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A Target Location Method Based on Swarm Probability Fusion

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Qian Bi, Shuang Wu, Yong Huang, Yalong Zhu, Zhuofei Hu
Southwest Electronic Equipment Research Institute
Chinese Electronics Technology Group Corporation
Chengdu, China
390482162@qq.com

***Abstract*—The existing target location methods either depend on the sensors' high performance or the communication bandwidth, which are not suitable to directly apply to the effective fusion and target recognition of observation information of the large-scale heterogeneous swarm. In this paper, a target location method based on swarm probability fusion is proposed, which can represent the sensor's data in the heterogeneous swarms as the probability distribution map, and then carry out image recognition processing after normalized distributed fusion to obtain target information. The effectiveness of the method is verified by the effectiveness tests, the single-node's direction finding accuracy tests, and the swarm nodes' number tests. Preliminary analysis shows that single-node's direction finding accuracy has a significant effect on the swarm positioning accuracy and the convergence speed, while the number of nodes has a small effect on positioning accuracy and mainly affects the convergence speed.**

Keywords—swarm, probability fusion, target location

I. BACKGROUND

A. Development Trends

With the further development of swarmed and intelligent robotics technology, research achievements in miniaturized unmanned systems, distributed self-organizing networks, and low-cost unmanned system platforms have enabled countries to carry out research on multi-unmanned systems for complex tasks such as cluster region perception, collaborative search, and cluster countermeasures [1-5]. In addition to the United States, the United Kingdom, Sweden, Japan and other countries have also carried out a series of research work on micro-cluster collaboration. Among them, for the cluster to survive and run efficiently in a complex environment, target positioning perception ability is the core of the vital capacity. However the traditional classical location methods are based on a handful of similar nodes as the carrier. Therefore further research is needed to apply to the heterogeneous swarm with many types of sensors and platforms.

B. Summary of the Status Quo

The problem of intelligent unmanned swarm target search and positioning is a typical cross-disciplinary and multi-field problem, which mainly involves two fields, namely the field of motion multi-station passive location technology and the field of distributed target state estimation technology. In the field of motion multi-station passive location technology, the classical technical systems include angle-measuring cross-positioning system [6-8], multi-station time difference positioning system [9-12], Doppler difference positioning system [13] and composite positioning system [14-18]. In terms of the field of distributed target state estimation technology, the key is to solve fusion estimation of multiple observation platforms on the target observation and consistency problem of distributed platforms [19-20]. At present three are mainly three kinds of fusion estimation methods for complex background, namely Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Particle Filter (PF) [21-23].

C. Difficulty of the Problem

For the distributed, dynamic, large-scale swarm intelligent system in practical application, usually it has limited individual abilities, including limited sensors' target perception accuracy and limited communication bandwidth between individuals, and it is vulnerable to the influence of complex environment. The target location methods for the above kind of system either depend on the high performance of sensors or the communication bandwidth, and these methods are oriented to multi-source isomorphism sensors. Therefore, these methods cannot be directly applied in large-scale heterogeneous swarm's search and positioning problem [24-31].

In other words, the difficulty of this kind of research lies in how to effectively integrate observation information of large-scale heterogeneous swarms and identify targets.

II. TARGET LOCATION METHOD BASED ON SWARM PROBABILITY FUSION

Aiming at the above problem, a target location method based on swarm probability fusion is proposed in this paper. In this method, the heterogeneous sensors' data is represented as probability distribution maps, and the image recognition processing is carried out after normalized distributed fusion to obtain target information.

A. Method's Diagram

The framework of the swarm positioning method described in this paper is shown in the figure below. The method described in this paper mainly includes four steps:

(1) Generate single-node's probability distribution. The node sensor obtains the detection data of the target, and selects

the corresponding sensor probability model according to the sensor type. Then the detection data is represented as the gridded probability distribution diagram P_i in the scene.

(2) Generate swarm probability distribution. Probability distribution diagrams $P_1, P_2, \cdots P_n$ shared by adjacent swarm nodes are weighted and fused to obtain the instantaneous joint probability distribution P_s at the current moment.

(3) Generate historical probability distribution. Combined with the historical joint probability distribution $P_{s(t-1)}$, the probability distribution description of the scene of the current node is obtained after forgetting iteration.

