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Divide and Hough Transform Method for Fast Track Initiation in Dense Clutters

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Abstract - This paper presents a novel method for fast track initiation in dense clutters by means of divide and Hough transform method. With time sequence information of the measurements and targets' kinematics information considered, this new algorithm avoids a single scan data accumulation effect, and can improve the reliability of formed tracks. In this new algorithm, measurements in observation space only vote to part lines instead of all in standard Hough transform that pass through them, so it can effectively reduce computation and memory, and improve the speed of track initiation. In addition, the simulation results also validate the superior performance of the new algorithm and indicate that it can effectively eliminate the false tracks, and is more robust to clutter inference.

Keywords: track initiation, Hough transform, target tracking.

1 Introduction

Track initiation is the primary problem of multi-target tracking, especially for establishing the records for new targets and terminating the records of inexistent targets [1-2]. Because of the long distance between the radar and targets, it is hard for the targets to be accurately measured by sensors, and there is no statistical rule to judge whether the measure is from target or clutter, track initiation itself is a very difficult issue. It is hoped that target tracks are initiated as early as possible, because the operators can get an early situation picture for the surveillance area. On the other hand, it is hoped that false track initiation rate is as low as possible. False tracks cause waste of radar resources, because radar beams for track maintenance are assigned to the area where there is no target [3]. In addition, to detect modern dim targets, radar needs to lower the threshold. Therefore, the false alarm rate will be very high, and how to deal with the track initiation of targets moving in such circumstance has been a challenging task now.

During the past several decades, a lot of research has been contributed to track initiation, and there are two main series, one is sequential data processing technique, such as the heuristic rule method [4], logic-based method [1]; another is batch data processing technique, such as multiple hypothesis tracking method [5], integrated probabilistic data association algorithm [6], the Hough transform technique [7], and the modified Hough transform technique [8]. The former method has low computational cost, and is easy to apply. However, it is just suitable for initiation in sparse clutter. Though the latter method has a better performance than the former method, and is effective in reducing false alarm probability, it has much more computational cost than the former method, in addition, it is difficult to apply.

As is known, Hough Transform has low sensitivity to local fault and good ability in suppressing noise and clutters. Because of this advantage, it has been widely applied to track initiation in dense clutter environment [9-12]. As a batch data processing method, Hough transform has the disadvantage of huge computation and memory [13-15]. A lot of research has been done to reduce computation and memory by researchers, and many advanced methods have been put forward, such as modified Hough transform, random Hough transform, etc [15-16]. A novel method for fast track initiation in dense clutters by divide and Hough transform method is proposed in this paper and this method is very effective in decreasing computation and memory. The measurement's time sequence information and targets' kinematics information also have been effectively utilized.

This paper is organized as follows. In Section 2, current techniques used for track initiation is simply reviewed. Section 3 describes our approach for fast track initiation in dense clutters by means of divide and Hough transform method. Simulation results are shown in Section 4. Section 6 gives conclusions of this work and discusses future work.

2 Review of current techniques

2.1 The heuristic rule method

Suppose that $\mathbf{r}_i, i=1,2,\cdots,N$ are position measurements from N consecutive scans. The heuristic method initiates a track if any M measurements from these N scans satisfy the following requirements:

The measured or estimated velocity is greater than a minimum value $v_{\min}$ and less than a maximum value $v_{\max}$. Mathematically, this rule can be expressed as

$$v_{\min} \le \left|\frac{r_i - r_{i-1}}{t_i - t_{i-1}}\right| \le v_{\max} \quad (1)$$

The measured or estimated acceleration is less than a maximum value $a_{\max}$. If there is more than one return, the one with the minimum acceleration is used to form the new track. Mathematically, this rule can be expressed as

$$\left|\frac{r_{i+1} - r_i}{t_{i+1} - t_i} - \frac{r_i - r_{i-1}}{t_i - t_{i-1}}\right| \le a_{\max}\left(t_{i+1} - t_i\right) \quad (2)$$

To reduce the possibility of forming false tracks, an optional, angle-limiting rule can be implemented in this heuristic track initiator as well. Let φ denotes the angle between the vectors $r_{i+1} - r_i$ and $r_i - r_{i-1}$, i.e.

$$\varphi = \arccos\left[\frac{\left(r_{i+1} - r_i\right)\left(r_i - r_{i-1}\right)}{\left|r_{i+1} - r_i\right|\left|r_i - r_{i-1}\right|}\right] \quad (3)$$

Then, the angle-limiting requirement can be expressed simply as

$$|\varphi| \le \varphi_0 \quad (4)$$

where $0 < \varphi_0 \le \pi$. When $\varphi_0 = \pi$, there is basically no limiting on angle φ. Note that the measurement noise is not taken into consideration in the heuristic rule method. However, the measurement noise and targets' kinematics parameters have a direct influence on the choice of φ_0. In practical applications, to improve the detection probability of targets, a larger value is usually chosen as φ_0.

