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ORIGINAL RESEARCH

Track initialisation for multiple formations based on neutrosophic Hough transform

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Abstract
Track crossing is a major issue in the initialisation of multiple-flight trajectories. To solve this problem, the authors propose a track initialisation algorithm. It uses characteristics of formation flight to find centroids of each formation with DBSCAN algorithm. Then, it initialises the track based on the centroid. The author use a Neutrosophic Hough Transform (NHT) method to improve accuracy and computational speed. That helps address errors caused by the approximation of straight lines between true points resulting from the clustering algorithm. The authors made three experiments using track initialisation data from two flight formations with five target aircraft each, over a span of three frames. NHT, Fuzzy HT, Improved Hough Transform (HT) and HT are compared. Results revealed that the average runtime of NHT was 10.2153 s. The F-measure of NHT was 100.00%, while that of Fuzzy HT was 9.8347 s. The F-measure of Fuzzy HT was 80.00%. The Improved HT was 12.0723 s. The F-measure of Improved HT was 11.76% and HT was 13.783 s. And the F-measure of HT was 6.87%. The authors lost some computation speed to achieve higher prediction accuracy. The accuracy of the NHT is higher than other methods.

KEYWORDS
air traffic control, aircraft, clutter, Hough transforms

1 | INTRODUCTION

Real-time tracking of target trajectories in both civil and military aviation remains a formidable challenge for passive radar tracking. Multitarget tracking contains four stages based on various tasks: track initialisation, track fusion, track prediction, and track termination. Track initialisation is the first concern in target tracking among these stages. Track initialisation methods fall into two categories: sequential processing techniques and batch processing techniques. Sequential processing techniques, such as logical and intuitive methods, are applicable in scenarios with relatively simple target tracking environments. In complex environments, such as those with interference from clutter, noise, and other factors, batch processing techniques outperform sequential processing techniques for initialisation [1]. However, the use of batch processing techniques significantly increases computational complexity and leads to an exponential growth in data association.

In real-life scenarios, most aviation targets fly in the form of formations to complete their missions. During formation flying, because each aircraft's speed and track are close to each other, problems such as track merging and track crossing often arise during passive radar tracking and track initialisation. Track initialisation methods for formation flying mainly fall into two categories: clustering-based methods and refinement-based methods.

The Hough Transform (HT) method was proposed in 1962 by Hough. It is initially used to extract linear features from images by employing a voting method. And it is further expanded by Smith for track initialisation recognition. Its main advantages include low sensitivity to local defects and strong robustness to random threshold detection. The HT method and its improved versions have been widely used in practical applications. However, due to its high computational complexity, the speed of the HT-TI method is slow and time-consuming, making it unsuitable for use in real-time monitoring. Some studies have focused on solving this problem, mainly by modifying the accumulation rule to reduce the computational complexity of the HT-TI method [2–4]. Most improved HT methods use rules for the accumulation of gradient magnitudes, probabilities, kernel functions, binary values, or fuzzy logic. However, these accumulation rules still need to calculate the contribution of each measurement value for every voting element in the accumulation matrix. That results in a complexity that is not significantly reduced. Although many improved HT-TI methods have been developed, they mainly focus on the structural design of the track initiation process. They do not pay enough attention to the problem of uncertain correlations between measurement values and different targets in complex monitoring environments, such as cross targets, close-range targets, and false targets. In these complex scenarios, the detection performance of traditional track initiation methods may decrease significantly. However, the influence of noise and clutter can potentially result in false peaks and consequently cause divergence and a reduction of peak values in the accumulator matrix. Fuzzy HT methods use fuzzy membership instead of binary accumulation and are typically applied in image detection [5, 6]. Later, some scholars [7–9] introduced it for track initiation research. Although FHT methods partially solve the problem of decreasing peaks in the accumulator matrix, they cannot adequately describe the uncertain correlation between measurements and different targets in complex environments. Therefore, this method is challenging to use in practical applications. This paper proposes a Neutrosophic Hough Transform (NHT) algorithm based on Neutrosophic sets to describe the uncertain correlation between measurements and different targets in complex environments.

