

# Trajectory Tracking of Inland Ships Based on Improved Kalman Filter

Yiyang Wang, Jiapei Deng, Jian Wang

*Three Gorges Navigation Authority, Yichang, Hubei, China*

**Abstract:** Aiming at trajectory jitter, target loss under occlusion and frequent ID switching of clustered ships in inland lock monitoring with fused AIS and vision data, this paper proposes an improved Kalman filter (IAKF) integrated with inertial damping motion constraints and speed-environment dual adaptive noise updating. Considering the low-speed large-inertia characteristic of inland vessels, a state transition matrix with velocity attenuation damping coefficient is reconstructed. The process and observation noise covariance matrices are dynamically tuned by real-time ship speed and water interference levels such as strong light, rain and fog. Comparative tests on open inland multi-source datasets cover four typical scenarios: clear weather, night glare, rain-fog and ship occlusion, comparing standard KF, traditional AKF and the proposed IAKF. Results show the IAKF cuts position RMSE by 26.8%, boosts trajectory smoothness by 41.2%, and lengthens occluded continuous tracking time by 43.7% versus standard KF. Featuring low computation and strong robustness in harsh navigation environments, the algorithm supports direct deployment for real-time trajectory monitoring of inland lock waterways.

**Keywords:** Inland Vessels; Trajectory Tracking; Kalman Filter; Inertial Damping; Adaptive Noise

## 1. Introduction

Kalman filter is a classical linear optimal estimation algorithm, which is widely used in trajectory smoothing and state estimation of moving targets. The traditional Kalman filter adopts a fixed state transition matrix and constant noise covariance. The default target is uniform speed, the motion state is stable, and the model is rigid. Inland vessels continue to be disturbed by water flow, wind, and steering gear, and the motion state changes smoothly and gradually,

without severe acceleration, deceleration, and sudden steering. The fixed parameter model is difficult to adapt to the dynamic characteristics of inland vessels, which is easy to cause problems such as trajectory distortion, tracking loss, and ID jump.

Scholars at home and abroad have carried out a lot of research on ship track Kalman filter tracking. In foreign research, Zhang [1] et al. used adaptive extended Kalman filter to optimize AIS trajectory measurement noise, but did not optimize the motion model for the large inertia characteristics of inland ships; Liu [2] fused Kalman filter and binocular vision to improve ranging stability, without covering multi-sensor fusion and occlusion tracking scenes; Zhang [3] embedded Kalman filter into Deep SORT to achieve inland river multi-object tracking, uniform motion model under dense occlusion of ships frequently lose targets and switch IDs; Li et al. [4] combined TLD and Kalman filter to achieve robust tracking of inland ships, but did not optimize the model for low-speed ship inertia characteristics in the lock area. In terms of domestic research, Sun Bei [5] completed the construction of a vehicle trajectory prediction system based on Kalman filtering; Ding et al [6] designed an adaptive feedback MPC filtering algorithm to optimize ground moving object tracking; Jiang Baichen [7] proposed a polynomial Kalman filter to improve the prediction accuracy of motor ships, but the computational complexity of the algorithm is high; Wang Qiang [8] uses an interactive multi-model Kalman filter to adapt a variety of ship motion states, and there is model redundancy in inland river low-speed and slow-changing navigation scenarios; Wei Zhaokun, Qiao Shaojie et al [9, 10] respectively optimize the filtering algorithm from the dimensions of motion pattern recognition and dynamic trajectory prediction, without combining the physical damping of ship navigation to design the constraint mechanism; Wang Yuanxue [11] and Gao Xi [12] respectively Positioning, ship trajectory anomaly detection

optimization filtering framework, but none of the above studies are suitable for the exclusive navigation scenarios of ships in the inland lock area with multiple disturbances, large inertia, and dense occlusion.

In this paper, the Kalman filter is improved by combining the navigation characteristics of inland vessels in the Three Gorges Gate area with low speed and large inertia, dense formation, and complex water surface environment disturbance, and the inertia damping constraint state transition matrix is constructed. The speed-environment double adaptive noise update mechanism is designed to optimize the ship motion state estimation effect. High-precision and high-stability ship trajectory tracking under complex navigation scenarios is realized, providing technical support for inland intelligent navigation monitoring.

