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DETECTION OF FAST RADAR TARGET TRAJECTORIES USING THE HOUGH TRANSFORM

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Abstract—*This paper addresses the problem of detecting trajectories of fast-moving radar targets in the presence of noise, missed detections, and K-distributed clutter. A Hough transform-based method is proposed using a physically interpretable parameterization in terms of initial range and velocity. An iterative multi-target detection procedure based on peak extraction and subsequent removal of the found control points, which allows separating even those trajectories that may intersect without data association. A weighted voting scheme based on signal intensity is introduced to improve robustness under low SNR conditions. Performance is evaluated using Monte-Carlo simulations. Results show high track detection probability and robustness to missed detections and clutter. The method is suitable for track initiation in multi-target radar systems.*

Keywords—Hough transform, radar detection, multi-target detection, trajectory estimation, K-distribution, clutter suppression.

I. INTRODUCTION

Radar detection and tracking of fast and small targets in a complex interference environment is one of the key tasks of modern surveillance, air defense and air or sea space monitoring systems. The main factors complicating the solution of this problem are the low signal-to-noise ratio (SNR), the presence of intense natural and artificial interference, as well as the possibility of the simultaneous appearance of several targets in the radar's viewing area [2], [6].

Traditional radar signal processing methods based on single-scan detection and subsequent tracking often demonstrate limited effectiveness in the case of weak signals or dense interference background. In particular, classical detection algorithms, such as CFAR detectors, operate on the basis of the analysis of local statistical characteristics of the signal, which leads to a decrease in the probability of detection at a low SNR. In such conditions, a significant number of measurements can be lost or interpreted as interference, which complicates the formation of target trajectories [12].

One of the promising approaches to increasing the detection efficiency is the approach of using information from multiple radar scans [9] to increase the probability of detecting weak signals. And as an effective tool for implementing the approach is the Hough Transform (HT) [8], [10], [11]. This method allows you to transform the problem of finding a trajectory in the measurement space into the problem of finding maxima in the parametric space. The main advantage of the Hough Transform is its high resistance to noise and local measurement errors, since the solution is formed on the basis of the global data structure [12].

In works devoted to the application of the Hough Transform in radar, it is shown that this approach allows you to effectively detect moving targets in multi-scan data and form initial trajectories without the need for a preliminary hard threshold selection of measurements [5].

In practical radar systems, multiple targets may be present simultaneously, which significantly complicates the detection process. Therefore, efficient methods for multi-target trajectory detection are required.

In this paper, a Hough transform-based framework for detecting fast radar target trajectories is proposed. The method is extended to multi-target scenarios using an iterative detection procedure in conditions of heterogeneous (K-distributed) clutter. The effectiveness of the approach is validated using Monte-Carlo simulations under various operating conditions.

II. PROBLEM STATEMENT

The problem of detecting fast-moving radar targets is considered in the range-time domain under conditions of noise, missed detections, and clutter. The observed data are represented as a set of measurements:

$$Z = \{(t_i r_i)\}, i = 1,\ldots, M, \tag{1}$$

where t_i denotes the discrete time index and r_i is the measured range corresponding to the detected signal.

The Z set contains:

- Measurements generated by one or more targets with trajectories with stochastic deviations due to process jitter.
- Missed detections caused by low SNR.
- False alarms generated by clutter.

The objective is to: detect the presence of target trajectories, estimate their parameters (initial range and velocity), ensure reliable detection in multi-target scenarios with intersecting trajectories and incomplete observations.

The detection performance is evaluated using track-level metrics, including track detection probability and false track rate.

In contrast to conventional detection approaches, the problem is formulated at the trajectory level rather than at the level of individual measurements.

III. System Model

1) *Target motion model*

A fast-moving target is assumed to follow a linear trajectory in the range-time plane:

$$r(t) = R_0 + vt, \tag{2}$$

where R_0 is initial range at where $t = 0$, and v is the velocity of the target. In discrete form:

$$r_i = R_0 + vt_i. \tag{3}$$

This model is valid under the assumption of constant velocity over the observation interval, which is commonly used in radar tracking problems [11].