(4) Detect and recognize targets. Finally, the probability distribution map is detected and identified, and the maximum probability point is extracted from it. The point is namely the target location.

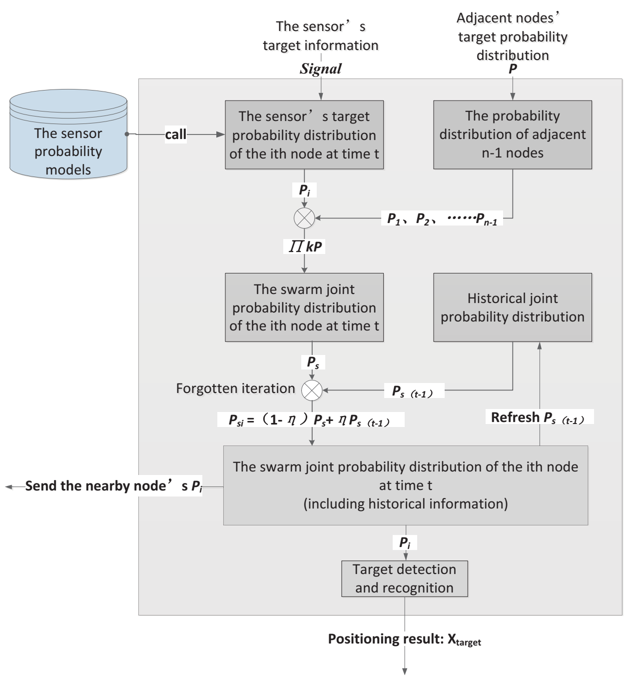


Fig. 1. Framework of the target location method based on swarm probability fusion.

This method is essentially a blend of spatial information (adjacent nodes) and time information (historical information) and represents the information interaction between different individual as the unified form of probability distribution at the same time. It is not only beneficial to fusion recognition of different types of nodes, but also can eliminate the demand of the nodes' formation configuration and the time synchronization, and is especially suitable for effective fusion and target recognition of large-scale heterogeneous swarm's the observation information.

B. Single Node's Probability Distribution

The probability distribution of a single node is mainly determined by the probability model of the sensor configured by the node. In order to facilitate discussion, the azimuth measurement sensor is taken as the object of discussion here.

Considering that the distribution range of the azimuth angle is a cyclic variable of (-π, π), so the probability distribution commonly uses the cyclic normal distribution function -Von Mises distribution (also known as Tikhonov distribution) in engineering, and its probability density function is

$$P_i(\phi) = \frac{\exp\left[v\cos(\phi-\mu)\right]}{2\pi I_0(v)}, \qquad -\pi \le \phi \le \pi \tag{1}$$

where v is the concentration coefficient, whoes effect is similar to reciprocal of Gaussian distribution's variance and repsents ϕ 's dispersion around μ . I_0 is the zero-order modified bessel function, μ is the mean value of the distribution. For direction finding applications, μ is the measured azimuth angle whoes value range is $(-\pi, \pi)$.

The variable ϕ is the angle of the different grid position in the scene relative to the current node:

$$\phi(x_{im}, y_{im}) = \begin{cases} \partial \tan \dfrac{y_{im}-y_i}{x_{im}-x_i}, & x_{im} \ge x_i \\ \partial \tan \dfrac{y_{im}-y_i}{x_{im}-x_i} - \pi, & x_{im} < x_i, y_{im} < y_i \\ \partial \tan \dfrac{y_{im}-y_i}{x_{im}-x_i} + \pi, & x_{im} < x_i, y_{im} \ge y_i \end{cases} \tag{2}$$

Where, (x_{im}, y_{im}) is the scene grid's coordinate, and (x_i, y_i) is the current node's coordinate. Substituting (2) into (1) can obtain the probability distribution of the current node i.

C. Swarm Probability Distribution

Because the azimuth errors measured at different nodes are independent random variables, so the swarm joint probability density function is

$$P_s(x, y) = k \prod_{i=1}^{N} q_i \cdot P_i(\phi) \tag{3}$$

where the function of the constant k is to normalize the value of probability density function of each grid on the whole grid surface, so as to avoid numerical stability problems. Meanwhile, q_i is the probability weight corresponding to the ith node, which is mainly used to adjust the difference characteristics of individuals in the swarm. $P_S = (x, y)$ is the probability of the target appearing on each grid.