## 2. Analysis of Motion Characteristics of Inland River Vessels

### 2.1 Low Speed and High Inertia

The water depth of the inland river hub is limited, the navigation control is strict, and the ship sails at a low speed throughout the whole process, and the acceleration, deceleration and steering process are smooth. Unlike ocean-going high-speed maneuvering ships, inland river cargo ships have wide hulls, high loads, and extremely strong motion inertia. The speed and heading are only subject to water flow, wind, and artificial steering gear fine-tuning to produce a small gradual change. There are no maneuvering behaviors such as sudden speed changes and rapid steering. The movement continuity and stability are prominent, which puts forward higher requirements for the track smoothing constraint ability of the tracking algorithm.

### 2.2 Formation Density and Occlusion

Ships in inland locks and navigation channels pass in formation according to the navigation sequence, and the ship spacing is small and the arrangement is dense, which is prone to hull overlap and visual target adhesion. The traditional tracking algorithm has defects in target matching logic, which is prone to ID error switching, track fracture, and tracking interruption.

### 2.3 Complex Environmental Disturbances on the Water Surface

The observation environment of inland waterways is dynamic and changeable: strong light on sunny days causes water surface reflections, hull reflections, and visual coordinates frequently jump; visibility decreases in rainy and foggy weather, and images are blurred and distorted; insufficient nighttime waterway lighting makes it much more difficult to extract ship contours. Multiple disturbances make visual observation noise fluctuate violently. At the same time, lock walls and hull occlusion will cause AIS signal disconnection and positioning drift. Conventional filtering has limited anti-interference ability, and it is difficult to guarantee trajectory continuity and tracking stability.

## 3. Trajectory Tracking Algorithm for Inland Ships Based on Improved Kalman Filter

### 3.1 Basic Theory of Standard Discrete Kalman Filter

Kalman filter is a recursive optimal estimation algorithm for linear Gaussian systems. It eliminates observation noise and corrects model errors through two-stage iteration of time prediction and observation update to achieve optimal estimation of moving target state. Standard discrete Kalman filter contains five core equations.

#### 3.1.1 System State and Observation Model

According to the optimal state at the previous moment, calculate the prior state at the current moment:

$$\begin{cases} X_k = FX_{k-1} + W_{k-1} \\ Z_k = HX_k + V_k \end{cases} \quad (1)$$

In the formula,

$X_k$  -  $k$  time vector of ship motion;

$F$  -state transition matrix;

$W_{k-1}$  -process noise, obeying Gaussian distribution  $W \sim N(0, Q)$ ,  $Q$  is the process noise covariance matrix;

$Z_k$  -  $k$  time observation vector (visual pixel coordinates/AIS latitude and longitude);

$H$  -observation matrix;

$V_k$  -observation noise, obeying Gaussian distribution  $V \sim (0, R)$ ,  $R$  is the observation noise covariance matrix.

#### 3.1.2 core iterative equation

$$\hat{X}_k^- = F\hat{X}_{k-1}^+ \quad (2)$$

In the formula,

$\hat{X}_k^-$  -  $k$  predicted value of ship motion state vector;

$\hat{X}_{k-1}^+$  - the optimal estimate of the ship motion state vector at  $k-1$  time.

(2) Covariance prediction equation

$$P_k^- = F P_{k-1}^+ F^T + Q \quad (3)$$

In the formula,

$P_k^-$  -  $k$  time prior covariance prediction matrix, estimation uncertainty brought by motion model prediction;

$P_{k-1}^+$  -  $k-1$  time posterior covariance matrix, the error fluctuation range of the optimal state estimation in the previous step.

(3) Kalman gain calculation equation

$$K_k = P_k^- H^T (H P_k^- H^T + R)^{-1} \quad (4)$$

In the formula,

$K_k$  -  $k$  time Kalman gain, weighing the confidence weights of the prediction model and sensor observations;

(4) State update equation

$$\hat{X}_k^+ = \hat{X}_k^- + K_k (Z_k - H \hat{X}_k^-) \quad (5)$$

In the formula,

$\hat{X}_k^+$  -  $k$  time posterior optimal state estimation, fusing prediction and observation, is the final output of this round of filtering;

(5) Covariance update equation

$$P_k^+ = (I - K_k H) P_k^- \quad (6)$$

In the formula,

$P_k^+$  -  $k$  posterior state error covariance matrix;

