Target Planning for UAV Merchant Ship Recognition Based on KNN Nearest Neighbor Algorithm

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Keywords: Merchant Ship Identification, UAV, KNN Nearest Neighbor Algorithm, Shortest Path Algorithm.

Abstract: The planning of the port closure and control force is an important issue related to the port defence in the face of war. According to the given information and the given coordinate information, this paper makes an initial classification of them, and uses KNN nearest neighbour algorithm to classify the location information of the given coordinates and obtain the central point by using its clustering information. After classification training, its accuracy is high, and it is most appropriate when k=5. After obtaining the best classification central point, take the classification central point as the initial starting position of the UAV, and take five points as the starting points to establish the shortest path problem based on the Dijkstra algorithm. Based on the idea of the shortest path, build the path planning strategy, analyse, model, and solve from a new perspective, and optimize the closure and control force planning.

1 INTRODUCTION

In recent years, with the increasingly fierce competition for maritime rights and interests of various countries and the increasingly severe anti-terrorism situation, coastal ports and bases have gradually become the targets of terrorists and enemies. With the military's awareness of the threat to the security of ports and important coastal bases, security measures at these strategic locations have been gradually strengthened in recent years, leaving fewer and fewer opportunities for terrorists and adversaries to carry out sabotage from the road. Therefore, the sealing-control operation planning of the port is an important issue concerning the port protection in the state of battle. In order to complete the combat task, it is necessary to identify and classify the merchant ships entering the port, and study how to use UAVs to plan and intercept the target and find the optimal strategy in the case of port sealing and control.

At present, the research on port containment and control operation planning mainly focuses on the safety identification of merchant ships and the target planning of coast guard ships and frigates in blockade and interception operations. Although most of the literature gives calculation methods from different perspectives, most of these calculation formulas are recursive formulas, which is rather complicated. This paper mainly solves the problem of optimizing the use of UAVs in the class identification of all merchant ships and the problem of sealing, control and interception and force adjustment strategy.

2 PERPROBLEM DESCRIPTION

It is assumed that the port's external route is located in a fan-shaped area with the port as the centre of the circle and the orientation between 20°and 70°clockwise with the direction of due north, and the course of merchant ships heading to a certain port points to the centre of the circle, and the interception disposal area is shown as the figure ABCD, as shown in Figure 1.

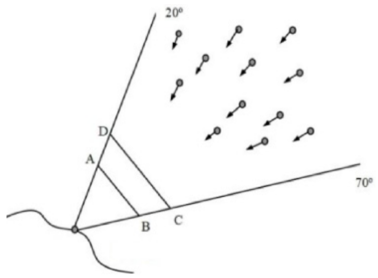

Figure 1: Port diagram.

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There are currently two frigates and three coast guard ships performing containment and control tasks. According to the given data, it is generally required that all Class III ships be intercepted, and the task planning of containment forces with the highest interception rate for Class II ships is given, including the initial position of deployment, interception objects, and movement trajectory.

3 RECOGNITION OF MERCHANT SHIPS -- ESTABLISHMENT AND SOLUTION OF KNN MODEL OF NEAREST NODE ALGORITHM

Target identification refers to the identification of target attributes, including motion attributes (tonnage, velocity, acceleration, etc.), friend or foe attributes (our side, friend, enemy, unknown), inter-class attributes (air, sea, underwater), type attributes (ship type or model) and class. The important significance of target recognition is that it is combined with target state estimation to form the basis of battlefield situation assessment and threat estimation and is an important basis for tactical decision-making.

In general, merchant ships are divided into three categories: merchant ships carrying general necessities (Class I), merchant ships carrying major strategic materials such as oil or gas (Class II), and merchant ships carrying contraband such as weapons and equipment (Class III). The significance of merchant ship identification is that it is combined with target state estimation, which forms the basis of battlefield situation assessment and threat estimation and is an important basis for tactical decision-making.

At present, the methods that can be used for security classification are decision tree (Kleinberg J M, 1999), genetic algorithm (Gongde Guo, 2006), neural network (Feng Guohe, 2012), naive Bayes (Tang Huxin, 2016), vote-based method (Liu Tong, 2018), Rocchio classification (Zhang Zitong, 2019), KNN classification (Shaozhong Cao, 2012), maximum entropy (Shen Yuqing, 2004), etc. KNN algorithm is one of the simplest methods in data mining classification technology.