D. Historical Probability Distribution

On the other hand, considering the problem of time dynamics, the forgetting factor η is introduced, as shown below.

$$P_{si}(x, y) = (1-\eta) P_s(x, y) + \eta P_{s(t-1)}(x, y) \tag{4}$$

Therefore the target's probability distribution contains not only different nodes' reconnaissance and direction finding information at the current moment, but also contains the historical moment's direction finding information. The method has good inhibitory effect on outliers and false-alarm of sensors, this is because the total probability density function is the product of N independent probability density functions, where variance of outliers' or false alarm's value is small, and their contribution to the total probability is small. so outliers and false-alarm of sensors are easy to inhibited by other measurement information.

E. Target Detection and Recognition

Statistically, there are usually two ways to find a target point in the probability distribution: 1) the expectation method, which takes the expectation $E(X)$ of the probability as the target; 2) the maximum probability method, which selects the largest point $X^* = \arg\max f(X)$ in the probability distribution as the target.

Concidering the expectation method often loses its practical significance and can only give one target point when the probability distribution is multimodal. Therefore, the maximum probability method is used to detect targets in this paper. For multi-target distribution, multiple local maximum values can be selected. Due to the deviation of the sensors, this paper selects the expectation of the certain range close to the local optimal value as the detection result, which is called the target region in this paper, namely binarize the probability image. In order to select the target region adaptively, Otsu (the maximum inter-class variance threshold segmentation method)is used.

The method is described as follows: Assuming that the proportion of pixels in the foreground area is w_1 and the average gray value is u_1 , the proportion of pixels in the background is w_2 and the average gray value is u_2 , and the average gray value of the whole image is u . Then the threshold can be obtained by maximizing the following targets:

$$g = w_1 (u - u_1)^2 + w_2 (u - u_2)^2 \tag{5}$$

The optimal threshold g can be solved by the traversal method.

The targets of the whole probability map can be obtained by calculating the expectation of each target region after binarization.

III. Simulation Experiment

A. Experimental Setting

In order to verify the effectiveness of the method in this paper and find out the main influencing factors, three groups of experiments are conducted in this paper:

(1) Test the effectiveness of the method;

(2) Verify the influence of direction finding accuracy of sensors on positioning accuracy;

(3) Verify the influence of the number of cluster nodes on positioning accuracy.

A square field with a size of 1km×1km is set up for simulation experiments. In order to speed up the calculation of probability map, the site is rasterized, that is, the site is discretized into a map of 100×100, and each small grid represents 10m×10m. The cluster nodes are uniformly arranged on the Y axis, and the target is located at (1,0.5), as shown in the figure below.