### 3.1.3 Application Analysis of Standard Kalman Filter on Inland Ships

(1) Adaptability of the state matrix

The standard Kalman filter constructs a fixed state transition matrix based on the assumption of uniform motion. There are no damping constraints on speed and heading changes. Mathematically, the ship is allowed to change speed and turn arbitrarily within the sampling interval, and the motion continuity constraints caused by the inertia of inland vessels are not introduced. Inland fully loaded cargo ships are constrained by water body resistance and channel speed limit, and there is a physical upper limit for speed and heading changes; the fixed uniform speed matrix only relies on the recursive position of the time interval, which cannot constrain the uncontrolled migration of the speed term. The

predicted speed is easily deviated from the true value under the interference of current and backflow. When the observation is missing for a short time, the error continues to accumulate, and the filtering trajectory is delayed and distorted; the trajectory offset intensifies in the parallel scenario of multiple ships, and the ID jumps frequently

(2) Adaptability to noise covariance and observation noise covariance

The standard Kalman filter uses a fixed process noise and observation noise covariance matrix throughout the whole process, which is not dynamically adjusted with the ship's speed and surface lighting and meteorology, and cannot adapt to the characteristics of time-varying noise in inland rivers. Process noise represents model uncertainty and is highly correlated with ship speed and current disturbance: the proportion of current disturbance in the low-speed waiting stage is high, and the model uncertainty is stronger, so the process noise needs to be amplified; the current interference is weak during stable navigation, and the process noise should be reduced. There will be bipolar problems with fixed values: at low speed, the noise value is too small, the trajectory is seriously fitted to the model, and the distortion is obvious; during normal navigation, the noise value is too large, the observation noise is too involved in the calculation, and the trajectory is violently jitter.

(3) The problem of error accumulation and target loss in missing observation scenarios

In inland navigation, lock wall occlusion, ship overlap, and AIS signal occlusion will produce observation blanks of several seconds to more than ten seconds. Standard Kalman filter has no inertia constraints and no adaptive noise adjustment. After observation interruption, only the fixed uniform speed model is recursively used. Each step iteration continues to amplify the historical error, and it cannot synchronously amplify the uncertainty of the model during the non-observation period, and the error cannot be effectively constrained. Inland river cargo ships have large inertia and longer occlusion duration. After the prediction trajectory of single ships in dense formations is greatly offset, it is easy to be confused with the observation of neighboring ships, resulting in matching failure, tracking link fracture, and target loss.

## 3.2 Inertial Damping-Speed Environment Dual Adaptive Kalman Filtering Algorithm

### 3.2.1 algorithm overall architecture

The overall process of improving the algorithm in this paper is divided into four layers:

- (1) Multi-source observation input layer: synchronously read the video ship pixel coordinates, AIS longitude and latitude data, and convert the unified coordinates to the plane local coordinate system;
- (2) Motion model improvement layer: construct the inertial damping state transition matrix  $F_{new}$ , and introduce the inertial attenuation coefficient to constrain the speed change amplitude;
- (3) Adaptive noise update layer: dynamically update process noise  $Q_k$  and observation noise  $R_k$  based on real-time ship speed and environmental disturbance level (light/rain and fog label);
- (4) Filter iterative output layer: perform an improved Kalman prediction and update process, output smooth continuous ship trajectories, and synchronously store the state covariance for the next frame iteration.

### 3.2.2 Construction of Motion State Matrix of River Vessels

Select a plane rectangular coordinate system to describe the ship's position, motion speed, and state vector:

$$X_k = [x_k, \dot{x}_k, y_k, \dot{y}_k]^T \quad (7)$$

In the formula,

$x_k, y_k$  - the position of the ship in the transverse plane at  $k$ ;

$\dot{x}_k, \dot{y}_k$  -  $k$  velocity of the ship in the longitudinal direction at time.