2) *Measurement model*

The observed measurements are corrupted by noise and can be expressed as:

$$z_i = r_i + \varepsilon_i, \tag{4}$$

where ε_i represents noise measurement, typically modeled as a zero mean random process. In radar systems, this noise is often approximated as Gaussian:

$$\varepsilon_i \sim N(0, \sigma_r^2), \tag{5}$$

In addition to noise measurement, two important effects are considered:

a) Missed detections.

Due to low SNR or signal fluctuations, target detections may be absent with probability P_{miss}, this results in incomplete trajectories and the expression of detection at the i-th moment of time is described as follows

$$P_d(t_i) = 1 - P_{\text{miss}}, \tag{6}$$

b) Clatter and false alarms.

Clutter is modeled as a random process generating false detections in the range-time space. The number of false alarms N_{FA} per frame is assumed to follow a Poisson distribution:

$$N_{\text{FA}} \sim \text{Poisson}(\lambda), \tag{7}$$

where λ is the average number of false detections per frame. However, radar systems operate in difficult interference conditions, when there are reflections from meteorological formations, vegetation, agitated water surfaces, etc. In these conditions, the noise model (7) is insufficient. Therefore, signal processing channel developers use the K-distribution (Fig. 1).

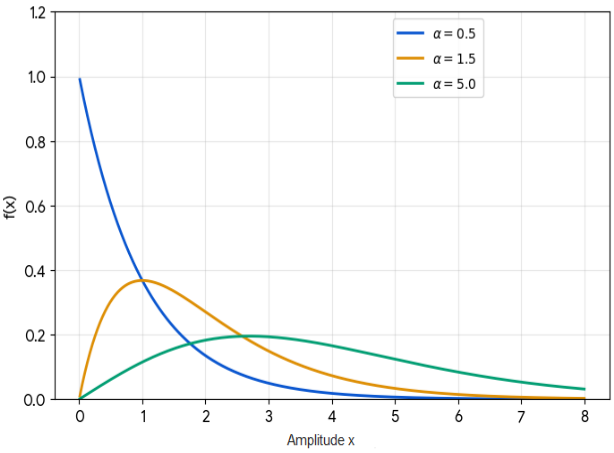

Fig. 1. The density of the K-distribution

The K-distribution is used to model radar background with textured structure and strong amplitude fluctuations. Unlike the Rayleigh model, it takes into account random changes in the local average signal power, which makes it suitable for describing marine and land clutter in high-resolution radar and SAR systems. Model

$$X = \sqrt{G}N, \tag{8}$$

is called a K-model, where X is total clutter signal, G is the Gamma distributed random values (power fluctuations) and N are Gaussian distributed random values. In other words, the K-distribution (8) is Gaussian noise with gamma random variance.

The density of the *K*-distribution (amplitude) is described by the following expression

$$f_A(x) = \frac{2}{\Gamma(\nu)}\left(\frac{\nu}{b(1+a)}\right)^{\nu} x^{\nu} K_{\nu-1}\left(2x\sqrt{\frac{\nu}{b(1+a)}}\right), \quad (9)$$

where *v* is the shape parameter; *b* is the scale parameter; *a* is the ratio of target signal intensity to clutter intensity; $\Gamma(\nu)$ is the gamma function; K_{v-1} is the McDonald function and *x* is a random variable (signal amplitude).

The K-distribution describes a very wide class of noise from Gaussian ($\nu \to \infty$) to noise with strong outliers ($\nu < 1$), what Fig. 1 demonstrates.

3) Detection model

The radar intensity measurements are modeled using an exponential distribution, which is typical for envelope-detected radar signals $A \sim \exp(\mu)$, where *A* is signal amplitude and μ determines the average signal intensity.

Trajectory processing involves quantizing the signal-noise mixture by a CFAR false alarm stabilization device, which converts the sequence (4) into a binary stream of zeros and ones. A one is generated when the adaptive threshold is exceeded and signifies a detection event of the reflected signal. The detection probability is denoted by P_d.