2.2 The logic-based (LB) method

Suppose $z_i^l(k)$ that is the l^{th} component of measurement i at time k, where $l = 1,\cdots,p$, $i = 1,\cdots,m_k$. The l^{th} component of the distance vector $\boldsymbol{d}_{ij}$ between the measurements $z_i(k)$ and $z_j(k+1)$ is then defined as

$$\begin{aligned}\boldsymbol{d}_{ij}^l(t) = &\max\left[0, z_j^l(k+1) - z_i^l(k) - v_{\max}^l t\right] \\ &+ \max\left[0, -z_j^l(k+1) + z_i^l(k) + v_{\min}^l t\right]\end{aligned} \quad (5)$$

where t is the time interval between the two scans. Assuming that the measurement errors are independent, Gaussian and zero-mean with covariance $\boldsymbol{R}_i(k)$, the square normalized distance is then defined as

$$D_{ij}(t) = \boldsymbol{d}'_{ij}(t)\left[\boldsymbol{R}_i(k) + \boldsymbol{R}_j(k+1)\right]^{-1}\boldsymbol{d}_{ij}(t) \quad (6)$$

where $D_{ij}(t)$ is a chi-squared distributed random variable with the degree of freedom p . Then threshold γ is obtained through chi-squared distribution table according to predetermined probability. If $D_{ij}(t) \le \gamma$, the two measurements $z_i(k)$ and $z_j(k+1)$ can be associated.

The searching procedure is carried out in the following fashion [1]:

(1) Starting with a measurement (detection) from the first scan, an acceptance or validation region is set up for the second scan. For every measurement from the second scan falling into this region, a potential track is set up.

(2) For every potential track, consisting of two measurements, a straight-line extrapolation (first-order polynomial) is used to the third sampling time. The size of the acceptance region for measurements from the third scan is determined by using the prediction error covariance. The return from the third scan that is closest to the prediction is used to extend the potential track.

(3) For every potential track, consisting of three or more returns, a second-order polynomial is used for prediction into the next scan. Again, the return closest to the prediction updates the potential track.

(4) The procedure in (3) is continued for a number of scans. The least squares method is used to estimate the residual (in order to determine the validation gate size).

(5) If no return is found in the validation region of a potential track, the track is terminated. Returns uncorrelated to any one of the tracks in each scan are used for starting new potential tracks as described in (1).

2.3 The Hough transform (HT) technique

The Hough transform (HT) maps points in the Cartesian coordinate to the $\rho - \theta$ plane by

$$\rho = x\cos\pi(\theta) + y\sin(\theta) \quad (7)$$

where ρ is the vertical distance from origin to the line and θ is the angle from x axis to the vertical line. Each point in the - plane defines a curve in the $\rho{-}\theta$ plane, and the family of curves generated by a set of collinear points will intersect at a point (ρ_0, θ_0). To initiate a straight-line target track in the $\rho - \theta$ plane is therefore equivalent to searching the intersection points in the $\rho - \theta$ plane [7].

The $\rho - \theta$ parameter space is equidistantly quantized into $N_\rho \times N_\theta$ cells with distance interval $\Delta\rho$ and angle interval $\Delta\theta$. The interval centers are given as

$$\theta_m = \left(m - \frac{1}{2}\right)\Delta\theta \quad m = 1,2,\cdots,N_\theta \quad (8)$$

$$\rho_n = \left(n - \frac{1}{2}\right)\Delta\rho \quad n = 1,2,\cdots,N_\rho \quad (9)$$

If there are several collinear points in $X - Y$ plane, these points will accumulate in corresponding cell. After several scans, points from targets which move along a line will accumulate in a specific cell. If the number of points in a specific cell is more than a predetermined threshold, the detection of a straight-line target trajectory is claimed.

