Multi-formation track initiation method based on Density clustering

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Abstract. Aiming at the problem that the existing track initiation algorithm has a poor effect when starting multiple formation tracks under strong clutter, based on the Hough transform method and its derivative algorithm, a multi-formation Hough transform route based on density clustering is proposed. Trace start algorithm. The algorithm first combines the motion information of the target and the timing parameters of the detection points to filter the detection data set to exclude as many points as possible from non-targets. Then it uses the Hough transform to process the obtained detection point set to obtain a preliminary threshold with a lower threshold Formation track; Finally, according to the characteristics of formation goals, the overall formation track is obtained by density clustering method, which solves the problems of track crossing and chaos. Simulation results show that, compared with the standard Hough transform method and its derivative algorithm, the algorithm can start the track of formation targets under strong clutter, and has good performance.

1. Introduction

So far, the track start technology at the initial stage of target tracking has been researched and developed for a long time. Its purpose is to determine the track information before the target starts stable tracking. The accuracy of the initial result directly affects the target tracking process. The track initiation process is present in all radar data processing problems and is the first problem in multi-target tracking \cite{1}. The existing track start algorithms are mainly divided into two categories: the first category is the target-oriented sequential processing technology, and the second category is the batch processing technology of surface vector measurement. Sequential processing technology is only suitable for clutter sparse environments, and representative algorithms include intuitive method and logic method \cite{2}. Batch processing technology is mainly suitable for clutter-intensive environments, and most of its algorithms are related to the Hough transform method\cite{3-4}.

In modern warfare, attack weapons such as aircraft and missiles often carry out attacks against the enemy in the form of formations, which has become a powerful form of combat. Compared with the traditional multi-target, the spatial positions of the targets in the formation are mostly close and the motion state is basically the same, making it easy to cross, alias and other phenomena at the beginning of the track. The traditional multi-target track start algorithm is difficult to effectively deal with the
formation target Therefore, the starting technology of formation target track has attracted the attention of scholars. According to the fineness of the initial formation target, the existing algorithms are divided into fine track start algorithm and overall track start algorithm. The basic principle of the fine track start algorithm [5-6] is to first use the movement state information of the formation target to segment the formation, then pre-interconnect the formation, and finally based on the characteristics of the formation target, the fine interconnection of all the targets in the formation, the start track. Therefore, when the targets in the formation are dense and severely interfered by strong clutter, the performance of the sensor is very high, which greatly reduces the practical value of this algorithm. The overall track start algorithm [7-9] mostly uses the formation target to be segmented, interconnected and speed estimated, and regards the formation target as a whole to start the track and obtain the overall formation track information. Although this algorithm has low requirements on sensor performance and is relatively easy to implement, the existing overall track start method is greatly affected by clutter. When the targets in the formation are dense and accompanied by serious clutter interference, the algorithm performance is limited and the start. The results are quite biased. For example, literature [7] does not consider the interference of clutter on formation targets, and the actual application value is not high; literature [9] lacks a powerful means to remove clutter, and the clustering process is severely interfered in the strong clutter environment. There is a large error between the track and the actual formation target track, which is prone to a lot of confusion and crossover.

Based on the above background, a track formation algorithm based on density clustering Hough transform is proposed. The algorithm is performed in two stages, namely the initial preparation stage and the initial completion stage. The purpose of the initial preparation stage is to eliminate the traces generated by the target as much as possible, find the real data of the target, and reduce the amount of calculation of the track start process; the purpose of the initial completion stage is to complete the entire track start work of the formation.

2. Initial preparation stage based on Hough transform

The main task of the initial preparation stage is to screen the set of detection points. Under the premise of ensuring that the true points originating from the target are not missing, the points that are not generated by the target are eliminated to the greatest extent, providing more accurate detection for the initial completion stage Point trace data collection. The initial preparation stage is mainly divided into two parts, the first part is the point trace processing, and the second part is the Hough transform.

2.1. Point processing

The point trace processing part aims to eliminate the interference caused by the strong clutter to the formation targets. The detection data set is combined with the target's motion information and the timing parameters of the detection point traces, and the non-target generated traces are excluded as much as possible.

The formula for filtering the trace data is

$$v_{\min} \leq \frac{|u(x_i(t_1) - x_j(t_2))|}{T_{t_1} - T_{t_2}} \leq v_{\max}$$  (1)

In equation (1), \(X(t) = \{x_1(t), x_2(t), \ldots, x_n(t)\}\) is the set of detected traces at time \(t\), \(n\) represents the number of traces, \(n_1\) and \(n_2\) are the number of detected traces in the set of traces at time \(t_1\) and \(t_2\), respectively, \(i = 1, 2, \ldots, n_1\), \(j = 1, 2, \ldots, n_2\); \(x_i(t_1)\) and \(x_j(t_2)\) are the \(i\) trace at time \(t_1\) and the \(j\) trace at time \(t_2\); \(u(x_i(t_1), x_j(t_2))\) represents the distance between trace \(x_i(t_1)\) and trace \(x_j(t_2)\); \(T_{t_1}\) and \(T_{t_2}\) represent the time at time \(t_1\) and \(t_2\); \(v_{\min}\) and \(v_{\max}\) are the minimum speed and maximum speed of the
target, respectively. Knowing that the movement parameters of the targets in the formation are approximately the same, using this particularity, through formula (1), find the true point traces from the target as much as possible, remove the traces that do not meet the target speed information, and reduce the calculation amount of the algorithm.