A zero is generated if the signal (4) does not exceed the threshold. The probability of not exceeding the threshold is denoted by P_{miss}.

A detection is declared if the intensity exceeds a threshold $A > \tau$. For amplitude-based detection under K-distributed clutter, the Neyman–Pearson threshold is determined from:

$$\tau = F^{-1}(1 - P_{fa}), \quad (10)$$

where $F^{-1}(...)$ is the inverse cumulative distribution function (CDF).

4) Multi-Target Scenario

In the general case, the presence of multiple targets can be described as follows

$$r_j(t) = R_{0,j} + v_j t,\ j = 1,...,M. \quad (11)$$

Such observed data consists of a mixture of true target detections (3), missed detections and clutter measurements, which modeled in accordance with (9). Thus, the detection problem reduces identifying multiple linear structures embedded in noisy data.

5) Performance metrics

To evaluate detection performance, the following metrics are used:

a) Detection probability

$$P_d = \frac{N_{dt}}{N_{tt}}, \quad (12)$$

where N_{dt} is the number of detected targets; N_{tt} is the number of true targets. This is the main performance indicator. It shows what percentage of real objects the radar was able to see.

b) False track rate N_{false}

Demonstrates the number of phantom trajectories generated by clutter which is presented *K*-distribution (9)

c) Missed targets

$$N_{\text{miss}} = N_{tt} - N_{dt}. \quad (13)$$

This is the flip side of detection probability. It shows the number of targets that were physically within range but were missed by the radar.

These metrics are estimated using Monte-Carlo simulations under varying conditions of SNR, N_{miss}, and clutter density.

IV. Methods

The detection of target trajectories in the presence of noise, missed detections, and clutter can be formulated as the problem of identifying linear structures in the range-time plane. In this work, HT is employed as a robust tool for detecting such structures by mapping measurements into a parameter space and accumulating evidence of trajectory presence.

1) Canonical Hough Transform

The canonical HT is a well-known technique for detecting parametric structures in noisy data. In radar applications, it can be used as a Track-Before-Detect (TBD) method by accumulating evidence across multiple scans. In its classical form, the Hough transform represents a line in Cartesian coordinates (*x*, *y*) using the normal parameterization:

$$\rho = x\cos\theta + y\sin\theta. \quad (14)$$

Each point (x_i, y_i) in the observation space corresponds to a sinusoidal curve in the parameter space (ρ, θ). The intersection of such curves indicates the presence of a line shared by multiple points. However, this representation is not optimal for radar applications, since it does not directly correspond to physically meaningful parameters such as velocity and initial range [8].

2) Physical parametrization

To improve interpretability and computational efficiency, a physically motivated parameterization is introduced based on the target motion model defined in (2) and the Hough transform can be expressed in the (R_0, v) parameter space:

$$R_0 = r_i - vt_i. \tag{15}$$

Thus, each detection (r_i, t_i) maps to a straight line in the parameter space. The intersection of multiple such lines corresponds to a common trajectory characterized by parameters (R_0, v). This parameterization provides a direct physical interpretation: R_0 is the initial range; v is the velocity.

Unlike the canonical representation (14), the proposed parameterization (15) is directly related to target motion parameters.

3) Accumulator and voting procedure

The Hough transform operates by discretizing the parameter space and accumulating votes from each detection point.

Unlike the canonical HT to improve robustness against clutter and noise, weighted voting applied. The weight

$$\omega_i = f(x_i), \tag{16}$$

where x_i is the signal amplitude of the i-th detection.

This allows stronger detections to contribute more significantly to the accumulator, improving detection performance in low SNR conditions. After accumulating votes, candidate trajectories correspond to local maxima in the accumulator space:

$$\left(R_0^*, v^*\right) = \arg\max_{R_0, v} A\left(R_0, v\right), \tag{17}$$

That is, the Hough accumulator already accumulates not just the number of points, but something closer to the weighted total energy along the trajectory.