In practical scenarios, most flight missions involve flying in formation. During formation flying, track crossing and merging may occur frequently due to different flying speeds and trajectories of each aircraft, which leads to difficulties in track initiation. Clustering-based algorithms group the track points based on certain clustering rules, while fine tracking initiation algorithms process the track points based on distance statistical characteristics or dynamic models [10].

Although fine tracking initiation algorithms are marginally more effective than clustering-based algorithms, they come at a significantly higher time complexity cost. Various clustering algorithms have been attempted in clustering-based algorithms. However, to use k-means clustering for track initiation, the number of clusters k must be predefined. The clustering outcomes rely heavily on the number of centres and the initialisation positions. In addition, it is sensitive to isolated and outlier points and only has good clustering effects on spherical clusters. Most clustering algorithms need a predetermined number of clusters. However, in practical scenarios, it may be challenging to identify the precise number of clusters that can be formed, which leads to significant challenges for these clustering algorithms [11]. By contrast, density-based clustering algorithms offer a superior alternative since they ease challenges posed by the need for a predefined number of clusters.

The major tasks and benefits are given as follows:

(1) Based on the sensor acquired data, this paper performs DBSCAN clustering to generate new data using cluster centres for the subsequent trajectory initialisation. This group-based global trajectory initialisation algorithm significantly reduces the time required for initialising multiple formation trajectories. In addition, DBSCAN can effectively solve the issues of trajectory fusion and trajectory intersection in formation trajectory initialisation.

(2) The trajectory is initiated by the Neutral HT algorithm using the traces obtained from (1). That obtains the initial positions of the entire formation. As the global trajectory initiation is based on the group centre, the accuracy of the group centre is somewhat inferior to that of initiating trajectories for each target in the formation. However, the Neutral HT has a higher fault tolerance and stronger ability to resist clutter interference, which results in better performance in formation trajectory initiation.

The remainder of this paper is organised as follows: Section 2 introduces the theory of neutral sets and neutral HT. Section 3 introduces the multi-formation trajectory initiation algorithm based on neutral HT and its algorithm process. Section 4 conducts simulation experiments and compares the performance of NHT and HT, MHT and FHT. Finally, Section 5 is the conclusion.

2 | PRINCIPLE OF NEUTROSOPHIC HOUGH TRANSFORM

2.1 | Principle of Hough transform

The core idea of HT is to convert coordinates (x, y) in the Cartesian coordinate system into coordinates (ρ, θ) in the polar coordinate system:

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

Here, $\theta \in [0, \pi]$. If three points, $(x_1,y_1),(x_2,y_2),(x_3,y_3)$ are on the same straight line, then when they are converted to polar coordinates, their three curves will intersect at the same point. This is illustrated in Figure 1.

In Figure 1, the intersection points (ρ_0,θ_0) of the three curves represent the size and slope of the line passing through the three points $(x_1,y_1),(x_2,y_2),(x_3,y_3)$ in the Cartesian coordinate system.

All the points of the HT algorithm handles are transformed into curves in the polar coordinate system. Then, the intersection points between them are calculated. By calculating the number of each intersection point in the accumulation matrix C, several peaks can be found after all intersection points are computed. Taking one of the peaks as an example, we can find all the points corresponding to this peak in the Cartesian coordinate system. The lines connecting these points are one of the trajectories we are looking for.