3.1 KNN Algorithm

KNN algorithm is mainly based on a limited number of adjacent samples to determine the category, so it can be classified by measuring the distance between different eigenvalues. Based on the KNN algorithm, the proximity of the distance between the initial information samples of merchant ships and the mathematical values of these points is generally measured by Euclidean distance. Assuming there are two points p and q in the position samples of merchant ships, the Euclidean distance formula between the two points is

$$d(p,q) = d(q,p) = \sqrt{\sum_{i=1}^{n} (q_i - p_i)^2}$$

In addition, its testing phase is slow and expensive in terms of time and memory, requiring large memory to store the entire training data set for prediction. Because KNN uses the Euclidean metric between two data points to find the nearest neighbour, we need to scale the number. In other words, KNN algorithm is not suitable for large-dimensional data, so it needs to reduce the dimension to improve performance, but it has a good classification effect for small data sets in this paper. Moreover, to get better results, we standardize data on the same scale, choosing a standardized range considered between 0 and 1.

In the KNN algorithm, k is the number of nearest neighbours, and this number of neighbours is the decisive core factor. If the number of classes is 2, then k is usually an odd number. When k = 1, the algorithm is called the nearest neighbour algorithm. Specific calculation steps are as follows, as shown in Figure 2.

Figure 2: Specific calculation steps.

The KNN algorithm is more accurate at performing a smaller number of features than a larger number of features. As the number increases, the amount of data required exceeds it. At the same time, the increase in size will also lead to the problem of overfitting. Its neighbourhood number k is a hyper parameter that needs to be selected during modelling, and k can be regarded as the control variable of the prediction model, as shown in Figure 3.

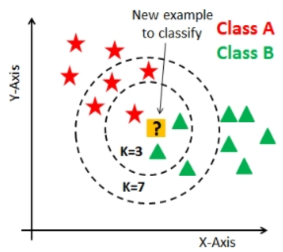

Figure 3: Category distance diagram.

To sum up, the nearest node algorithm is used to classify the location information of a given coordinate and obtain the central point. The position of each merchant ship is displayed through KNN model clustering by MATLAB software program, so that the merchant ship is recognized and detected by UAV. Figure 4 shows the positions of the three classes of merchant ships on the left, and the red dot on the right of Figure 4 shows the central points of the three classes of merchant ships.

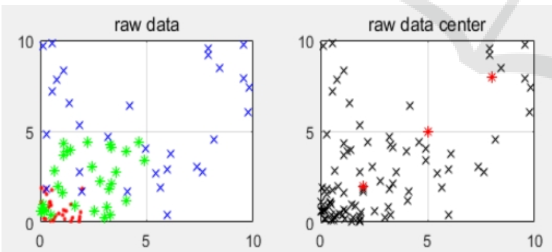

Figure 4: Classification and central points of merchant ships.

The above results are summarized in Figure 5, which shows the positions of class I, II, and III merchant ships and their central points respectively.

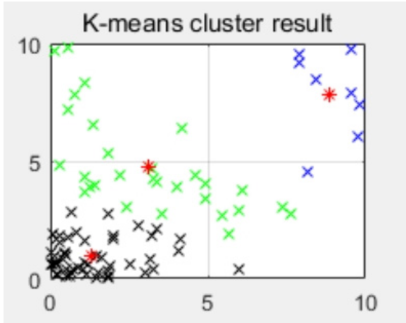

Figure 5: Merchant vessel category classification and central point.

The problem of identification and safety classification of merchant ships uses the thought information of clustering to classify the location information of a given coordinate and obtain the central point. After classification training, its accuracy is high, that is, the most appropriate K=5.

3.2 Dijkstra Algorithm

The existing means can find out the geographical location, course speed and other information of the commercial ship to enter the port at a long distance, but the nature of the cargo carried by it needs to use the UAV close-in reconnaissance.

The unmanned reconnaissance aircraft is equipped with TV cameras, forward-looking infrared instrument, synthetic aperture radar and other loads, with an endurance time of more than 30 hours, a cruise speed of 120km/h, and strong mobility (turning radius is not considered) and can be independently deployed in important sea areas to implement long-term and continuous reconnaissance and surveillance tasks on maritime targets. The UAV approaches the target at sea according to the location information provided by the intelligence. When the weather conditions are good, the target can be found at 20-30km, and the altitude can be lowered after approaching 10km. The UAV will circle the target for several weeks at a distance of no more than 2km and take pictures from multiple perspectives. Shore-based operators can identify the ship name (side number), ship type (such as container ship, oil tanker, natural gas tanker, cruise ship), material type (such as oil, natural gas, coal, iron ore, container material), flag (nationality), etc., and compare with the information and ship database obtained by the red side to determine whether the ship name and appearance are consistent. Whether the ship name is altered or forged, whether the bad records are in the case, whether the weapons and equipment are smuggled, etc., climb and fly away after the completion of the identification, the entire identification process takes 10 minutes, and the identification results can be shared to any demand party in real time.