Considering expressions (16) and (17) the accumulator function is defined as:

$$A\left(R_0, v\right) = \sum_{i=1}^{N} \omega_i \delta(R_0 - (r_i - vt_i)), \tag{18}$$

where ω_i is the weight assigned to detection (16); $\delta(...)$ represents a discretized voting operation.

In practice, due to measurement noise and range jitter, an exact match is unlikely. Therefore, a tolerance region (voting tube) is introduced:

$$| R_0 - (r_i - vt_i) | \le \Delta, \tag{19}$$

where Δ is a predefined tolerance parameter.

4) Multi-target detection and track initialization

In practical radar scenarios, multiple targets may be present simultaneously, resulting in overlapping trajectories in the range–time domain. In addition to noise and clutter, this significantly complicates the detection process, as measurements from different targets may intersect or partially overlap. Therefore, an extension of the HT framework is required to enable reliable multi-target detection and track initialization.

To enable detection of multiple and intersecting trajectories, an iterative detection-and-removal procedure is proposed.

Let the observation set be defined as in (1). In the multi-target case, measurements originate from several targets (11). The observed dataset Z is superposition of detections from multiple targets, missed detections and clutter measurements. Thus, the problem reduces identifying multiple parameter pairs $\left\{(R_{0j}, v_j)\right\}_{i=1}^{M}$, corresponding to different trajectories in the parameter space.

The procedure can be summarized as follows:

- compute the accumulator $A\left(R_0, v\right)$ using (18);
- find the dominant peak according to (17)

$$\left(R_0^*, v^*\right) = \arg\max A\left(R_0, v\right);$$

- verify detection using threshold condition $A\left(R_0^*, v^*\right) \ge \tau_A$, where τ_A is a detection threshold determined empirically or based on statistical considerations
- extract supporting points satisfying (19)
- remove these points from the dataset;
- repeat the procedure until termination criteria are met.

For each detected peak $A\left(R_0^*, v^*\right)$, the corresponding set of supporting measurements is defined as:

$$S = \{\left(t_i, r_i\right) : | r_i - (R_0^* + v^* t_i) | \le \varepsilon, \tag{20}$$

where ε is an association tolerance accounting for measurement noise and discretization.

The number of supporting points is given by $N_{\text{sup}} = |S|$ from (20) and valid trajectory is declared if $N_{\text{sup}} \ge N_{\min}$, where $N_{\min}$ is predefined threshold.

After identifying a valid trajectory, the supporting points are removed from the dataset. This step prevents the same measurements from contributing to multiple detections and enables separation of overlapping trajectories. This approach avoids explicit combinatorial data association, which is typically required in multi-target tracking systems [6], [11].

The proposed method extends conventional Hough transform-based track-before-detect (TBD) approaches in several key aspects. First, a physically interpretable parameterization in terms of initial range and velocity is employed instead of canonical representation. Second, an iterative detection-and-removal procedure is introduced for multi-target trajectory extraction. Third, a weighted voting scheme based on signal intensity is applied to improve robustness under low SNR conditions and in heavy-tailed clutter. Finally, the method operates without explicit data association, thereby reducing computational complexity in multi-target scenarios.

In contrast to classical TBD approaches, the proposed method enables trajectory-level detection with reduced dependence on local thresholding.

V. Simulation Results

To evaluate the performance of the proposed Hough transform-based approach, a set of simulation experiments was conducted for a multi-target scenario in the presence of noise, missed detections, and clutter.

Figure 2 illustrates the distribution of sparse detections in the range–time domain. The observed data consists of both true target returns and randomly distributed clutter points. Despite the significant level of noise, the underlying linear structures corresponding to target trajectories remain partially visible. The true trajectories, shown as dashed lines, correspond to targets with different velocities and initial ranges. It can be observed that detections are irregularly distributed along these trajectories due to missed detections and measurement noise.

Figure 3 presents the Hough accumulator in the (R_0, v) parameter space. Several distinct high-intensity regions (peaks) are clearly visible. Each peak corresponds to a consistent linear structure in the observation space, i.e., a potential target trajectory. Notably, despite the presence of significant clutter, the true trajectories produce dominant peaks in the accumulator. This confirms the ability of the Hough transform to integrate weak and fragmented measurements into coherent parameter estimates.