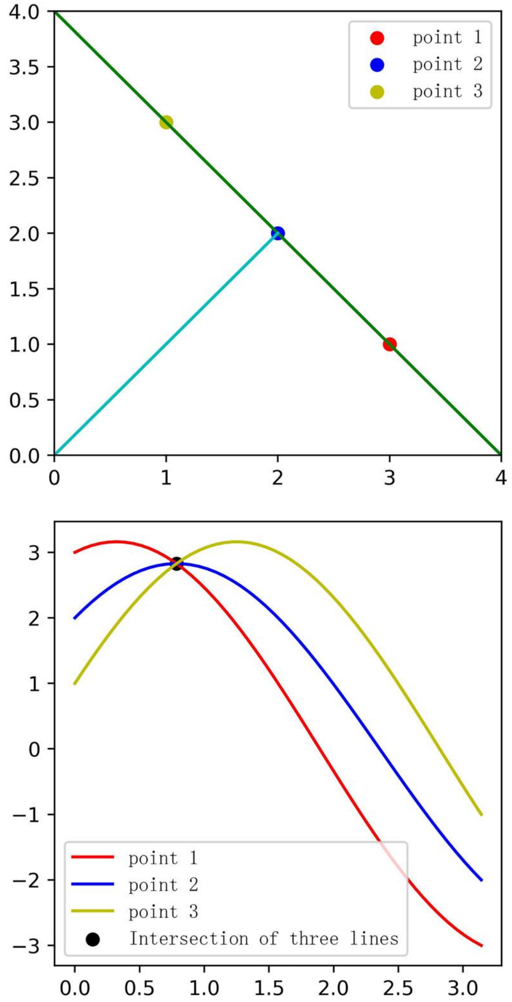

FIGURE 1 The principle of Hough transform.

2.2 | Neutrosophic Hough transform algorithm

2.2.1 | Neutrosophic set theory

To introduce neutrosophic set theory, it is essential to first introduce fuzzy set theory [12]. Fuzzy set theory postulates that membership relationships of all elements to a set is not crisp and binary. But rather, it introduces the concept of the membership degree of an element to a set. The definition of fuzzy set theory is as follows:

Given a domain U, a mapping u_A from U to the unit interval [0,1] is called a fuzzy set on U.

Neutrosophic set theory [13, 14] introduces the concept of indeterminate subsets on top of the usage of true subsets and false subsets in ordinary fuzzy sets. In neutrosophic sets, each element has three parameters: truth membership (T), indeterminacy (I), and falsity membership (F), which are independent of each other. The specific definition is as follows:

$$\tilde{A} = \left\{ < u, T_{\tilde{A}}(u), I_{\tilde{A}}(u), F_{\tilde{A}}(u) \} > | u \in U \right\}$$

Here, U is a non-empty set, $\tilde{A}$ represents a neutrosophic set, $T_{\tilde{A}}(u)$ is the truth membership function of $\tilde{A}$, I_Ã(u) is the indeterminacy membership function of $\tilde{A}$, F_Ã(u) is the falsity membership function of $\tilde{A}$, for $\forall u \in U$, $T_{\tilde{A}}(u), I_{\tilde{A}}(u), F_{\tilde{A}}(u) \in [0,1]$, and $T_{\tilde{A}}(u) + F_{\tilde{A}}(u) = 1$.

Neutrosophic sets offer several advantages over fuzzy sets. First, they can handle incomplete and imprecise information in complex problems. Second, they can provide reliable results in many multicriteria decision-making problems. Third, they can handle information from different data sources. Therefore, neutrosophic sets are a powerful and reliable algorithm with excellent applications in various fields such as image processing, natural language processing, multicriteria decision-making, strategic planning, and blockchain. In this paper, neutrosophic sets are utilised to reduce the computational time complexity of the HT.

2.2.2 | Principle of the neutrosophic Hough transform algorithm

Neutrosophic Hough transform was initially applied in the field of image processing. A neutrosophic set $\tilde{A}$ is defined as $\tilde{A} = \{A_1, A_2, A_3, \ldots, A_m\}$, where A_i is composed of $\{T_{\tilde{A}}(u), I_{\tilde{A}}(u), F_{\tilde{A}}(u)\}/A_i$ for each A_i. $T_{\tilde{A}}(u)$ represents the truth membership function of $\tilde{A}$, $I_{\tilde{A}}(u)$ represents the indeterminacy membership function of $\tilde{A}$, and $F_{\tilde{A}}(u)$ represents the falsity membership function of $\tilde{A}$.