2.4 The modified Hough transform (modified HT) technique

Suppose that there is a set of measurements $\{(x_i, y_i), i = 1,2,\cdots,N\}$ from N consecutive scans. For each pair of measurements i and $i+1$, one can always find a $\theta = \theta^{(i)}$ such that

$$\Delta\rho_i\left[\theta^{(i)}\right]=\rho_{i+1}\left[\theta^{(i)}\right]-\rho_i\left[\theta^{(i)}\right]=0 \tag{10}$$

Note that $\theta^{(i)}=\theta_0$ for $i=1,2,\cdots,N-1$ if all the N measurements are collinear. In practice, each $\theta^{(i)}$ is obtained by searching for the θ_n that minimizes $\left|\Delta\rho_i(\theta)\right|$, namely,

$$\theta^{(i)}=\arg\min\left\{\left|\Delta\rho_i(\theta_n)\right|\right\} \tag{11}$$

The modified HT method initiates a track for $\left\{(x_i,y_i),\, i=1,2,\cdots,N_s\right\}$ if

$$\Delta\theta^{(i)}=\left|\theta^{(i+1)}-\theta^{(i)}\right|\le\phi_0 \tag{12}$$

is held for $i=1,2,\cdots,N-1$, where ϕ_0 is a predetermined threshold for $\Delta\theta^{(i)}$ [8].

3 Our approach

For Hough Transform, any point in data space is corresponding to the only one curve in parameter space, and points of the same line in data space are corresponding to different curves in parameter space, and those curves intersect at one point in parameters. If A_i, A_{i+1}, A_{i+2} denotes as an echo in the i^{th}, $(i+1)^{th}$, $(i+2)^{th}$ scan respectively, then A_i and A_{i+1} are connected to form a line $\overline{A_iA_{i+1}}$, which is corresponding to a point C_1 in parameter space with Hough Transform. In the same way, A_{i+1} and A_{i+2} are connected to form a line $\overline{A_{i+1}A_{i+2}}$, which is corresponding to a point C_2 in parameter space with Hough Transform. If A_i, A_{i+1}, A_{i+2} are collinear, C_1 and C_2 must coincide as shown in figure 1 and figure 2. If A_i, A_{i+1}, A_{i+2} are approximately collinear, then C_1 and C_2 will be very close, conversely, they will be far apart. According to this principle, a track can be detected through the intensive degree of point distribution in parameter space.

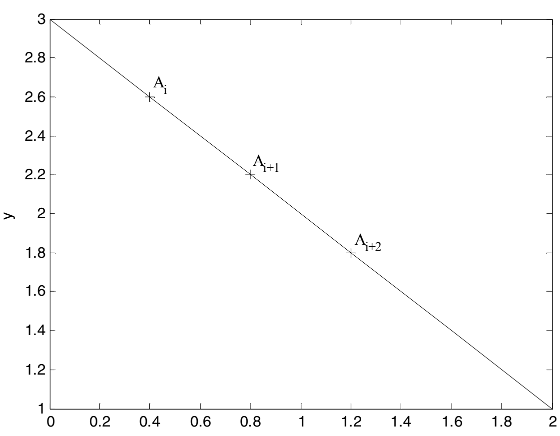

Figure 1. Three collinear points in $X-Y$ plane.

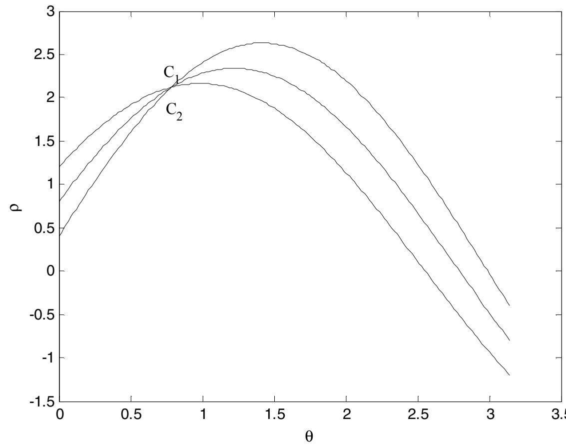

Figure 2. The Hough transform sketch map.

