Target Tracking Algorithm based on Electromagnetic and Image Trajectory Matching

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Abstract—**The types of maritime rights protection tasks are complex. Reconnaissance equipment can use multiple modal information, such as visible light and infrared images, passive electromagnetic signals, etc. However, how to use multi-modal information to accurately conduct marine reconnaissance is still a challenging task at home and abroad. There is still a big gap in the research in this area, so this paper proposes a method of matching electromagnetic detection trajectory with image reconnaissance trajectory, making full use of different modal information to achieve more accurate target tracking.**

Keywords: electromagnetic trajectory; image trajectory; target tracking; trajectory matching Introduction

I. INTRODUCTION

Maintaining marine equity is related to national interests, and countries around the world attach great importance to marine rights and regard them as core interests. The type of marine rights task is complicated. It is mainly divided into: related objects and personnel daily reconnaissance and monitoring, suspicious targets and identification, suspicious boats, alerts of the aircraft, boarding check, combat control, warning to remove suspicious people, capture control, check and investigate and so on.

Ocean reconnaissance unmanned equipment can collect multi-modality signals, such as visible light image, infrared light image, active radar image, and passive electromagnetic signal, but currently for marine targets, more focused on utilizing single-mode information, there is a large limitation. How to effectively utilize more modal reconnaissance information to achieve precise identification, control ocean environment and situation, and enhance the objective perceived ability in complex environments is a problem that needs to be solved. Research on image-based transmission tracking focuses on tracking and shooting through image recognition, directly utilizing captured image or video to fit and predict algorithm trajectory [1]-[3]. At present, the trajectory prediction technology has gradually matured, and Z. H. Chen et al. [4] proposed a method of automatic detection and tracking method in the modified video sequence based on mean drift. It not only improves the seismic robustness of the system during ship tracking, but also has a high success rate in automatically tracking ships in the corrected video sequence. Reference [5] proposed a marine tracking framework based on kernel correlation filter (KCF) and curve fitting to complete the target ship tracking tasks, which can better fit the target ship sailing trajectory when the target ship is obscured. X. Mu et al. [6] used frame difference method for target detection and used Kalman filter to smooth the trajectory, and then fit the target path adaptively using the least square method. Y. Zhu et al. [7] utilizes the target trajectory prediction model of the LSTM network for battlefield prediction and identification, which is highly accurate and easy to achieve.

Research on electromagnetic target positioning technology based on radio signal is mainly based on the distance problem in the measurement of radio systems, and it can be roughly divided into the following methods [8]: Based on the Received Signal Strength (RSS) [9],[10], based on the Time of Arrival (TOA) [11], based on the Time Difference of Arrival (TDOA) [12], based on the Phase of Arrival (POA) [13] and based on the Angle of Arrival (AOA) [14]. Q. Wang et al. [15] proposed a method of mixing the source positioning of RSS/AOA measurement, and converted the optimization problem based on maximum likelihood (ML) to the semidefinite programming (SDP), and has good performance. Reference [16] realized a stable and independent indoor positioning system based on the electromagnetic tracking system, combined with the indoor positioning technology

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based on spatial information mode. In addition, electromagnetic positioning technology is widely used in virtual reality technology. H. Wang et al. [17] used second-order and third-order polynomial fitting algorithms to compensate the sensor's position and antimagnetic errors to improve the positioning accuracy.

Whether it is target tracking based on images or positioning based on radio signals, it is only used with single mode information for investigate. Facing complex battlefield situations and increasingly mature anti-reconnaissance technologies, single-modal information cannot meet marine reconnaissance demand. Therefore, it is necessary to explore further reconnaissance technology to achieve accurate identification, and control the ocean environment and the situation. H. J. Liu et al. [18] proposed a scheme that fused synthetic aperture radar (SAR) images with electronic reconnaissance data, and proved its superiority through simulation experiments. G. Ho et al. [19] used multi-sensor to perform data fusion and used it in military monitoring and reconnaissance, significantly improved accuracy and speed. Current research has proved that the use of tracking fusion in military environments to track ships and aircrafts has obvious advantages over single-modal data tracking, but how to effectively use the various modal information collected by marine reconnaissance unmanned equipment, there is still a big vacancy in the current study. Therefore, this paper combines the algorithm of target detection and trajectory tracking using images with the algorithm of trajectory tracking based on electromagnetic positioning, and proposes a multi-modal trajectory matching method for marine monitoring and reconnaissance missions.

II. PRINCIPLES AND METHODS

This paper uses YOLOv3 to obtain multiple detection targets in each frame, and then the same target needs to be tracked in successive frames and trajectories are generated successively. The Kalman filter model is used to predict the location of the target in the next frame, and then the Hungarian algorithm is used for data correlation. However, considering that if only the crossover rate of the area is used as a matching basis between the posts when the target is close, the original Hungarian algorithm is improved in this paper, and color histograms are introduced to distinguish different similar targets so that the results are more accurate.