The image I_{NT}, which needs to undergo the HT, is mapped to the domain of neutrosophic sets. In polar coordinates, for a point $P(\rho,\theta)$, T_{NH}, I_{NH}, F_{NH} are used to represent the truth membership function, indeterminacy membership function, and falsity membership function, respectively. $P_{NHT}(\rho, \theta) = \{T_{NH}, I_{NH}, F_{NH}\}$.

$$T_{NH}(\rho,\theta) = \frac{g(\rho,\theta) - g_{\min}}{g_{\max} - g_{\min}}$$

$$I_{NH}(\rho,\theta) = \frac{Gd(\rho,\theta) - Gd_{\min}}{Gd_{\max} - Gd_{\min}}$$

$$F(\rho,\theta) = 1 - T_{NH}(\rho,\theta)$$

Here, $g(\rho,\theta)$ represents the Hough value of image I_{NT} at point $P(\rho,\theta)$, while $Gd(\rho,\theta)$ represents the gradient of image I_{NT} at point $P(\rho,\theta)$.

3 | MULTIPLE FORMATION TRACK INITIATIONY BASED ON NEUTROSOPHIC HOUGH TRANSFORM

3.1 | DBSCAN algorithm

The rules of formation flight are flight direction and speed of formation are the same, there is a certain distance between the members of the formation, and the distance is not far. Because the distance between different formations is much greater than the distance within the same formation. This paper adopts the method of treating the entire formation for track starting. The DBSCAN clustering algorithm classifies the traces and finds the centre of each subgroup as the starting point of the track. The advantage of the DBSCAN algorithm is that it does not need to set the number of clusters in advance and can divide clusters automatically. And the algorithm has the role of removing noise to some extent. However, the disadvantage of Algorithm is that it needs to set the scanning radius eps and the minimum point minPts within the radius. That has a significant impact on the clustering. Besides, manual parameter setting may result in poor cluster division [15]. Nevertheless, because of the characteristics of formation flight, manually setting parameters will not bring problems to the clustering division.

3.2 | Data preprocessing

To reduce the impact of noise on track starting and the computational complexity of HT, this paper needs to preprocess the track points first. It uses $v_{\max}$ and $v_{\min}$ to calculate the maximum and minimum distances for a point to perform the HT, namely:

$$v_{\min}t' \le d(i_k, j_{k+1}) \le v_{\max}t'$$

Here, t' represents the time for radar to scan one frame, and $d(i_k,j_{k+1})$ represents the distance from the i-th point in frame k to the jth point in frame $(k+1)$. If it does not meet the above requirements, the two points will not undergo HT.

3.3 | Neutrosophic Hough transform for track initiation

The globally accumulated matrix C_k [16]obtained can be expressed as follows:

$$\tilde{C}_k = \sum_U \frac{u_c(\rho_{ijl}, \theta_{ij})}{(\rho_{ijl}, \theta_{ij})}$$

Here, $\theta_{ij} = \theta_i - \theta_{tol} + (j-1) * \Delta\theta$, $j = 1, 2, \ldots, n_\theta$; $\rho_{ij} = x_i cos\theta_{ij} + y_i sin\theta_{ij}$, $j = 1, 2, \ldots, n_\theta$;$\rho_{ijl} = \rho_i$-$\rho_{tol} + (L-1) * \Delta\rho$,$l = 1, 2, \ldots, n_\rho$.

Here, (ρ_i,θ_i) is the kernel element, that is, the membership degree of the point is 1. $\theta_{tol} and \rho_{tol}$ are the maximum allowable error ranges, $\Delta\theta and \Delta\rho$ are the discrete intervals, $n_\theta = \frac{2\theta_{tol}}{\Delta\theta} + 1$ is the number of support sets in the θ direction, and $n_\rho = \frac{2\rho_{tol}}{\Delta\rho} + 1$ is the number of support sets in the ρ direction.

The membership degree function $u(\rho_{ki},\theta_{ki})$ is a Gaussian function:

$$u\left(\rho_{ijl}, \theta_{ij}\right) = \exp\left[-\frac{\left(\rho_{ijl} - \rho_{ij}\right)^2}{2\varepsilon_\rho^2}\right] * \exp\left[-\frac{\left(\theta_{ij} - \theta_i\right)^2}{2\varepsilon_\theta^2}\right]$$

$$u\left(\rho_{ijl}, \theta_{ij}\right) = \max(u_T, u_I, u_F)$$

where ε_ρ and ε_θ respectively represent the mean square deviation on the ρ axis and θ axis.