In this new method, any two observed data from different cycles is connected, which avoids loss of echo data. If only observed data from two adjacent cycles can be connected, when the target echo appears flashing, for example, a target echo is lost every other cycle, then echo data from two adjacent cycles can not be connected, which will cause loss of target information. However, not all observed data from two different cycles are from the same target, only when distance between the two points satisfies some condition, they can be from the same target. If $z_1(x_1,y_1)$, $z_2(x_2,y_2)$ is the measurement in time t_1,t_2 respectively, then distance between the two points is

$$d=\sqrt{(x_2-x_1)^2+(y_2-y_1)^2} \tag{13}$$

where d is the distance. Then the average speed is

$$v=\frac{d}{|t_2-t_1|} \tag{14}$$

where v denotes as the average speed. If v satisfies

$$v_{\min}\le v\le v_{\max} \tag{15}$$

z_1 and z_2 can be from the same target. In formula (15), $v_{\min}$ and $v_{\max}$ denote as the minimum and maximum speed of the target respectively. Through this process, the number of combinations is greatly reduced. If z_1 and z_2 satisfy the above condition, then the corresponding curve through Hough Transform in parameter space are

$$\begin{cases}\rho=x_1\cos(\theta)+y_1\sin(\theta)\\ \rho=x_2\cos(\theta)+y_2\sin(\theta)\end{cases} \tag{16}$$

By solving equations (4) and (5), the intersection of the line consisting of z_1 and z_2 in parameter space is

$$\tan\theta=-\frac{x_2-x_1}{y_2-y_1} \tag{17}$$

Let $a=-\frac{x_2-x_1}{y_2-y_1}$, because $\theta\in[0,\pi]$, then

$$\theta=\begin{cases}-\arctan(a) & a>0\\ -\arctan(a)+\pi & a\le 0\end{cases} \tag{18}$$

Bring formula (19) back into equations (16), ρ is obtained.

$$\rho = \frac{|x_2 y_1 - x_1 y_2|}{d} \tag{19}$$

During the initiation period, targets are far away from sensors, so they are often thought to move in a straight line. According to the above discussion, any two measurements from a target must be mapped to the same (ρ, θ) in the parameter space. However, because of target's motion and measurement error, it is impossible that all (ρ, θ) is the same, but they will be concentrated in a small area. These small areas can be detected through the density of point distribution in the parameter space, and then the corresponding tracks are detected.

Suppose there are N intersections in parameter space, to detect target trajectory from observed data, the $\rho - \theta$ parameter space is equidistantly quantized into $N_\rho \times N_\theta$ cells with distance interval $\Delta\rho$ and angle interval $\Delta\theta$. Define parameter space array according to $\Delta\rho$ and $\Delta\theta$, if an intersection votes to accumulated cell $A(k,l)$, $A(k,l) = A(k,l) + 1$. Search for the peak values in accumulated cells, and N_ξ denotes as the threshold. If $A(k,l)$ satisfies

$$A(k,l) > N_\xi \tag{20}$$

output the corresponding observed data as the initial tracks of targets.

In this method, only the accurate intersections are calculated, there is no need to evaluate the value of ρ at each centre of the histogram bins for every measurement data, so the computational cost is greatly decreased compared with the conventional Hough method.

4 Simulation and results

In this section, suppose the surveillance area is 100000m long and 100000m wide. And assume 5 targets move in a straight line with constant velocity, and these targets are tracked with 2D radar. The initial position of 5 targets are (55000m, 55000m), (45000m, 45000m), (35000m, 35000m), (45000m, 25000m), (55000m, 15000m), and 5 targets move in the same speed, v_x=500m/s, v_y=0m/s. And assume radar's PRI is T=5s, azimuth observation square root error is $\sigma_\theta = 0.3°$, while distance observation square error is $\sigma_r = 40$ m. For a fair comparison, we make $N' = 100$ independent Monte Carlo runs, and the number of false measurements in the surveillance area satisfies the passion distribution with density λ.

Define the false track initiation probability as

$$P_F \triangleq \sum_{i=1}^{N'} f_i \Big/ \sum_{i=1}^{N'} n_i$$

where N' is the number of Monte Carlo simulation, f_i is number of false tracks in i^{th} Monte Carlo simulation, and n_i is number of all tracks in i^{th} Monte Carlo simulation.

In the same way, the detection probability of target t is given as

$$P_D = \frac{\sum_{t=1}^{N_t} \sum_{i=1}^{N'} l_{it}}{N_t \times N'}$$

where l_{it} indicates whether track of target t is correctly initiated in i^{th} Monte Carlo simulation, and l_{it} is defined as

$$l_{it} = \begin{cases} 1 & \text{if track of target t is correctly initiated} \\ 0 & \text{else} \end{cases}$$

As shown in Figure 3, $\lambda = 50$, "$+, \bullet, *, \square$" denote clutter points in 4 consecutive cycles, and "o" denotes target points in 4 consecutive cycles. The result of heuristic rule method is shown in Figure 4. Figure 5 is the result of logic-based method. The result of Hough transform method is shown in Figure 6, where $N_\theta = 90, N_\rho = 90$, the threshold in parameter space is 4. Figure 7 is the result of modified Hough transform algorithm. And the result of algorithm presented in this paper is shown in Figure 8, in which $v_{\min} = 50\,m/s, v_{\max} = 1000\,m/s$, $\Delta\rho = 600\,m, \Delta\theta = 2°$, the threshold in parameter space is 3.