Figure 4 illustrates the three-dimensional representation of the Hough accumulator. The surface plot clearly shows pronounced peaks corresponding to detected targets, as well as a relatively low background level associated with noise and clutter. The separation between dominant peaks and background confirms the effectiveness of the weighted voting scheme and the robustness of the proposed method to random detections.

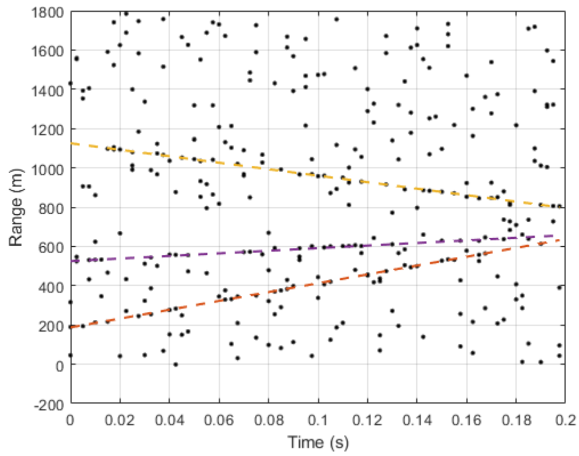

Fig. 2. Sparse detections in the range–time domain

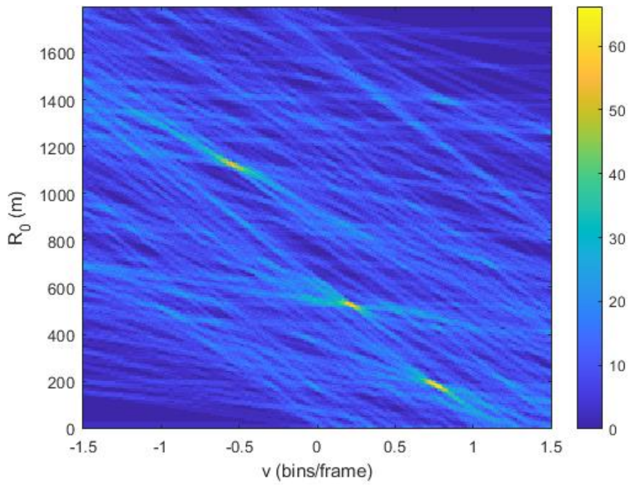

Fig. 3. Two-dimensional Hough accumulator in the (R_0, v) parameter space

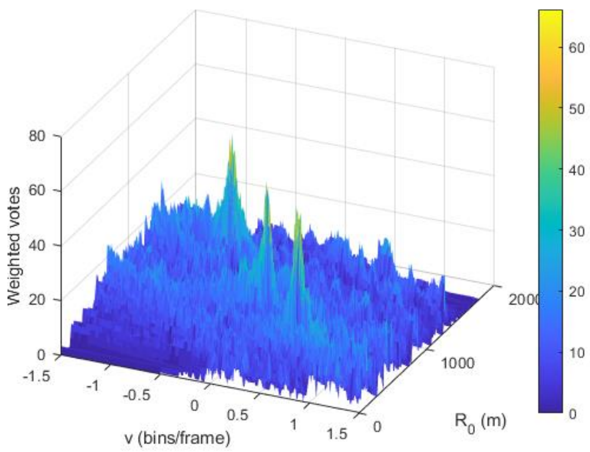

Fig. 4. Three-dimensional representation of the Hough accumulator

Figure 5 shows the results of the multi-target detection procedure. The detected trajectories are represented by solid lines, while supporting points are highlighted. The results demonstrate that the proposed iterative detection-and-removal algorithm successfully identifies multiple target trajectories, including those with intersecting paths. The detected trajectories closely match the true ones, indicating high estimation accuracy in both initial range and velocity.

Figure 6 illustrates the dependence of the track detection probability P_d^{track} on the SNR. The results demonstrate a strong monotonic increase in detection performance with increasing SNR. Specifically, at low SNR values (0–2 dB), the detection probability remains at a relatively low level, indicating insufficient coherence of detections. As the SNR increases to 4–8 dB, the detection probability rapidly improves the detection probability approaches unity.