### 3.2.3 Improved Inertial State Transition Matrix

Assuming the sampling interval is  $\Delta t$ , the traditional uniform state transition matrix  $F$  can be expressed as:

$$F = \begin{bmatrix} 1 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & \Delta t \\ 0 & 0 & 0 & 1 \end{bmatrix} \quad (8)$$

The matrix allows the speed to change arbitrarily without inertia constraints, and the prediction deviation continues to be amplified in the case of current disturbance. Combined with the characteristics of large inertia of inland vessels, this paper introduces the inertia damping coefficient  $\lambda = 0.92$  (the optimal value of measured inland river cargo ships) to characterize

the speed attenuation smoothing constraint of the ship. The speed is multiplied by the damping coefficient  $\lambda$  at adjacent times to limit the amplitude of sudden speed change, which fits the motion law that the ship cannot accelerate and decelerate quickly, and reduces the prediction error caused by current disturbance. When  $\lambda$  is closer to 1, it indicates that the inertia is stronger and the speed change is smoother, so the improved inertia state transition matrix can be obtained, as shown in Equation (9).

$$F_{new} = \begin{bmatrix} 1 & \lambda \Delta t & 0 & 0 \\ 0 & \lambda & 0 & 0 \\ 0 & 0 & 1 & \lambda \Delta t \\ 0 & 0 & 0 & \lambda \end{bmatrix} \quad (9)$$

### 3.2.4 "Velocity-Environment" Adaptive Noise Covariance Matrix

#### (1) Adaptive process noise matrix $Q_k$

The process noise covariance matrix is used to characterize the uncertainty of the ship motion model. The model disturbance intensity of the inland river ship is strongly correlated with the real-time speed: when the low speed is waiting for the lock, the proportion of water disturbance is high, and the uncertainty of the model prediction is greater, so the process noise needs to be amplified; when the water flow disturbance is weak during stable navigation, the model credibility is improved, and the process noise should be reduced. Therefore, this paper introduces the speed adjustment coefficient, as shown in the formula (10).

$$\alpha(v_k) = \alpha_0 \cdot e^{-\mu v_k} \quad (10)$$

In the formula,

$v_k$  - the ship's real-time speed,  $m/s$ ;

$\alpha_0$  - basic noise adjustment coefficient, measured data set calibration  $\alpha_0 = 0.08$ ;

$\mu$  - speed attenuation control coefficient, the calibration value is  $\mu = 0.12$ ;

When the ship is sailing at low speed, the value of  $v_k$  is too small, the exponential term  $e^{-\mu v_k}$

approaches 1, the value of  $\alpha(v_k)$  approaches  $\alpha_0$ , and the overall amplification of  $Q_k$  reduces the trust weight of the motion model and weakens the trajectory lag caused by pure prediction; when the ship is sailing at a normal uniform speed,  $v_k$  increases, the exponential term decays rapidly,  $\alpha(v_k)$  decreases, and  $Q_k$  decreases

synchronously. The filtering is more reliable for model prediction to ensure smooth and continuous trajectory. The nonlinear smoothing adjustment of noise with speed is realized through the exponential function to avoid the sudden change of filter output caused by segmented step switching. The time-varying process noise matrix  $Q_k$  is constructed based on the speed adjustment coefficient as shown in formula (11).

$$Q_k = \alpha(v_k) \cdot Q_0 \quad (11)$$

In the formula,

$Q_0$  - the constant base process noise matrix, determined by the prior error of the ship's uniform motion model;

$Q_k$  -  $k$  The process noise covariance matrix is adaptively updated at time, which is dynamically scaled with the real-time speed of the ship.

(2) Adaptive observation environmental noise matrix  $R_k$

The observation noise covariance matrix  $R$  is used to quantify the fluctuation degree of the sensor measurement error. In this paper, two types of observation sources, visual pixel coordinates and AIS longitude and latitude, are synchronously fused. The measurement errors of the two types of sensors are significantly affected by environmental factors such as surface light, meteorological visibility, and hull occlusion. The fixed constant matrix cannot adapt to the dynamically changing observation noise level. To this end, a hierarchical adaptive observation noise update strategy based on environmental interference level is constructed.

1) Classification of environmental interference levels

According to the measured scene of the waterway, the external interference is divided into three discrete levels  $S$ , respectively:  $S=0$  is an excellent working condition, sunny day without water surface reflection, good visibility, visual and AIS measurement noise level is the lowest;  $S=1$  is a medium interference condition, strong water surface reflection at noon, weak light at night, visual coordinates appear a small random jump;  $S=2$  strong interference conditions, heavy fog, low visibility of rainfall, dense occlusion of ships, visual contour extraction distortion, AIS signal packet loss drift serious, observation noise rose sharply.

