines and evaluation of Bessel functions, they are computationally intensive and therefore inappropriate for evaluation of large data sets. Abraham [19] recommended a moment estimators based on the first and second moments, which can be used as our estimator in this work.

4. Simulation

In this paper, the detection performances of conventional DP-TBD and proposed strategy for Swerling type 1 target are assessed. We assume that the measurement noise satisfies K-distribution, each measurement frame consists of $M_r \times M_\theta$ = 180 × 90 resolution cells. The number of frames processed in a DP batch is $N = 6$, while the number of possible state transition in a scan is q=9. This scenario is run 1000 times for various SCR and shape parameters while the false alarm is fixed as $P_{FA} = 10^{-3}$.

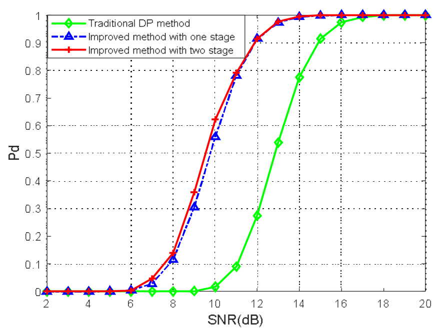
4.1. Performance Analysis

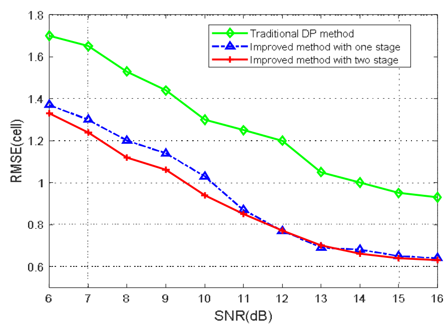
We assess the performances of different strategies via the probability of track detection P_d, which is a performance metric for both detection and tracking performance. P_d is defined as the probability of the maximum integration value exceeding detection threshold, and its final position is within certain range of the actual target position. In addition, the root-mean square error (RMSE) on the estimation of the target position is also considered, which is defined as

$$RMSE = \sqrt{E\left[e^2(s_n)|H_1\right]} \tag{21}$$

where H_1 is the event that target is confirmed, and $e^2(s_n)$ is the Euclidean distance between the true and estimated target position.

Performance and RMSE comparison of conventional DP method and proposed method based on prior information is shown in Figure 6. For K-distributed clutter and Swerling 1 target, proposed method performs better than the traditional integration method. It can also be concluded that for proposed method, which processed with only one stage (blue solid line) or two-stage (red solid line) could achieve almost identical performance while the latter one obtains further computational reduction.





(**b**)

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(a)

Figure 6. Performance and RMSE comparison of different DP-TBD integration method with α=0.5 and β=1 against SNRs from 2dB to 20dB (a) The detection probability P_d (b) The RMSE on estimated position.

For different parameters of K-distributed clutter, detection performances are shown in Figure 8. With the increasing of shape parameter α, both conventional DP and proposed method on prior information, achieve significant performance improvement. That's because when α is increasing, the K-distributed clutter is smoother and the frequency of target-like outliers is lower. Note that when α = 50, since K distribution almost degenerates to Rayleigh distribution in this case, the detection performances are nearly identical.