Suppose there are n_k potential target points in the kth frame, and continuous scanning of s frames, the accumulated matrix can be represented as follows:

$$C(\rho, \theta) = \sum_{t=k+1}^{k+s} \sum_i u_C(\rho, \theta)\delta(\rho - \rho_i)\delta(\theta - \theta_i)$$

Here, $\delta(\cdot)$ is the Dirac function:

$$u_C = \max(u_T, u_I, u_F)$$

$$u_T = u^k$$

$$u_I = \left|u^k - u^{k-1}\right|$$

$$u_F = 1 - u_T$$

Normalise $C(\rho,\theta)$ and obtain $\tilde{C}(\rho, \theta)$,

$$\tilde{C}(\rho, \theta) = \frac{C(\rho, \theta)}{\max\left(C(\rho, \theta)\right)}$$

Choose a threshold τ. If $\tilde{C}(\rho, \theta) \ge \tau$, then the track (ρ,θ) exists. If $\tilde{C}(\rho, \theta) \ge \tau$, then the track (ρ,θ) does not exist.

In the NHT-TI, the detected targets mainly include true targets, false targets, and crossover targets. The uncertainty correlation between the measured values and the three types of targets is calculated using a Neutrosophic Set. Then, a correlation model for the measured values between different targets is established. The Neutrosophic accumulated matrix is used to calculate the candidate temporary trajectory, replacing the traversal operation in the standard HT. Finally, peak detection is achieved in the Neutrosophic accumulated matrix corresponding to the true positions of the targets through the maximum inverse transformation. In addition, in order to reduce the uncertainty of the measurement-target correlation, the time and dynamic information of the measurement sequence are introduced in the neutrosophic cell mapping, while considering the influence of measurement noise on the measurement uncertainty.

Algorithm. The process of track initiation based on the neutrosophic Hough transform.

Initialisation-I:

  Data Set W = $\{\boldsymbol{W}_1, \boldsymbol{W}_2, \ldots, \boldsymbol{W}_n\}$

A = DBSCAN(W, eps = 25, minPts = 5)

Data preprocessing, Get data set A

Initialisation-II:

  $C = 0,\ T_{NH} = 0,\ I_{NH} = 0,\ F_{NH} = 0, \tau = 0.9$

For i in n:

  $\boldsymbol{A_i} = \{\boldsymbol{X}_1, \boldsymbol{X}_2, \ldots, \boldsymbol{X_m}\}$

  For j in m

   Performing polar coordinate transformation, $\boldsymbol{X_j} = (\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})$

   Calculate

$\boldsymbol{T}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})_{\boldsymbol{NH}}, \boldsymbol{I}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})_{\boldsymbol{NH}}, \boldsymbol{F}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})_{\boldsymbol{NH}}$

   $\boldsymbol{C}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}}) = \boldsymbol{max}\{\boldsymbol{T}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})_{\boldsymbol{NH}}, \boldsymbol{I}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})_{\boldsymbol{NH}}, \boldsymbol{F}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}})_{\boldsymbol{NH}}\}$

  End

End

Normalise the accumulation matrix C

For i in n:

  For j in m

   If $\boldsymbol{C}(\boldsymbol{\rho_{ij1}}, \boldsymbol{\theta_{ij}}) > \boldsymbol{\tau}$

    Track exists

  End

End

4 | EXPERIMENTAL SIMULATION

4.1 | Simulation environment

We assume the monitoring range of a two-dimensional radar device is $5000 \times 5000\ m^2$. There are two squadrons flying within the range, with each squadron having five targets. The five targets in the first squadron are uniformly distributed in an area where $x \in [3000,3100]$,$y \in [4200,4300]$. The five targets in the second squadron are uniformly distributed in an area where $x \in [0,200]$, $y \in [1200,1300]$. The initial velocity is (270 m/s, 230 m/s), the maximum velocity is $v_{\max} = 500$ m/s and the minimum velocity is $v_{\min} = 20$ m/s. Clutter follows a uniform distribution with a parameter of [0,5000], and the radar's lateral error is $\sigma_\theta = 0.1$, and the measurement error is $\sigma_r = 10$ m. The reference space map below is in the ratio of 1:10 to the actual space.