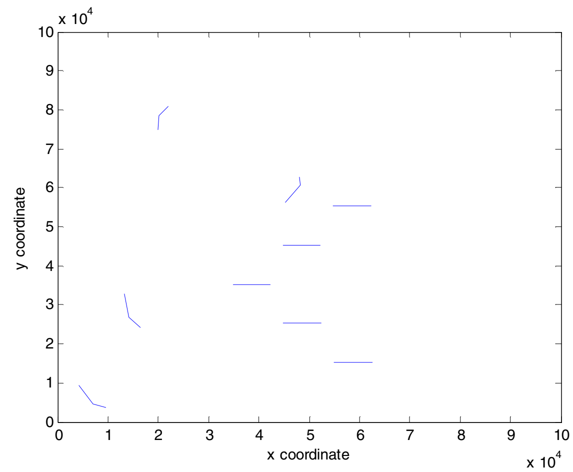

Figure 4. The heuristic rule method with $\lambda = 50$.

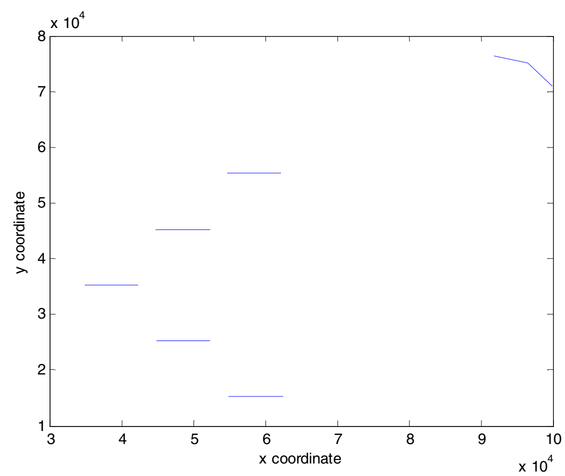

Figure 5. The logic-based method with $\lambda = 50$.

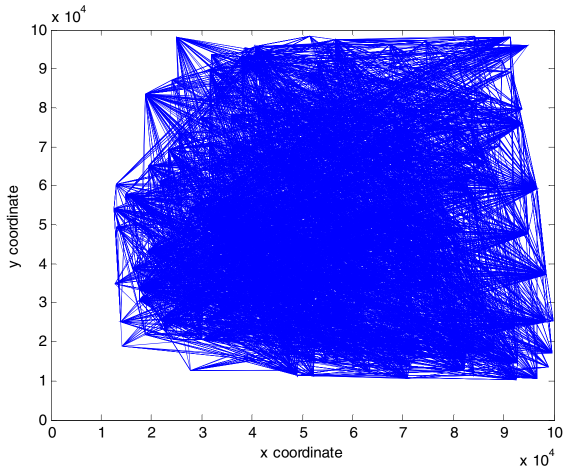

Figure 6. The Hough transform techniqe with $\lambda = 50$.

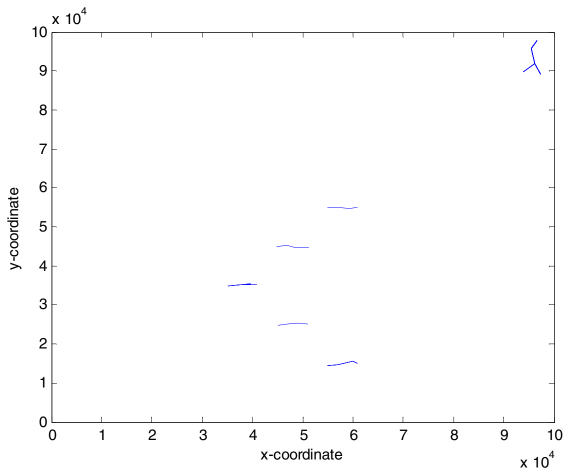

Figure 7. The modified Hough transform techniqe with $\lambda = 50$.