Figure 7 shows the dependence of the track detection probability on the missed detection probability P_{miss}. It can be observed that the proposed method demonstrates strong robustness to moderate levels of missed detections. The detection probability decreases significantly, typically falling below 0.6. This is due to the reduction in the number of supporting points forming the trajectory, which directly affects the accumulation process in the Hough space.

Figure 8 presents the dependence of the average number of false tracks on clutter density, measured as the number of false alarms per frame. The results show that the number of false tracks begins to increase with increasing obstacle density.

Figure 9 shows the dependence of the track detection probability on the target SNR under the action of a complex interference with a *K*-distribution clutter.

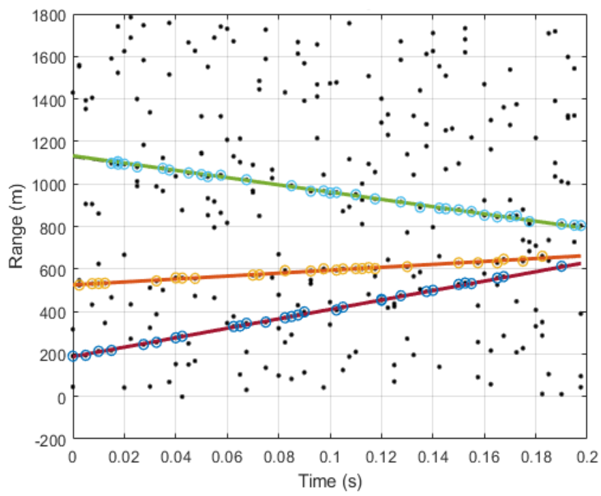

Fig. 5. Detected multi-target trajectories obtained using a detection algorithm based on the Hough transform

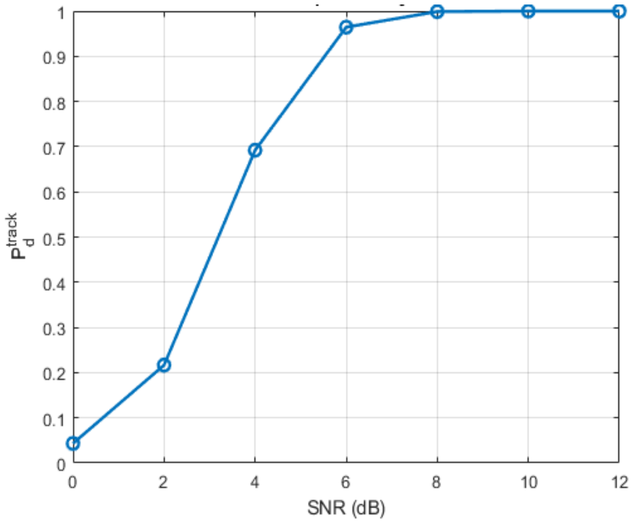

Fig. 6. Track detection probability as a function of SNR

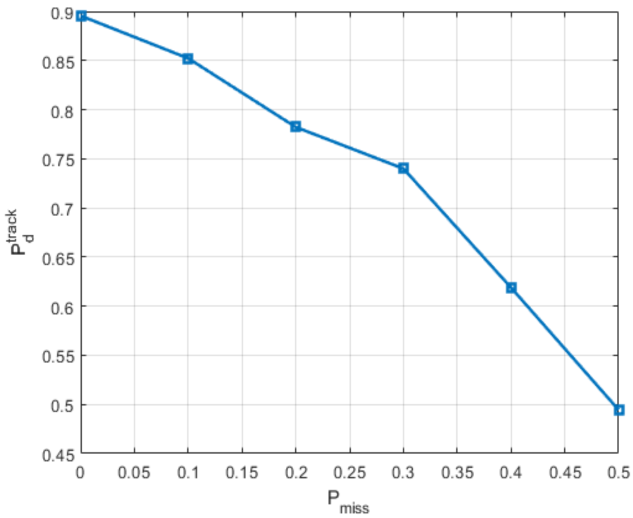

Fig. 7. Dependence of track detection probability on missed detection probability

