Research on Clustering Method of Airborne Threat Target Based on Density

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Abstract. In the ship Anti-air warfare defense, situation analysis is an important auxiliary information for combat command. Anti-ship missiles are the main source of airborne threats to ships, not only in terms of speed, but also in the form of missile groups. Based on the improved DBSCAN algorithm, this paper proposes a density-based clustering algorithm. By filtering the input target attributes and optimizing the distance algorithm and the distance radius value, the missile target group can be effectively improved. Based on the identified target group, the situation analysis is further carried out, and the target group attribute calculation method and threat assessment method are proposed to provide support for the operational command.

1. Introduction
Modern warfare usually operates in the form of formations or group. Therefore, in ship Anti-air warfare defense, situational analysis directed to a single target is not sufficient to provide comprehensive support for command and decision-making. Different types of target entities are often deployed according to certain rules. They have a certain organizational and spatial structure. This structure is called the target group [1]. Because of the countermeasures of military operations, the commander cannot know the intention of the enemy in advance, nor can it accurately determine the interconnection between multiple incoming targets. Therefore, it is necessary to group air targets and then perform group feature recognition and threat estimation to support the next situation analysis.

In the situation analysis of the air target, the target grouping method is mainly divided into two types: one is based on the calculation of fixed constraint values [2-3], that is, a set of classification thresholds is fixed, and the similarity between the two targets is calculated, and then Divided according to a fixed threshold. The accuracy of such algorithms is high and the algorithm steps are understandable. However, due to the practical application, the fixed threshold is often determined by expert experience, and it is difficult to update in real time. In the absence of actual combat information and historical data reserves, this method is difficult to promote and use [4]. The other is to use the clustering idea in machine learning to solve the problem of target grouping [5-7], which belongs to unsupervised learning. The method can be calculated according to the real-time situation data, and can be quickly updated, and is more suitable for the actual battlefield situation. However, these clustering algorithms do not completely depend on the actual situation in the selection of attribute values. For example, [8] proposes a cooperative gain measure as a clustering attribute. In actual combat, such attributes are generally unknown, thus reducing the availability of the algorithm. This paper proposes an air target grouping algorithm that can be used to analysis the situation. Firstly, the problem is described, and the reasonable target attribute is selected as the input of the situation analysis. Then, the similarity measure and the discriminant method of the target group feature are given in turn. Finally, a
method for group feature calculation and threat estimation based on clustering results is proposed, provides reliable support for situation analysis.

2. Description of air target grouping and threat estimation

In Anti-air warfare, target grouping is an important basis for situational analysis. Its main function is to classify air targets according to certain attributes, so as to find out the interconnections between targets, such as common strike missions. In the single-ship combat problem domain, for enemy incoming missile targets, the group can better conduct threat estimation and situation analysis to assist the commander to further formulate air defense decisions.

2.1. Input description

The situation analysis of the air target, the bottom input is the attributes of the threat targets at the current moment, such as the motion parameters, the enemy and the enemy type. At time \( t \), \( m \) target tracks \( t_1, t_2, ..., t_m \) are received through the sensor or data link, and the set of all targets can be recorded as vector \( T \), ie

\[
T = \{t_1, t_2, ..., t_m\}
\]

Where \( t_i(1 \leq i \leq m) \) is the attribute vector of the \( i \)-th target at that moment, assuming that \( n \) attributes are selected, and the \( k \)-th attribute of \( t_i \) is recorded as \( t_{ik} \), then

\[
t_i = \{t_{i1}, t_{i2}, ..., t_{in}\}
\]

Therefore, the set \( T \) of all targets can be regarded as an \( m \times n \) matrix, ie

\[
T = \begin{bmatrix}
t_{11} & \cdots & t_{1n} \\
\vdots & \ddots & \vdots \\
t_{m1} & \cdots & t_{mn}
\end{bmatrix}
\]

2.2. Target attribute selection

Choosing a reasonable attribute for an air target is the basis for clustering based on the clustering method. In a single-ship air defense and anti-missile system, the allocation of firepower channels is usually prioritized according to the target's threat level [9]. Therefore, the attributes of a single target selected in this article are as follows:

2.2.1. Spatial location. Among the targets of the missile group, each missile with the same target is unified, so the distance between the missiles belonging to the same group is significantly different from that of the missiles of the same group. Therefore, the position can be used as a judgment condition for grouping. For target \( i \), the position attribute can be recorded as \( P_i \), and the longitude \( x \), latitude \( y \), and height \( h \) are used to represent the target position, that is,

\[
P_i = \{P_{ix}, P_{iy}, P_{ih}\}
\]

2.2.2. Speed. Since the goals in the group target have a common purpose of action, the speed of each goal should be roughly the same. Let the travel speed of the \( i \)-th target be expressed by a scalar and denoted as \( v_i \).