4.2 | Simulation results and analysis

In this experiment, three frames of data that were selected from the flight process and track initialisation using HT and NHT were carried out.

Figures 2 and 3 show results of the first frame before and after using the DBSCAN clustering algorithm to find the centre points:

Figures 2 and 3 show that the number of track points significantly decreases after applying the DBSCAN clustering algorithm. This not only reduces the runtime of HT but also helps avoid issues that may arise due to track crossing and fusion.

Figures 4–7 show the initial trajectory results of HT, MHT, FHT and NTH. From Figures 4–7, it shows that the Hough transformation and the improved Hough transformation display low accuracy in predicting with only three frames. On the other hand, the predictive accuracy of the fuzzy Hough transformation and the neutrosophic Hough transformation is much higher.

To evaluate the comparison results quantitatively, we computed the F-measure values for each method, which is defined as follows:

$$F - \text{measure} = \frac{2 \times (\text{precision} \times \text{recall})}{\text{precision} + \text{recall}}$$

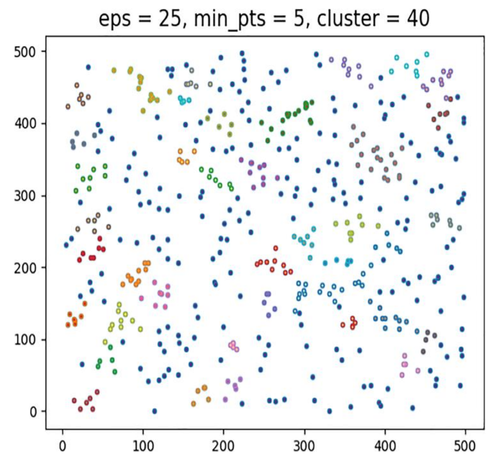

FIGURE 2 First frame before clustering.

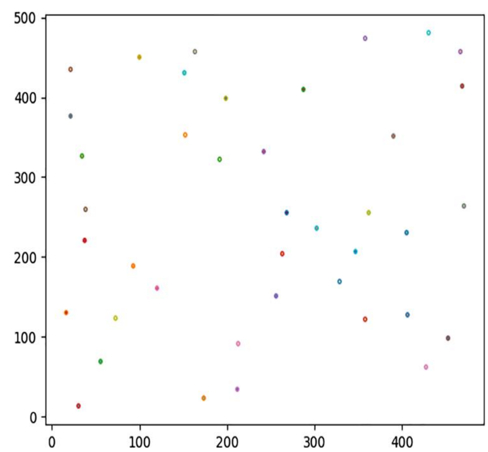

FIGURE 3 First frame after clustering.

where precision is the number of correct results divided by the number of all returned results. The recall is the number of correct results divided by the number of results that should have been returned.

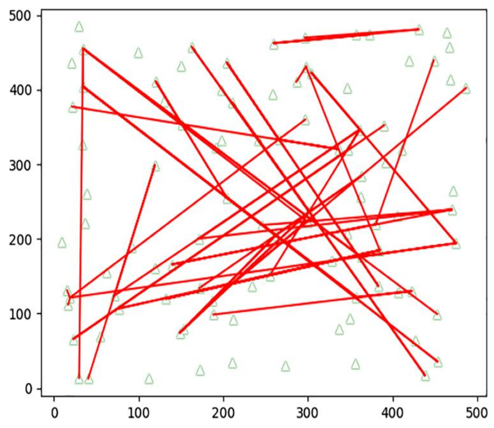

FIGURE 4 HT transformation method.