Considering that the number of detection points is large, it is easy to cause the calculation of the algorithm to be too large and affect the speed of the algorithm. Therefore, according to the timing parameters when acquiring the detection points, only the speed screening between the detection points and traces at adjacent times is performed, which effectively reduces the cumbersome calculation between the detection points and traces, and saves the collection of detection points and traces at one time and multiple times. The amount of calculation between the set of detection points.

2.2. Hough transform

This part aims to use the threshold threshold of the Hough transform method to screen the detection points more deeply, and provide accurate detection point data for the initial completion stage to the greatest extent.

According to literature [1], the core formula of Hough transform function is

\[ \rho = x\cos\theta + y\sin\theta \]  

(2)

In formula (2), \(x\) and \(y\) represent the coordinates of any point data in the Cartesian coordinate system in the horizontal and vertical directions; \(\theta\) and \(\rho\) represent the coordinates of the point data in the horizontal and vertical directions converted into the parameter space, \(\theta\) is the angle between the normal and the abscissa axis, and \(\theta \in [0, \pi]\). \(\rho\) is the normal distance from the origin of the coordinate axis to the straight line.

According to the core formula of Hough transform, all the detected trace data are processed, and they are converted from the rectangular coordinate system to the parameter space. Then use the threshold threshold to filter out all the peaks in the parameter space that meet the conditions. Finally, the selected peak value is converted back into the Cartesian coordinate system, so that a more accurate set of data of the detection points and traces is obtained, and the track preparation phase is completed.

3. Initial completion stage based on density clustering

Considering that the formation target is composed of multiple targets that are close in space and have a stable formation structure, the track of the target in the formation will have problems such as crossover and confusion when starting the trajectory. It is difficult to accurately start the target of each target in the formation track. Therefore, based on the characteristics of a large number of detection points and a large distribution density in the area where the formation target is located, the overall formation trajectory is initiated based on the density clustering algorithm to achieve the initial completion of the trajectory.

The DBSCAN algorithm [10] is a classic density clustering algorithm. It can cluster the data in the area according to the density and find a data set of any shape. Therefore, the algorithm combines the DBSCAN algorithm to start the overall trajectory of the formation target.

The steps at this stage are as follows:

1) Use the radius parameter \(\varphi\) to divide the set of probe points obtained after the initial preparation stage, and find the set \(Y_k\) to which each point belongs. Among them, \(\varphi\) represents the radius parameter in the DBSCAN algorithm, which reflects the density of the targets in the formation, and the value is related to the distance between the targets in the formation. Since the movement states of the targets in the formation are basically the same, \(\varphi\) can take the maximum distance between the targets in each formation.

2) Based on the characteristics of stable formation of formation targets, pick out the set of points not less than the quantity parameter MinPts (MinPts represents the number of targets in the formation,
usually the default MinPts=3), and get the set \(D^q_k\). Among them, MinPts is the quantity parameter in the DBSCAN algorithm, affected by the formation target density, the value of \(q\) is related to the number of targets in the formation; \(D^q_k\) is the data set of the detection points of the \(q(0 \leq q \leq k_{\text{dbscan}})\) formation at time \(k\), and \(k_{\text{dbscan}}\) is the number of formation at time \(k\).

3) Find the center position of the \(q(0 \leq q \leq k_{\text{dbscan}})\) detection point track data set at time \(k\), this center position is the center of the \(q(0 \leq q \leq k_{\text{dbscan}})\) formation, and the center position corresponding to each formation at all times is connected, and the overall trajectory of the formation can be started.

4. Simulation experiment and result analysis

4.1. Simulation environment
Suppose that a two-dimensional radar is used to track 15 uniformly linear moving targets. These 15 targets are divided into 3 formations, each of which has 5 targets. The initial positions of the five targets in the first formation are evenly distributed in the \(x \sim [15000,15100]\) and \(y \sim [6000,6100]\) areas; the initial positions of the five targets in the second formation are evenly distributed in the \(x \sim [3000,4000]\) and \(y \sim [15000,16000]\) areas; the initial positions of the five targets in the third formation are evenly distributed in the \(x \sim [0,5000]\) and \(y \sim [0,5000]\) areas. Assuming that the initial speeds are \(270 \text{m/s}, 230 \text{m/s}\), the upper limit of the target movement speed is \(500 \text{m/s}\), and the lower limit of speed is \(20 \text{m/s}\).