2.2.3. Heading angle, target angle, pitch angle. The target headings of the group targets should be roughly the same and move in a common direction. Normally, these two values can be read directly from the track information reported by the sensor. For the target \( i \), the heading angle can be recorded as \( \phi_i \), the target angle is recorded as \( \psi_i \), and the pitch angle is recorded as \( \sigma_i \).

2.2.4. Friend or foe attributes. The battlefield situation of surface ships is more complicated, so the results of enemy and enemy identification are very important for target grouping. For target \( i \), you can mark the Friend or foe attributes as \( I_i \).
As shown in Figure 1, when the positional relationship between the target groups is as in (a), it is better to use only the spatial position and velocity for grouping, but in both cases (b) and (c), other attributes such as heading angle are used to accurately group.

![Image](image_url)

(a) Separated         (b) Connected together          (c) Intersect

Figure 1. Schematic diagram of the spatial relationship of the target group

2.3. Target attribute data preprocessing

According to the description of 2.2, the above four attributes each describe one dimension of the target feature, so their measurement units and numerical types have large differences. In cluster analysis, the data needs to be pre-processed to solve the error caused by the amount of data and the type of data.

The enemy's attributes of the target belong to discrete data types, usually with enemies, me, friends, neutrals, etc. Traditionally, these four attributes are regarded as unordered. However, according to the principle of defensive operations, in the situation analysis, the four attribute values have an order relationship. For example, the enemy target and the friendly target are differently threatening to us. So, it can be converted into continuous values by continuous, and the enemy, neutral, friend, and me attribute values can be transformed as follows:

\{3.0, 2.0, 1.0, 0.0\}

The spatial position, velocity, angle and continuous enemy and ego attributes of the target are all continuous data types. In order to eliminate errors caused by different dimensions, self-variation or large differences in values, it is necessary to centralize and standardize the data. Let the value of a continuous attribute of the target $i$ be $x_i$, and the centering is the variable minus its mean, so for the attribute $x$, the mean is:

$$\bar{x} = \frac{1}{m} \sum_{i=1}^{m} x_i$$  \hspace{1cm} (1)

The result of $x_i$ centralization is: $x'_i = x_i - \bar{x}$;

Standardization refers to subtracting the mean from the data and dividing by the standard deviation. For the attribute $x$, the standard deviation is:

$$s = \sqrt{\frac{1}{m-1} \sum_{i=1}^{m} x_i^2}$$  \hspace{1cm} (2)

The result of implementing standardized variables is:$x''_i = \frac{x'_i}{s}$

After centralization and standardization, the data is transformed into a normal distribution with a mean of 0 and a standard deviation of 1.

3. Improved target grouping model for DBSCAN algorithm

DBSCAN is a classic density-based clustering algorithm. Unlike K-means and BIRCH, which are only suitable for clustering algorithms with convex sample sets, DBSCAN can find classes of arbitrary shapes in a noisy environment, so the scope of application more extensive. According to the basic concept definition of DBSCAN and the description of the basic algorithm [10], the DBSCAN algorithm has the following disadvantages: 1. It is necessary to jointly coordinate the two parameters of $\epsilon$ and $MinPts$, and it is generally easier to determine $MinPts$ in advance. 2. Since the two parameters of $\epsilon$ and $MinPts$ are globally unique, if the density of the samples is not uniform or the
difference between the classes is large, the cluster quality is poor. There are many improved
algorithms in the academic world to solve these two problems. This paper mainly improves the fourth
input distance measurement function of the algorithm to improve the accuracy of grouping.

3.1. Distance measure function
For the two targets $t_1$ and $t_2$, the distance calculation of the next few attributes should be considered
in the space group division process.

Spatial location.

$$ Dis(P_i, P_j) = \sqrt{\left( (P_{ix} - P_{jx})^2 + (P_{iy} - P_{jy})^2 + (P_{iz} - P_{jz})^2 \right) } $$

(3)

Speed.

$$ Dis(v_i, v_j) = |v_i - v_j| $$

(4)

Heading angle, target angle, pitch angle.

$$ Dis(\phi_i, \phi_j) = |\cos(\phi_i - \phi_j)| $$

(5)

$$ Dis(\psi_i, \psi_j) = |\cos(\psi_i - \psi_j)| $$

(6)

$$ Dis(\sigma_i, \sigma_j) = |\cos(\sigma_i - \sigma_j)| $$

(7)

Friend or foe attribute.

$$ Dis(l_i, l_j) = |l_i - l_j| $$

(8)

3.2. Target group attribute calculation and threat estimation
After the space group is divided, each attribute of the target group needs to be calculated to support the
situation analysis and command decision in the next step. Common group attributes such as group
target group, group centre point, group speed, group assault direction, group range. For the $k$-th group
$C_k$ containing $n$ targets, the respective attributes are calculated as follows.