A. *Image Based Object Detection and Trajectory Tracking Algorithm*

1) Target detection network

YOLOv3 is a target detection algorithm based on direct regression, which achieves good results in detection speed and accuracy. The YOLOv3 algorithm divides the image into a grid, and makes use of the features of the whole image to predict the target whose center point falls within the grid. For each grid region, the network needs to predict the confidence and four coordinate values of each prediction box, as well as the category probability distribution of the prediction box. The whole detection network outputs three feature maps of different scales, uses a multi-scale method to detect targets of different sizes, and draws on the idea of multi-layer feature fusion in the FPN model, and the deep features are up-sampled and sent back to the shallow layer. Features enrich the semantic information of shallow features, effectively improving the detection accuracy of small targets. The network structure is shown in Figure 1.

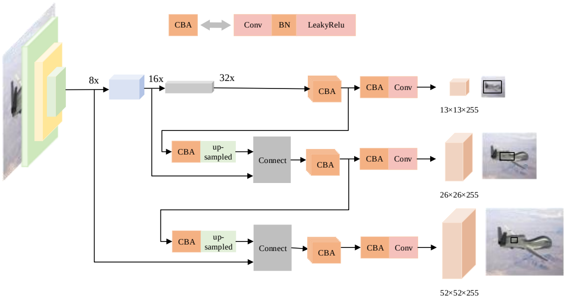

Figure1. Structure diagram of YOLOv3

2) Kalman filtering algorithm

Kalman filter algorithm (KF) is a process in which some observational data is input and output, and the influence of noise on the system is considered, and the linear system equation is used to obtain the optimal estimation or optimal solution of the system state. This method can be regarded as a search algorithm prediction model, which can effectively predict the position of linear moving target. When the algorithm is used to predict the next time, the state information of the target in the previous time should be considered. After the prediction is completed, the model is modified according to the actual output detected. The process is shown in Figure 2.

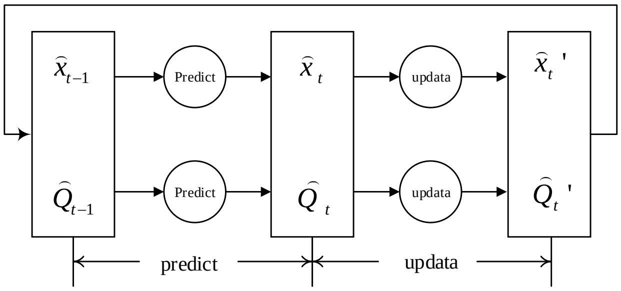

Figure 2. Schematic diagram of Kalman filtering algorithm

In order to make the Kalman filter model work continuously, some parameters in the model need to be updated to ensure the real-time and accuracy of tracking. In the prediction stage, according to the state at the previous moment, the target transfer matrix F and the control matrix B are used to estimate the state at the next moment. The state prediction formula is shown in equation (1), where U is the control quantity.

$$\hat{x}_t = F_t \hat{x}_{t-1} + B_t u_t . \tag{1}$$

Let Q be the covariance matrix of the noise, then the matrix sigma represents the transfer relationship between the uncertainties at each moment. The specific calculation process is shown in equation (2).

$$\sum\nolimits_t = F\sum\nolimits_{t-1} F^T + Q \quad (2)$$

In the target update stage, the Kalman coefficient K is calculated by the state transition matrix Σ and observation matrix H, and the Kalman coefficient and the detected target state are used to modify the target state at the next moment. The calculation of Kalman coefficient K is shown in equation (3)

$$K_t = \sum\nolimits_t H^T \left(H\sum\nolimits_t H^T + R\right)^{-1}, \quad (3)$$

and the correction of the target state is shown in equation (4).

$$\hat{x}_t^{'} = \hat{x}_t + K_t\left(y_t - H\hat{x}_t^{-}\right). \quad (4)$$

The above is the whole process of using Kalman filtering algorithm to estimate the position of the moving target. This method can reduce the search scope in the target search strategy and improve the matching efficiency.

3) Hungarian algorithm

For data association in multi-target tracking, YOLOv3 first detects multiple targets and their coordinates and boundary box range in the current frame. KF is used to estimate the target position in the current frame according to the tracking results of the previous frame, and n prediction results, namely n tracks, are obtained. After all the detection and prediction results are obtained, the cross-union ratio of the two regions is first calculated, and then the color histogram of the detected image is obtained. Then, the correlation matrix is obtained by weighting the crossover ratio and histogram features, and the equation is as follows:

$$C = \alpha(i,j) + \beta(i,j) \quad (5)$$

In the equation (5), C is the intersection ratio of the two, which can be obtained from the pasteurization distance, α and β are the weight coefficients, and are 1. Finally, the Hungarian algorithm is used to match the detection results with the predicted results, complete the data association, and form the tracking trajectory of multi-frame images.

B. Target trajectory tracking based on electromagnetic positioning

In this paper, electromagnetic positioning and trajectory tracking are carried out based on RSSI ranging algorithm. Given the transmitted signal strength of the transmitting node, the receiving node calculates the transmission loss of the signal according to the received signal strength, and then converts the transmission loss into the distance between the two nodes according to the theoretical or empirical model.