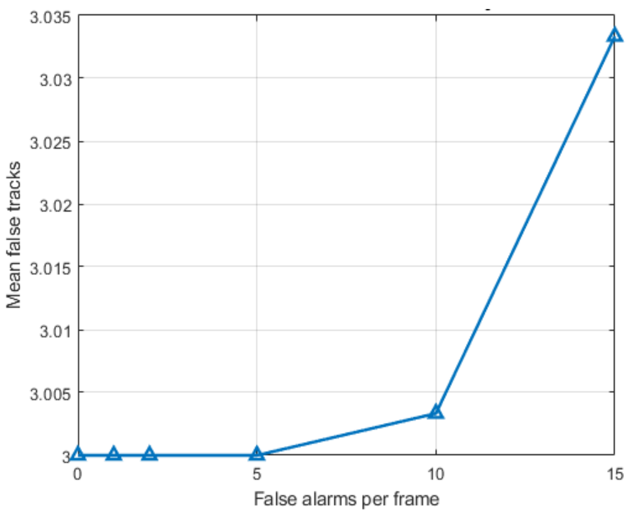

Fig. 8. Mean number of false tracks as a function of clutter density

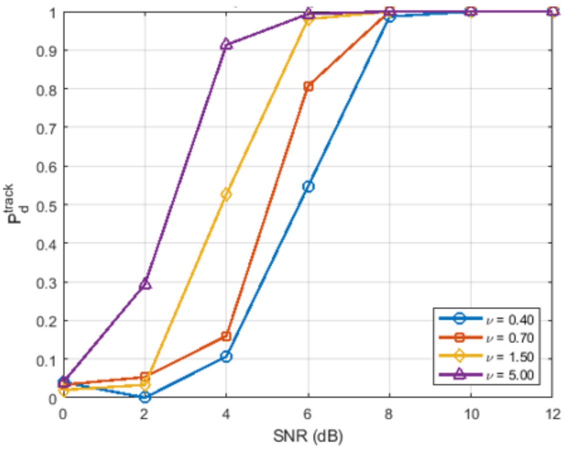

Fig. 9. Track detection probability on SNR in K-clutter

A key parameter of the *K*-distribution is the shape parameter *v*, which controls the degree of heterogeneity of the clutter. As the shape parameter of the *K*-distributed clutter decreases, the clutter becomes increasingly heavy-tailed, resulting in stronger amplitude fluctuations and a higher occurrence of spurious high-intensity returns. The effect of the shape parameter on detection performance is illustrated in Figs 10–12.