The most commonly used routing algorithms include Dijkstra algorithm (Liu Xuhong, 2005), SPFA algorithm (Nannicini, 2008), Bellman-Ford algorithm (Bang-Jensen, 2000), Floyd algorithm /Floyd-Warshall algorithm (Shi Ren, 2009) to adjust and intercept strategy schemes. In order to solve the UAV reconnaissance route after the classification results in the model, the shortest path can be solved for the UAV starting from the fixed point. It is solved by Dijkstra algorithm. The position information is turned into a graph to facilitate its subsequent calculation of the shortest flight path. The Dijkstra algorithm is effective to solve this problem. The interception problem and the merchant ship entering the port need to be calculated and analysed immediately, and the computational complexity of this algorithm is low.

The complexity of Dijkstra's algorithm: (1) Time complexity $O(e\log v)$, where e is the number of edges and v is the number of vertices. (2) Space complexity $O(\log v)$.

The Dijkstra algorithm is effective to solve this problem. The interception problem and the merchant ship entering the port need to be calculated and analysed immediately, and the computational complexity of this algorithm is low, as shown in Figure 6.

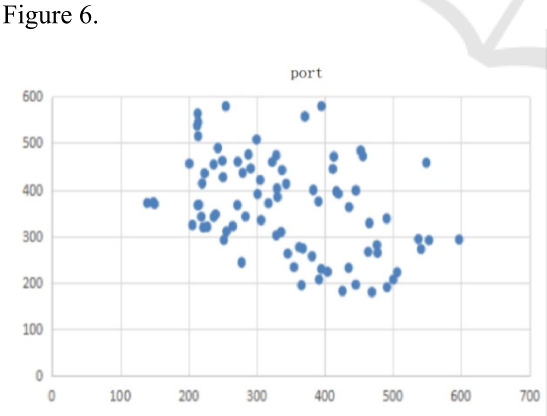

Figure 6: Dijkstra solution.

The model takes points 18, 23, 49, 53, and 60 as the starting points, and follows 18, 15, 7, 6, 48, 57, 17, 67, 45, 79, 84, 66, and 23, 55, 64, 46, 73, 56, 63, 71, and 39, respectively. Python was used to analyse and solve the model, and the results were obtained after 100 iterations. Iterating the python solution 100 times. By substituting the model for calculation, it is obtained that its initial position is (113.6410, 353.4564), and its intercepting objects include all of the ship marks of the three types and can intercept 83% of the part of the second type. Its motion trajectory starts from point (15) and intercepts along the shortest path of the three types, and most of the ships of the second type can be intercepted.

Using MATLAB software, we get the best route for the UAV to travel through all merchant ships, and the UAV can travel according to this route, which can make the UAV spend the shortest time and experience the shortest path, as shown in Figure 7.

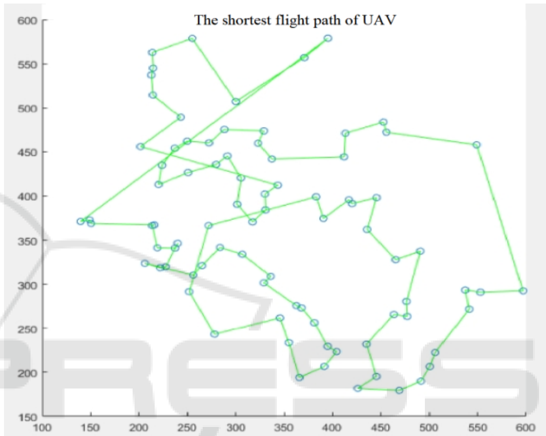

Figure 7: The shortest flight path of UAV.

4 CONCLUSION

Through the research and demonstration in this paper, we first use KNN algorithm to classify and identify merchant ships. This method has strong robustness to noise training data. Starting from the geographical coordinate position of merchant ships, this algorithm solves the problem of merchant ships category well. Through the research and demonstration in this paper, we know that it is easy to implement KNN algorithm, and this method has strong robustness to noise training data. From the perspective of algorithm performance comparison, take Floyd algorithm and Dijkstra algorithm as an example. On the one hand, if Floyd algorithm is applied to a certain vertex successively, then compared with Dijkstra algorithm, many path and result calculations are repeated. Although the complexity is the same, the calculation amount is much different. At the same time, more importantly, Floyd's algorithm requires no loops with a sum less than 0, while Dijkstra's algorithm uses the prerequisite that as long as the length of the path in the graph is greater than or equal to 0. Therefore, we use Dijkstra algorithm to calculate the shortest path of UAV classification of merchant ships and optimize Floyd algorithm.

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