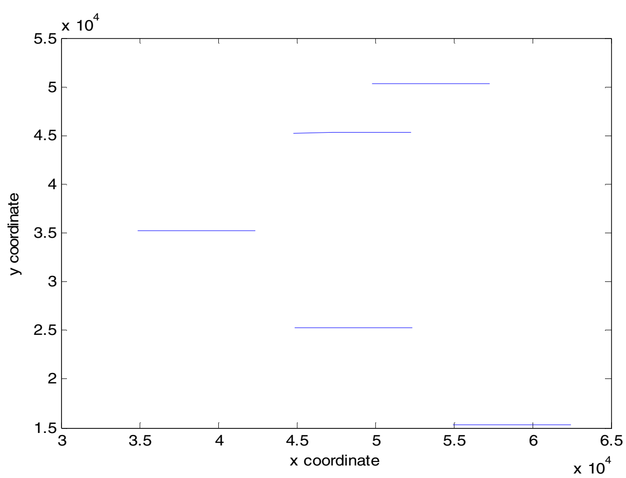

Figure 8. Divide and Hough transform method with $\lambda = 50$.

From Figure 3 to Figure 8, the results show that performance of HT method is the worst, and it almost can not correctly initiate targets' tracks. The remaining four algorithms achieve perfect performance. They all initiate true tracks for 5 targets, and effectively suppress false tracks. They are relatively better than HT method for track initiation and are almost of the same performance.

Now the clutters are increased, When $\lambda = 100$, under the same simulation environment, the results are shown in Figure 9, 10, 11, 12, 13, 14 respectively.

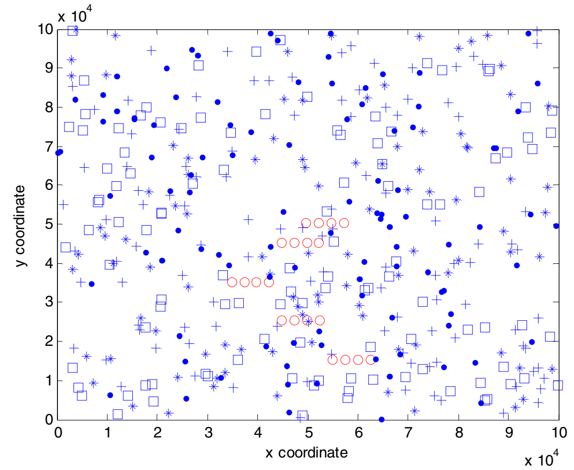

Figure 9. Echoes from 4 consecutive scanning cycles with $\lambda = 100$.

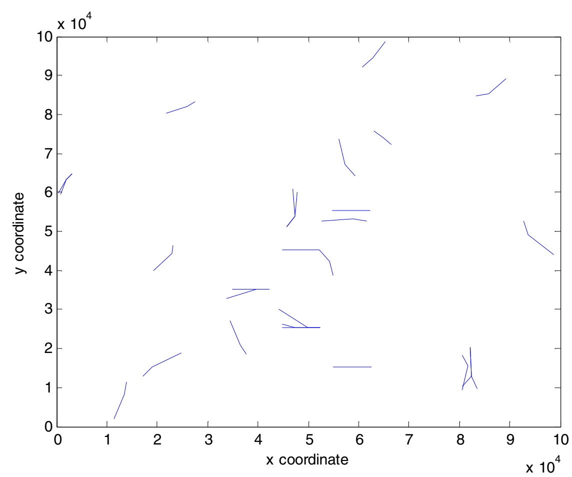

Figure 10. The heuristic rule method with $\lambda = 100$.

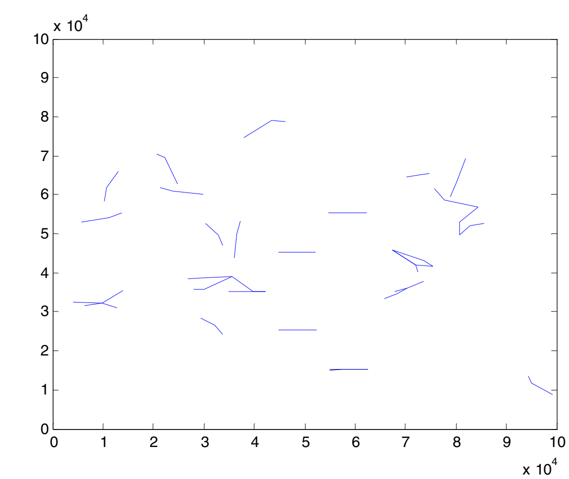

Figure 11. The logic-based method with $\lambda = 100$.