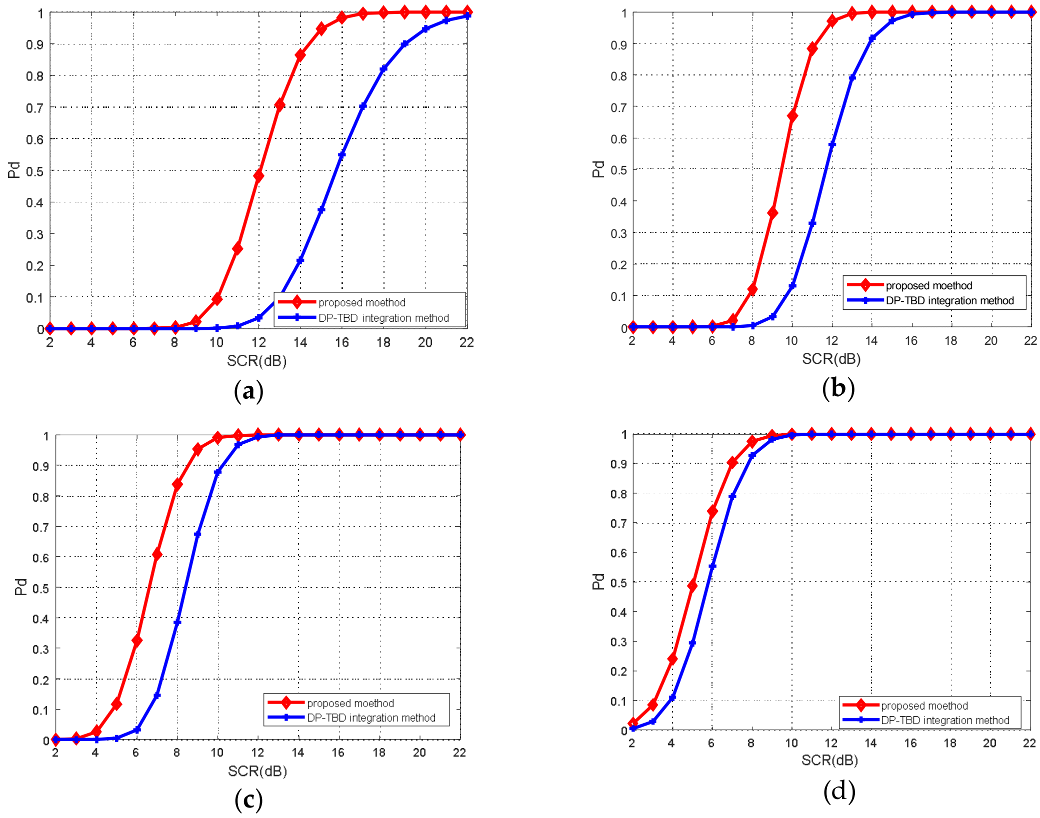

Figure 7. Performance comparison of DP-TBD integration method (red solid line with diamond) and proposed moethod in this paper (blue solid line with cross) for K-distributed clutter and Swerling 1 target (**a**). α=2 and β=2 ; (**b**). α=5 and β=2 ; (**c**). α=10 and β=2 ; (**d**). α=50 and β=2 ;

4.2. Computational Complexity Analysis

The complexity of the conventional DP-TBD method is $\mathcal{O}(M_r M_\theta qN)$, where M_r and M_θ are the number of range and azimuth resolution elements, q is the number of possible state transition in a scan and N is the number of the integration scans. In comparison with the conventional method, the two-stage detection approach schemed in Figure 3 has low computational complexity. The computational cost in stage 1 is $\mathcal{O}(M_r' M_\theta' qN)$, where $M_r{}' \times M_\theta{}'$ denotes grid cells re-discretized by $\Delta r'$ and $\Delta\theta'$ to realize the target search with larger cell size. Since the DP integration in stage 2 is concentrated on the part of states, which are indicated by stage 1, the computational cost is small enough to be neglected.

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Table 1. Computational cost with different parameters

Parameters	$M_r \times M_\theta = 180 \times 90$	$M'_r \times M'_\theta = 90 \times 45$	$M'_r \times M'_\theta = 60 \times 30$
q=4	308ms	224ms	146ms
q=9	935ms	684ms	370ms

The computational cost of strategies is listed in Table 1 for different parameters. It can be seen that the computational cost depends on the number of possible state transition q and the resolution elements. For the same resolution cells, scenario at q=9 costs almost three times as long as the scenario q=4. Meanwhile, the computational cost reduces rapidly as the number of resolution elements decreases. For example, when q=4, the CPU times for $M_r \times M_\theta = 180 \times 90$, $M'_r \times M'_\theta = 90 \times 45$ and $M'_r \times M'_\theta = 60 \times 30$ are 308ms 224ms and 146ms, respectively.

5. Conclusion

This paper has presented the systematic treatment of heavy-tailed clutter from a target detection and tracking perspective. Target detection in K-distributed clutter is more challenging than in Gaussian- or Rayleigh-distributed clutter due to the higher likelihood of target-like outliers, especially for fluctuating target. In this work, we dealed with the fluctuating target detection and tracking problem using modified DP-TBD method. The contributions are as follows: First we have solved the target detection problem using two-stage detection architecture to avoid calculations of less meaningful states. Secondly, for Swerling 1 target in K-distributed background, merit function was derived and implemented in the integration process of DP-TBD to enhance radar detection performance. In order to reduce the complexity of integral calculation, we also resorted to the trapezoidal rule with a generating lookup table.

Numerical analysis demonstrated that performance improvement could be applied via proposed DP-TBD algorithm based on prior information, especially for heavy-tailed K-distributed clutter. Moreover, simulation results suggested that a tradeoff between performance and computational complexity exists.

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Conflicts of Interest: The authors declare no conflict of interest.

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