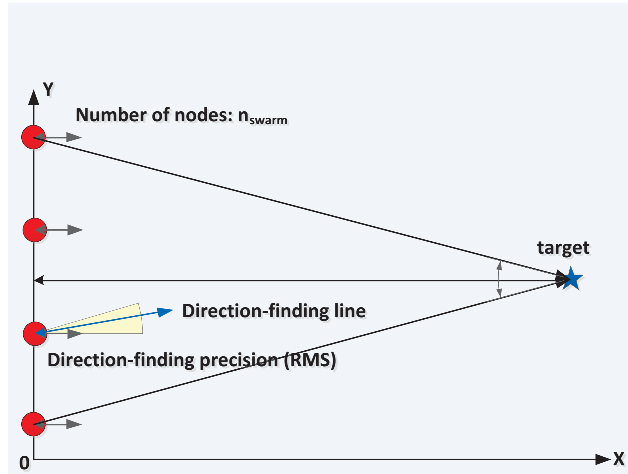
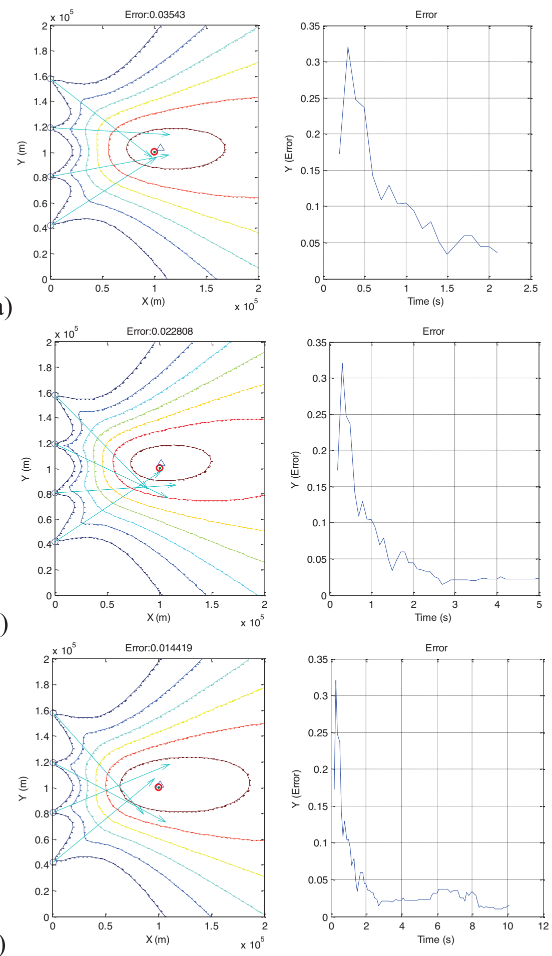


Fig. 2. Schematic diagram of simulation scene.

B. Method's Effectiveness Test

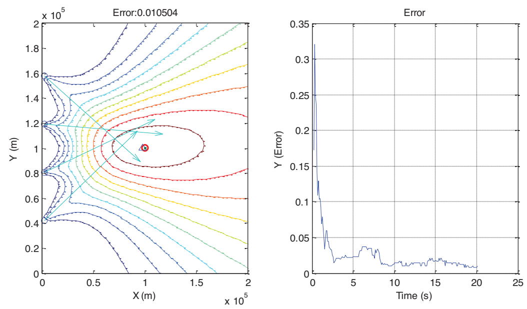
In this test, the cluster nodes'number is set as 4, they are uniformly arranged on the Y axis, the direction finding accuracy of a single node is 5° rms, and the target is located at (1,0.5). The test results are shown in the figure below.



a)

b)

c)



d)

Fig. 3. Simulation results of method effectiveness test: a) t=2s, b) t=5s, c) t=10s, d) t=20s.

The left side of the above figure is the swarm probability distribution contour plot, in which the cyan arrow is the instantaneous direction finding line of each node, the red circle is the real target position, the blue triangle is the estimated target position, and the right side is the relative error curve of the target, namely the absolute error divided by the distance between the swarm and the target. When t=2s, the target estimation begins to converge to the true value after initial oscillation. When t=5s, the relative error basically converges to about 2%R. It can be seen from the figure on the left that the triangle representing the estimate of the target is very close to the circle representing the real target; When t=10s, the relative error reaches about 1.4%R after a small oscillation. When t=20s, the swarm positioning result is basically convergent and stable. It can also be seen from the figure that the estimated target basically coincides with the real target, which fully demonstrates the effectiveness of the method.

C. Influence of Sensors' Direction Finding Accuracy on Positioning Accuracy

In this experiment the change of swarm positioning accuracy is verified when the direction finding accuracy of a single node changes. The cluster nodes' number is set as 4, they are uniformly arranged on the Y axis, and the target is located at (1,0.5). A total of 6 tests are carried out. The single node direction-finding precision is 20° rms, 15° rms, 10° rms, 5° rms, 3° rms and 1° rms respectively. The test results are shown in the figure below.

The above figures respectively give the curve of the relative error of swarm positioning and the BOX chart of error statistics (the red line represents the median line and the red dot represents the outlier point). It is not hard to see, the direction finding accuracy of the single node has significant impact on the result of the swarms positioning. When e = 20 ° rms, the positioning result is almost impossible to convergence, which has been oscillating wildly. When the accuracy is improved, oscillation amplitude decreases obviously, the convergence rate is significantly accelerated and the final positioning accuracy is also significantly improved. When the direction finding accuracy is promoted to 5 ° rms, positioning accuracy has reached about 1% ~ 2% R, which coincides with the aforesaid effectiveness tests' results and also shows the effectiveness and repeatability of the tests; With the further improvement of direction finding accuracy, positioning accuracy continues to improve. The experiment shows that the direction finding accuracy of a single node has a significant effect on the swarm location accuracy and convergence speed when the swarm nodes' number is determined.