3.2.1. Group center point. Use the geometric center point of the target within the group to represent:

$$ C_k \cdot x = \frac{1}{n} \sum_{i=1}^{n} P_{ix} $$

(9)

$$ C_k \cdot y = \frac{1}{n} \sum_{i=1}^{n} P_{iy} $$

(10)

$$ C_k \cdot h = \frac{1}{n} \sum_{i=1}^{n} P_{ih} $$

(11)

Where $P_{ix}, P_{iy},$ and $P_{ih}$ represent the spatial locations of the $i$-th target of the group, respectively.

3.2.2. Group speed. The vector is used to represent the group velocity, which is divided into three
directions and is also expressed by the mean of the targets within the group:

$$ C_k \cdot v_x = \frac{1}{n} \sum_{i=1}^{n} v_{i,x} $$

(12)

$$ C_k \cdot v_y = \frac{1}{n} \sum_{i=1}^{n} v_{i,y} $$

(13)

$$ C_k \cdot v_h = \frac{1}{n} \sum_{i=1}^{n} v_{i,h} $$

(14)

Where $v_{i,x}, v_{i,y}, v_{i,h}$ represent the components of the speed of the $i$-th target of the group in
three directions, respectively.

3.2.3. Group assault direction. Knowing the group velocity vector and position, its assault direction is
calculated as:

$$ C_k \cdot \phi = \cos^{-1} \frac{C_k v_x}{\sqrt{(C_k v_x)^2 + (C_k v_y)^2}} $$

(15)

$$ C_k \cdot \psi = 180 - \phi + \tan^{-1} \frac{C_k y - O.y}{C_k x - O.x} $$

(16)

$$ C_k \cdot \sigma = \sin^{-1} \frac{C_k v_h}{\sqrt{(C_k v_x)^2 + (C_k v_y)^2 + (C_k v_h)^2}} $$

(17)

Where $O.x$ and $O.y$ are the spatial locations of the ship.
3.2.4. Group range. That is, the maximum distance between all the targets in the group and the center position of the group $C_k \cdot r = \max_i \text{Dis}(P_i, C_k)$, Where $P_i, C_k$ represent the spatial position of the $i$-th target and the group center point of the group, respectively.

4. Algorithm simulation experiment
According to the foregoing algorithm, this section verifies the algorithm through simulation experiments. The original target parameter table entered therein is shown in Table 1.

| Numbering | x     | y     | z     | v    | $\phi$ | $\psi$ | $\sigma$ | I      |
|-----------|-------|-------|-------|------|--------|--------|----------|--------|
| 1         | 159   | 121.495 | 2.955 | 176  | 45     | 52.5   | 25.4     | enemy  |
| 2         | 122.99| 146.14 | 3.015 | 114.3| 48     | 40     | 11.73    | enemy  |
| 3         | 186.34| 163.26 | 5.03  | 161  | 36     | 48.8   | 12.2     | friend |
| 4         | -89.57| 259.38 | 4.89  | 156  | 52     | -19    | -39.7    | enemy  |
| 5         | -152.57| -30.45| 3.011 | 240  | 79     | -78.75 | -20.25   | friend |
| 6         | -25.025| 237.87| 3.023 | 296  | 68     | -6     | -34.15   | enemy  |
| 7         | -165.56| 177.45| 3.119 | 286  | 89     | -43    | -5.1     | enemy  |
| 8         | -116.72| -109.70| 3.021 | 172  | 50     | -38    | -14.6    | enemy  |

The data pre-processing is omitted here. By adjusting the parameter values of the algorithm, the grouping results are improved. Finally, there is a better grouping effect when $\text{MinPts} = 3, \ \epsilon = 4.8$, as shown in Fig. 2. It can be seen that the clustering result conforms to the expectation set by the algorithm, and the target with similar properties is divided into one group, and the group labeled with ①, even if it is close to ② in space, but because of its large difference in the enemy and the enemy attributes, thereby it can be correctly divided into two groups.

![Figure 2. Air target group situation map](image)

5. Conclusion
Based on the theory of warfare, this paper proposes an improved DBSCAN algorithm to achieve air target grouping and group attribute calculation. The simulation experiment shows that by filtering the input target attribute and optimizing the distance algorithm and the distance radius value, the algorithm can effectively improve the division of the missile target group and provide support for the operational command.
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