In this paper, the mainstream logarithmic distance path loss model, namely logarithmic model is adopted. The propagation model indicates that the average received signal power decreases with the logarithm of the distance in both indoor and outdoor channels. This model has been widely used. For any distance, the path loss is expressed as:

$$PL(d) = PL(d_0) - 10N\log\left(\frac{d}{d_0}\right). \quad (6)$$

Wherein, d is the distance between the point to be measured and the reference point, d_0 is the reference distance, $PL(d)$ is the signal strength (unit dBm) of the reference point received by the point to be measured at d, $PL(d_0)$ is the signal strength (unit dBm) of the reference point received by the point to be measured at d_0, the range is 2 to 4, N is the path loss factor. The value ranges from 2 to 6 in different environments.

Due to the influence of various factors in the transmission process of the signal, the RSSI value received by the positioning node has a large random error, thus affecting the positioning accuracy. To further improve the positioning accuracy, it is necessary to filter the received RSSI value, so as to achieve the purpose of reducing random error. Here, the average value of the received RSSI is estimated. The setting bit node receives m RSSI of the same reference node, and the mean value of these values is estimated:

$$\overline{RSSI} = \frac{1}{m}\sum_{i=1}^{m} RSSI_i \quad (7)$$

C. Electromagnetic and image trajectory matching algorithm

The description of the target's motion state needs to be carried out in the coordinate system. Since the target has different coordinates on different sensor platforms and different moments in the image and the electromagnetic sensor, it is necessary to complete the unification of time and space through preprocessing before the target trajectory is matched.

1) Time registration

It is assumed that the time interval between the image sensor and the electromagnetic antenna in the system to sample the target is respectively τ and T, and $\tau / T = n$. In this case, the electromagnetic antenna has formed a sequence of measurements in the process of generating two measurements from the image sensor. measurements of the electromagnetic antenna are synthesized into one value by the least square method, and it is synchronized with the observation data of the image sensor.

2) Space registration

Because the position of the target is calibrated by pixel coordinates after it is collected to the two-dimensional plane by the image sensor, through the transformation relationship among the world coordinate system, camera coordinate system, image plane coordinate system and computer graphics coordinate system, the transformation relationship between the three-dimensional space coordinate of object and the pixel coordinate of two-dimensional image can be obtained. Assume that the world coordinate of an object points to be measured exists in the three-dimensional scene is (X_W, Y_W, Z_W), the corresponding pixel coordinate of the image is (u,v), and the transformation relationship between the two coordinates is deduced as follows:

$$Z\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{d_x} & 0 & u_0 \\ 0 & \frac{1}{d_x} & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix}$$

$$= \begin{bmatrix} f_x & 0 & u_0 & 0 \\ 0 & f_y & v_0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} R & T \\ 0^T & 1 \end{bmatrix} \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix} \tag{8}$$

$$= M_1 M_2 \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix} = M \begin{bmatrix} X_W \\ Y_W \\ Z_W \\ 1 \end{bmatrix}$$

Where, f_x, f_y is the pixel coordinate system u and v axis and the effective focal length on the axis, M_1 is the internal parameter matrix, M_2 is the external parameter matrix, and $M = M_1 M_2$ is the projection matrix.

In a distributed multi-sensor system, each sensor node independently tracks the target and generates the tracking trajectory, and then sends the generated trajectory data to the fusion center of the system for trajectory matching. The RSSI-based target trajectory and the image-based target trajectory are registered in time and space, and the convex group fusion algorithm is used for trajectory matching. Assume that the predicted covariance matrices of the sensor are p_1 and p_2, respectively. The main work of trajectory fusion is to obtain a better target state estimation $\hat{x}$ and prediction covariance matrix P_F through the fusion algorithm. During trajectory fusion, the estimation errors of the two trajectories are independent of each other.

The convex group trajectory fusion algorithm fuses two trajectories through the principle of least mean square estimation error, and the estimated value of target trajectory state after fusion is as follows:

$$\hat{x} = P_2\left(P_1 + P_2\right)^{-1}\hat{x}_1 + P_1\left(P_1 + P_2\right)^{-1}\hat{x}_2 = P_F\left(P_1^{-1}\hat{x}_1 + P_2^{-1}\hat{x}_2\right) \tag{9}$$

Where, P_F is the prediction covariance after fusion, and its expression is:

$$P_F = P_1\left(P_1 + P_2\right)^{-1} P_2 = \left(P_1^{-1} + P_2^{-1}\right)^{-1} \tag{10}$$

Convex group algorithm assumes that the trajectory errors of different sensors are not correlated, so it can get the optimal solution, but its result is suboptimal when the trajectory estimation errors are correlated.

III. CONCLUSION

In order to make full use of the detected multi-modal information, this paper proposes an algorithm that matches the electromagnetic reconnaissance trajectory with the image reconnaissance trajectory for target tracking. The two trajectories of the target are registered in time and space, and the convex group fusion algorithm is used to match the trajectories, which aims to improve the accuracy of ocean reconnaissance. In summary, using the intelligent method, establish a marine intelligence aware framework, improve the sea reconnaissance identification system, explore the intrinsic knowledge of the characteristic data, and provide important support for accurate judgment marine goals and analytical threats, has significant research value.

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