Let the radar’s direction finding error and ranging error be \(\sigma_\theta = 0.1^\circ\) and \(\sigma_r = 10 \text{m}\) respectively; the radar scan period is 1 s; the radar measurement range is \(H = 20000 \text{m}\), and the sight range is \(x \sim [0,H]\), \(y \sim [0,H]\); the number of clutters in each scanning period follows the Poisson distribution with the parameter \(\lambda\), and the positions of the clutters are evenly distributed within the radar field of view. Assuming that the quantization levels of orientation and distance in the Hough transform are \(N_\theta = 90\) and \(N_\rho = 90\), respectively, the orientation quantization unit \(\Delta\theta = 2^\circ\) and the distance quantization unit \(\Delta\rho = 222.2 \text{m}\).

4.2. Simulation results and analysis
To simplify the language description in the text, let the algorithm in [9] be the C-H algorithm, the standard Hough transform method is the B-H algorithm, and the algorithm mentioned in this paper is the D-H algorithm. This paper compares the effects of the three algorithms of B-H algorithm, C-H algorithm and D-H algorithm to initiate the formation target track.

Figure 1 is a graph of the detection data in 10 scan cycles at time \(\lambda = 1\).
Fig. 2, Fig. 3 and Fig. 4 are the trajectory chart of the initial formation target of the three algorithms of B-H algorithm, C-H algorithm and D-H algorithm when $\lambda = 1$. Comparing the three figures, it can be seen that at $\lambda = 1$, there is a wrong track in the track started by the B-H algorithm, and there are phenomena such as track crossing and overlap, and the effect of the algorithm starting track is general; the initial trajectory effect of the C-H algorithm and the D-H algorithm is relatively good. There is no obvious false trajectory, and the overall trajectory of the formation target is found.

**Fig 2.** the B-H algorithm starts the track graph when $\lambda = 1$

**Fig 3.** the C-H algorithm starts the track graph when $\lambda = 1$

**Fig 4.** the D-H algorithm starts the track graph when $\lambda = 1$
Fig. 5 is a graph of detection data in 10 scanning periods at time $\lambda = 50$.

![Fig 5. $\lambda = 50$ at 10 scan cycles of detection data](image)

Fig. 6, Fig. 7 and Fig. 8 are the trajectory chart of the initial formation target of the three algorithms of B-H algorithm, C-H algorithm and D-H algorithm at time $\lambda = 50$. Comparing the three figures, it can be seen that at $\lambda = 50$, there are a large number of erroneous trajectories in the trajectory initiated by the BH algorithm, which is also accompanied by a large number of trajectory intersections and overlaps. The algorithm performance is extremely poor; there are false tracks in the track started by the C-H algorithm, only a small part of the movement trend can be seen, and the accurate formation target movement track cannot be seen; the D-H algorithm has the best track start effect and is not affected by strong clutter. It can clearly see the overall movement trend of the formation and the initial track is accurate.

![Fig 6. the B-H algorithm starts the track graph when $\lambda = 50$](image)
Fig 7. the C-H algorithm starts the track graph when $\lambda = 50$

Fig 8. the D-H algorithm starts the track graph when $\lambda = 50$

Fig. 9 is a graph of detection data in 10 scanning periods at time $\lambda = 100$.

Fig 9. $\lambda = 100$ at 10 scan cycles of detection data
Figure 10, Figure 11 and Figure 12 are the trajectory charts of the initial formation target of the three algorithms of B-H algorithm, C-H algorithm and D-H algorithm at time \( \lambda = 100 \). Comparing the three figures, it can be seen that at \( \lambda = 100 \), the track start effect of the B-H algorithm is very poor; the initial track effect of the C-H algorithm is poor, and some false tracks appear, and along with the phenomenon of many tracks crossing and overlapping, the accurate track of the formation target cannot be found; the D-H algorithm’s track start effect is still very good, the performance is not affected by strong clutter, and it can output an accurate overall track of the formation.

Fig 10. the B-H algorithm starts the track graph when \( \lambda = 100 \)

Fig 11. the C-H algorithm starts the track graph when \( \lambda = 100 \)
In general, the B-H algorithm is not suitable for starting the trajectory of the formation target. As the clutter intensity continues to increase, the C-H algorithm’s track start effect becomes worse and worse, and it is not suitable for starting the track of the formation target under the strong clutter environment. However, the DH algorithm is less affected by clutter. It is suitable for both the trajectory of formation targets in a sparse initial clutter environment and the trajectory of formation targets in a dense initial clutter environment.

5. Conclusion
In this paper, the problem of formation target track trajectory under strong clutter is studied, and it is difficult to effectively solve this problem with the existing track start algorithm. A multi-form Hough transform track start algorithm based on density clustering is proposed. Simulation results show that this algorithm has two advantages compared to existing algorithms:

1. Aiming at the problem of strong clutter, a large amount of clutter is removed by combining the motion information of the target and the timing parameters of the detection trace. Based on the Hough transform method, the set of detection points and traces is further processed, and the points generated by the real target are selected as much as possible, which increases the accuracy of the initial track and reduces the amount of algorithm calculation.

2. Considering the close distance between the targets in the formation and the similar movement status, a formation is regarded as a whole, and the overall formation trajectory is obtained by density clustering. It solves the problems of crossing and overlapping of the starting track, and has good practical application value.

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