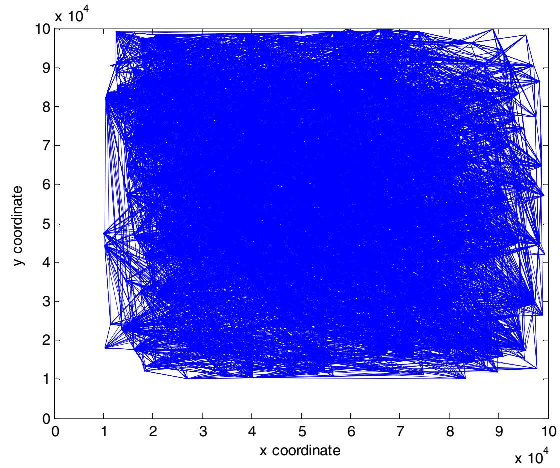

Figure 12. The Hough transform technique with $\lambda = 100$.

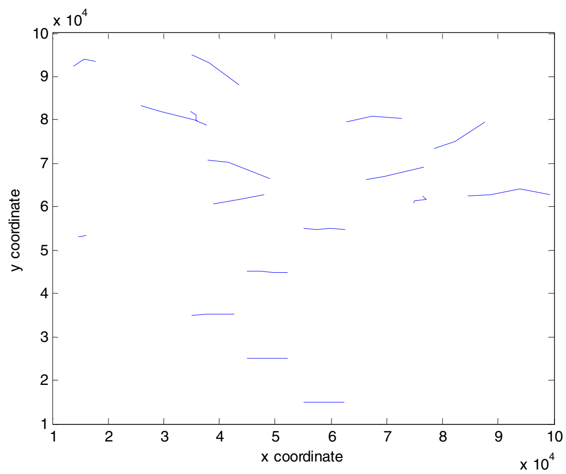

Figure 13. The modified Hough transform technique with $\lambda = 100$.

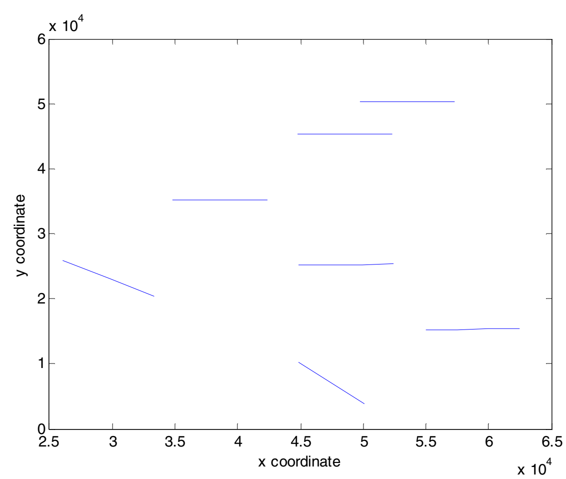

Figure 14. Divide and Hough transform method with $\lambda = 100$.

As is shown in above figures, with the increase of clutters, when $\lambda = 100$, there are many false tracks in the former 4 algorithms. Especially in HT method, a great number of false tracks make it impossible to detect the exact tracks for targets. All these false tracks will cause a lot of trouble for subsequent target tracking and waste of radar resources. However, the method proposed in this paper is very robust to clutter interference, which can correctly initiate targets' tracks and suppress false tracks generated by clutters.

To make it more clear, performance comparison of 5 track initiation methods is given in Table 1.

Table 1. Comparison of 5 track initiation methods

Track initiation method		P_D	P_F
$\lambda = 50$	The heuristic rule method	82.3%	57.6%
	The logic-based method	82.5%	58.7%
	The HT method	12.1%	88.6%
	The modified HT method	85.2%	44.8%
	Divide and Hough transform method	89.3%	38.5%
$\lambda = 100$	The heuristic rule method	20.4%	82.7%
	The logic-based method	25.2%	76.3%
	The HT method	0.1%	95.2%
	The modified HT method	45.3%	64.2%
	Divide and Hough transform method	63.2%	42.1%

For all these methods, divide and Hough transform method always keeps the highest probability of detection in both simulation scenarios. Even when $\lambda = 100$, it still keeps 63.2%, while the highest detection probability of the remaining methods is 45.3%. These simulation results indicate that the new method has a superior performance for track initiation, and is very robust to clutter interference.