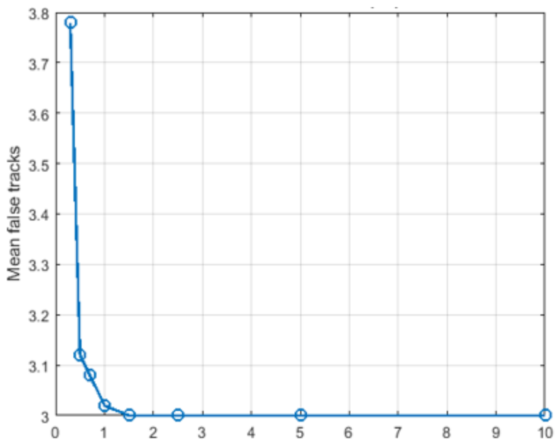

Fig. 10. False tracks on *K*-clutter shape parameter *v*

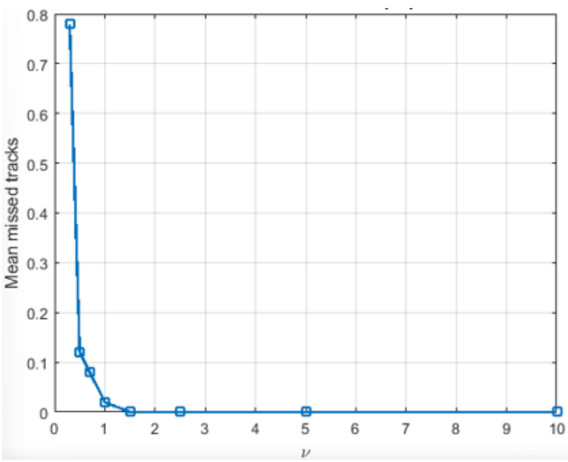

Fig. 11. Missed tracks on *K*-clutter shape parameter *v*

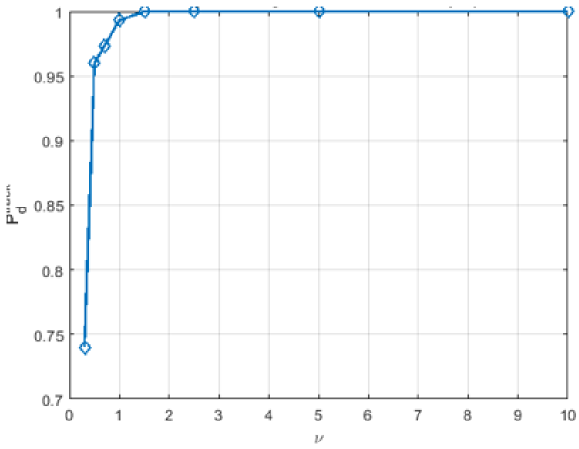

Fig. 12. Track detection probability on *K*-clutter shape parameter *v*

As shown in the figures, the impact of the shape parameter *v* becomes significant only for $v < 2$, where the clutter exhibits pronounced heavy-tailed behavior. In this region, the number of false tracks increases, while missed tracks also become more frequent due to masking by clutter spikes. This confirms that the proposed method is less sensitive to decreasing shape parameter, as it relies on global evidence accumulation in the Hough Transform parameter space and incorporates a weighted voting mechanism that mitigates the influence of isolated clutter spikes.

VI. CONCLUSIONS

A Hough transform-based method for detecting fast radar target trajectories has been developed for operation in the presence of noise, missed detections, and K-distributed clutter.

Simulation results demonstrate that the proposed approach provides high track detection probability, approaching 0.9–1 for SNR values above 6–8 dB. The method remains robust under moderate missed detection probabilities and increasing clutter density, due to the global accumulation of evidence in the Hough parameter space.

The iterative detection-and-removal procedure enables reliable separation of multiple and intersecting trajectories without the need for explicit data association. The introduction of weighted voting based on signal intensity improves detection performance under low SNR and heavy-tailed clutter conditions.

The proposed method can be effectively applied as a preprocessing stage for track initiation in multi-target radar systems operating under uncertain and noisy measurement conditions.

The results confirm that the Hough transform provides effective trajectory-level integration, enabling detection in conditions where conventional single-frame methods fail.

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І. Г. Прокопенко, С. М. Смалюга. Виявлення швидких радіолокаційних цілей за допомогою перетворення Хафа

У статті розглянуто проблему виявлення траєкторій швидкорухомих радіолокаційних цілей за наявності шуму, пропущених виявлень та K-розподілених перешкод. Запропоновано метод на основі перетворення Хафа з використанням фізично інтерпретованої параметризації з точки зору початкової дальності та швидкості. Ітеративна процедура виявлення кількох цілей заснована на виділенні піків та подальшому видаленні знайдених контрольних точок, що дозволяє розділити навіть ті траєкторії, які можуть перетинатися без асоціації даних. Для підвищення стійкості в умовах низького співвідношення сигнал/шум впроваджено схему зваженого голосування на основі інтенсивності сигналу. Продуктивність оцінюється за допомогою

моделювання Монте-Карло. Результати показують високу ймовірність виявлення треку та стійкість до пропущених виявлень та перешкод. Метод підходить для ініціації треку в радіолокаційних системах з кількома цілями.
Ключові слова: перетворення Хафа, радіолокаційне виявлення, виявлення кількох цілей, оцінка траєкторії, K-розподіл, придушення перешкод.

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