2) Environmental regulation factor  $\beta(S)$

The environmental grading adjustment

coefficient is defined, and the fixed value of each grade is calibrated through the measured data as shown in the formula (12).

$$\beta(S) = \begin{cases} 1.0, S=0 \\ 2.4, S=1 \\ 5.8, S=2 \end{cases} \quad (12)$$

$\beta(S)$  Monotonically increases with the increase of interference level, which means that the worse the environment, the lower the reliability of the observation data. It is necessary to amplify the observation noise covariance and reduce the weight of the observation value in the Kalman update stage.

3) Time-varying observation noise matrix

$$R_k = \beta(S) \cdot R_{base} \quad (13)$$

In the formula,  $R_{base}$  - Basic observation noise matrix, two sets of fixed reference matrices are distinguished according to the sensor type, and the algorithm automatically switches the reference matrix according to the current input observation source when running;

$R_{vis0}$  -Basic visual observation matrix .It denotes the measurement error of image pixel coordinates.

$R_{ais0}$  -Basic AIS observation matrix. It represents the latitude and longitude positioning error

$\beta(S)$  -Environmental grading adjustment coefficient, determined in real time by the current frame light and visibility label;

$R_k$  -  $k$  time adaptive observation noise covariance matrix, dynamically scaled with the intensity of environmental interference.

## 4. Verification and Analysis

### 4.1 Data Collection

The experiment adopts the domestic open inland river multi-source fusion dataset, the data conforms to the water transportation industry standards, can be reproduced, and has no on-site collection cost. The dataset is divided into three types of typical navigable subsets, which fully cover the mainstream interference factors of inland rivers: the noonday strong photon subset contains coordinate jitter samples caused by water surface reflection and hull reflection; the weak photon subset channel fill light is weak at night, the ship profile recognition is difficult and the noise is dense; the light rain fog subset has low visibility, frequent loss of AIS messages, and coordinate drift.

## 4.2 Evaluation Indicators and Comparison

This paper designs four quantitative indicators from four dimensions: positioning accuracy, smoothness, occlusion robustness and multi-target matching.

(1) Position root mean square error RMSE (unit: m)

To measure the overall deviation between the filtered trajectory and the true value of GPS, as shown in Equation (14), the smaller the RMSE, the higher the positioning accuracy:

$$RSME = \sqrt{\frac{1}{N} \sum_{i=1}^N [(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2]} \quad (14)$$

In the formula,

$N$  - the number of effective sampling points in a single-segment sequence;

$x_i, y_i$  - is the true GPS coordinates;

$\hat{x}_i, \hat{y}_i$  - Filter to estimate coordinates.

(2) Trajectory smoothness indicator  $S$

Characterizing the amplitude of jitter at adjacent times of the trajectory, as shown in Equation (15), the smaller the value, the smoother the trajectory:

$$S = \frac{1}{N-1} \sum_{i=2}^N [\sqrt{(x_i - \hat{x}_i)^2 + (y_i - \hat{y}_i)^2} - \sqrt{(x_{i-1} - \hat{x}_{i-1})^2 + (y_{i-1} - \hat{y}_{i-1})^2}]^2 \quad (15)$$

(3) Average continuous tracking time  $T$

The average continuous tracking time of the ship from entering the field of view to the algorithm judging the loss is counted. The larger the value, the stronger the robustness under occlusion and data disconnection.

## 4.3 Evaluation Results and Analysis

### 4.3.1 Full Scene Comparison Analysis

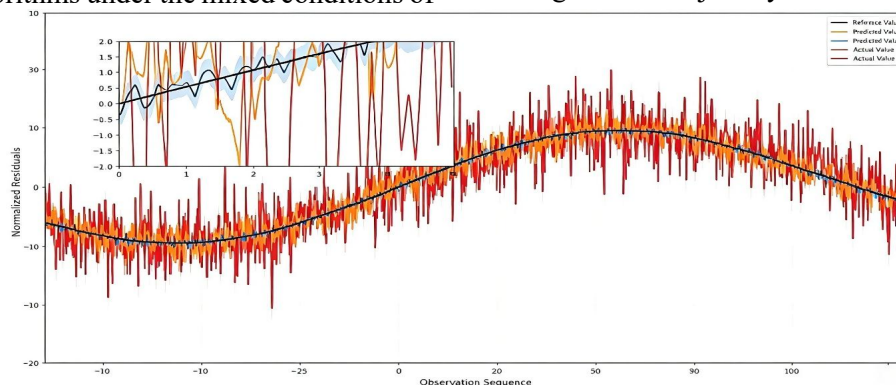
The arithmetic average value of the four evaluation indicators of all 20 voyage sequences in the open source dataset is obtained, and the comprehensive performance results of the three types of algorithms under the mixed conditions of