To further validate the effectiveness of the proposed algorithm, Table 2 describes the computational cost for methods based on Hough transform. From the table we know that the proposed method is less computational than the HT method and the modified HT method, and is more suitable for fast track initiation in dense clutters.

Table 2. Comparison of computational cost of methods based on Hough transform

Track initiation method		computational cost
$\lambda = 50$	The HT method	4.7×10^7
	The modified HT method	3.6×10^6
	Divide and Hough transform method	2.1×10^4
$\lambda = 100$	The HT method	3.3×10^8
	The modified HT method	5.2×10^7
	Divide and Hough transform method	8.6×10^5

5 Conclusions

In this paper, a novel method for Fast track initiation in dense clutters by divide and Hough transform method is proposed, which connects any two points from different cycles and calculates the exact intersection of the two points in parameter space. With the measurement's time sequence information and targets' kinematics information considered, this new algorithm avoids a single scan data accumulation effect, and can improve the reliability of formed tracks. In this new algorithm, measurements in observation space only vote to part lines instead of all in standard Hough transform that pass through them, so it can effectively reduce computation and memory, and improve the speed of track initiation. In addition, the simulation results also validate the superior performance of the new algorithm and indicate that it can effectively eliminate the false tracks, and is more robust to clutter inference.

References

[1] Y. Bar-Shalom, P. K. Willett, and X. Tian, "Tracking and Data Fusion: A Handbook of Algorithms," Academic, New York, 2011.

[2] Seung-Woo Kim, Young-Taek Lim, Taek-Lyul Song, "A Study of a New Data Association and Track initiation Method with Normalized Distance Squared Ordering," *International Journal of Control, Automation and Systems*, 2011, vol. 9, no. 5, pp. 815-822.

[3] Yasushi Obata, Ryoji Maekawa, et ,al, "Track Initiation Algorithm for Dim Target Using Backward Prediction," *SICE Conference 2013*, Japan, 2013, pp. 1267-1273.

[4] Farina, Alfonso, and Flavio A. Studer, "Radar Data Processing: Introduction and Tracking," vol. 1, Research Studies Press Ltd, 1985.

[5] Blackman, Samuel S, "Multiple Hypothes for Multiple Target Tracking," *Aerospace and Electronic Systems Magazine*, 2004, vol. 19, no. 1, pp. 5-18.

[6] Musicki, Darko, Robin Evans, and Srdjan Stankovic, "Integrated Probabilistic Data Association," *Automatic Control*, 1994, vol. 39, no. 6, pp. 1237-1241.

[7] CASASENT, D.P., and SLASKI, J, "Optical Track Initiator for Multitarget Tracking," Appl. Opt., 1988, vol. 27, pp. 4546-4553.

[8] Lo, T., et al., "Multitarget Track Initiation Using a Modified Hough Transform," *Pointing and Tracking Systems*, 1994, vol. 1, pp. 12-18.

[9] Dong, Xia, et al., "A New Hough Transform Applied in Track Initiation," *International Conference on Consumer Electronics, Communications and Networks*, 2011, pp.30-33.

[10] Chen X, Leung H, Tian M. "Multitarget detection and tracking for through-the-wall radars," IEEE Transactions on Aerospace and Electronic Systems, 2014, vol. 50, no. 2, pp. 1403-1415.

[11] Onera, Thibaut, et al. "Track initiation in low-earthorbit objects using statistical modeling of sparse observations,"IEEE Transactions on Aerospace and Electronic Systems, 2015, vol. 51, no. 1, pp. 258-269.

[12] Wang S S, Feng J F, Che W F, et al. "Track initiation for near space bistatic radar network," Control and Decision, 2013, vol. 28, no. 4, pp. 552-556.

[13] H. Li, M.A. Lavin and R.J. Le Master, "Fast Hough Transform," *Computer Vision, Graphics and Image Processing*, vol. 36, 1986, pp. 139-161.

[14] Yen-Kuang Chen, Wenlong Li, Jianguo Li, et al. "Novel Parallel Hough Transform on Multi-core Processors," *IEEE International Conference on Acoustics, Speech and Signal Processing*, 2008, pp. 1457-1460.

[15] HE You, XIU Jianjuan, "Radar Data Processing with Application," Publication House of the Electronics Industry, Beijing, 2006, pp. 87-96.

[16] Jiang X, Harishan K, Tharmarasa R, et al. "Integrated track initialization and maintenance in heavy clutter using probabilistic data association," Signal processing, 2014, vol. 94, pp. 241-250.