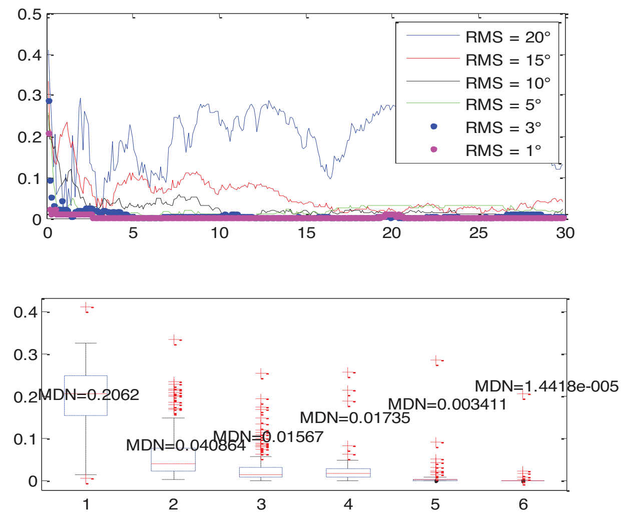


Fig. 4. Simulation results of the influence of the different sensor's direction finding accuracy on positioning accuracy.

D. Influence of the Number of Swarm Nodes on Positioning Accuracy

In this experiment, the change of the swarm positioning accuracy is verified when the number of swarm nodes changes. The direction finding accuracy of a single node is set as 5° rms, the target is located at (1,0.5), and the swarm nodes' numbers are 2, 4, 8 and 16 respectively. These nodes are uniformly arranged on the Y axis, and a total of 4 tests are carried out. The test results are shown in the figure below.

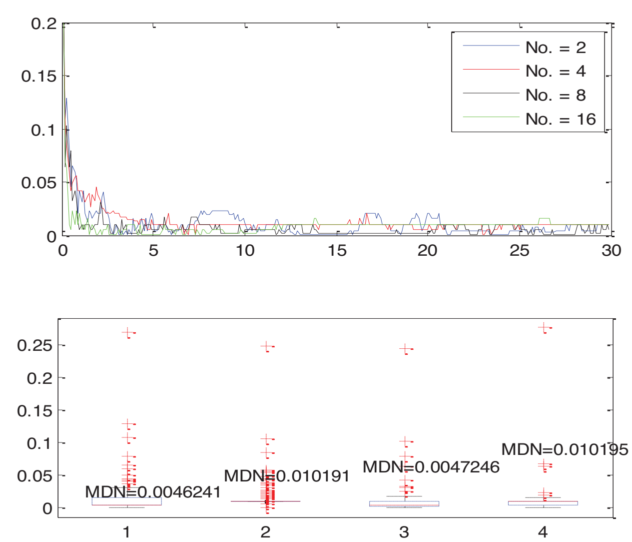


Fig. 5. Simulation results of the influence of different swarm nodes' numbers on positioning accuracy.

It can be seen from the figure above that the number of swarm nodes has little influence on the swarm positioning accuracy and only has a certain influence on the convergence speed when the direction finding accuracy and swarm configuration remain unchanged.

IV. Conclusion

In this paper, a target location method based on swarm probability fusion is proposed, which can represent the sensors' data in the swarm as a probability distribution map, and then perform image recognition processing after normalized distributed fusion to obtain target information. The effectiveness of the method is verified by the effectiveness tests, the single-node's direction finding accuracy tests, and the swarm nodes' number tests. Preliminary analysis shows that single-node's direction finding accuracy has a significant effect on swarm positioning accuracy and convergence speed, while the number of nodes has a small effect on positioning accuracy and mainly affects the convergence speed.

Subsequent research will focus on the engineering practice of this method, and relevant test verification will be carried out with the help of the swarm unmanned system.

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