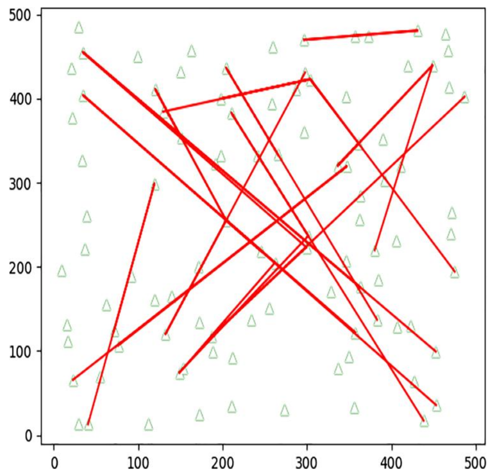

FIGURE 5 MHT transformation method.

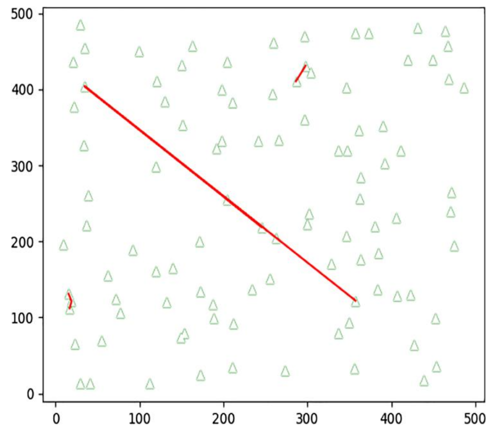

FIGURE 6 FHT transformation method.

Table 1 shows the F-measure percentages for HT, MHT, FHT and NHT. It shows that the predictive accuracy of neutrosophic Hough transformation is the highest.

Table 2 shows the running time cost for HT, MHT, FHT and NHT.

As shown in the table above, when only three frames are considered, HT and its improved version consume significantly more time than blurred HT and Neutrosophic HT. Besides, if we want to improve accuracy by considering more frames, the time consumption of Hough Transformation and its improved version will only increase compared with that of the blurred Hough transformation and Neutrosophic Hough transformation. This finally stems from the fact the former method modifies the accumulation rule, while the latter replaces it with a fuzzy or Neutrosophic set.

In summary, the HT method is inferior to NHT method in both the accuracy of the result prediction and the computational speed.

5 | CONCLUSION

This article uses the DBSCAN clustering algorithm and NHT to realise the track initialisation of formation flight. Through theoretical analysis and experimental comparison, this method has several advantages:

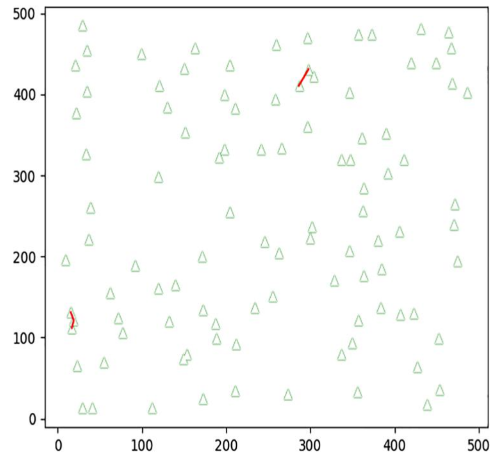

FIGURE 7 NHT transformation method.

TABLE 1 F-measure percentages for compared methods.

Method	HT	MHT	FHT	NHT
F-measure percentages (%)	6.87	11.76	80.00	100.00

TABLE 2 Time consumption table for Hough transform and Neutrosophic Hough transform.

Method	HT	MHT	FHT	NHT
Time consumption(s)	13.783	12.0723	9.8347	10.2153

(1) Due to the characteristics of formation flight, the clustering effect of the DBSCAN clustering algorithm is better, which can solve problems such as track intersection and confusion in track initialisation.
(2) The prediction of NHT is less sensitive to clutter and can find track points that generate errors due to clustering.

In the future, we will optimise the track prediction of NHT through more period data to further improve the running speed of the algorithm.

AUTHOR CONTRIBUTIONS

Yang Penggang: Conceptualisation (equal); methodology (equal); writing – review & editing (equal); supervision (equal); validation (equal). **Wang Kun**: Investigation (equal); visualisation (equal). **Feng Guangdong**: Supervision (equal); validation (equal).

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts to disclose.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analysed in this study.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES

None.

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