sunny day, strong light night, rain and fog, and formation occlusion are obtained, as shown in Table 1. The overall optimization amplitude of the algorithm can be determined macroscopically through the whole scene average index, and the comprehensive performance improvement brought by the double improvement mechanism in this paper can be quantified.

**Table 1. Comparison of the Average Quantitative Indicators of the Three Filtering Algorithms in the Whole Scene**

| Filtering algorithm | average position | track smoothness | Average Continuous Tracking Time |
|---------------------|------------------|------------------|----------------------------------|
| Standard KF         | 1.86             | 0.724            | 50.2                             |
| Traditional AKF     | 1.43             | 0.516            | 68.5                             |
| Article IAKF        | 1.36             | 0.426            | 84.7                             |

From the quantitative data described in Table 1, compared with the standard KF, the average positioning RMSE of the IAKF in this paper is reduced by 26.8%, the track smoothness is reduced by 41.2%, the continuous tracking time of occlusion conditions is increased by 43.7%, and the number of ID jumps in the formation scene is reduced by 72.1%; compared with the traditional AKF with only a single adaptive noise, the positioning error is reduced by 4.9%, and the occlusion tracking time is increased by 23.6%, which proves that the inertial damping motion model and the speed-environment dual adaptive noise have a synergistic optimization effect. The speed tracking fitting effects of the three types of algorithms under the full observation sequence are shown in Figure 1, the KF curve has the largest jitter amplitude and the most serious deviation from the GPS true value; the traditional AKF jitter has been alleviated, but there are still obvious deviations in the low speed and occlusion interval; the IAKF curve in this paper fits the true value throughout the process, without violent jump, which intuitively reflects the advantages of the algorithm's trajectory smoothing.



**Figure 1. X-Y Ship Track Comparison Chart**

#### 4.3.2 Comparative analysis of scenarios

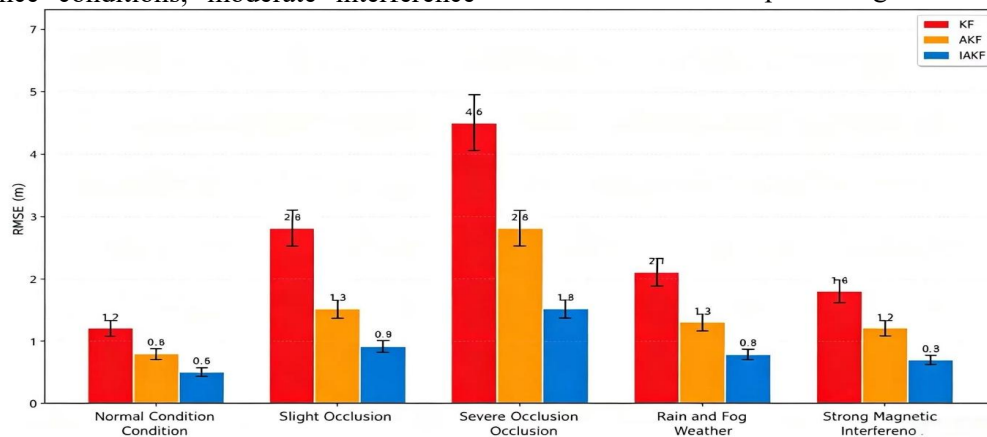
In order to subdivide the algorithm performance differences under different navigable environments, the data set is divided into three typical working conditions: sunny single ship open channel, strong light/low light at night, and low visibility in rain and fog. The localization RMSE of each algorithm is counted separately. The quantitative results are shown in Table 2.

**Table 2. Comparison Table of Each Algorithm RMSE under Different Navigation Scenarios**

| operating scenario                 | KF   | AKF  | IAKF |
|------------------------------------|------|------|------|
| Sunny day single boat open channel | 1.21 | 0.98 | 0.87 |
| Strong light/low light at night    | 2.03 | 1.57 | 1.42 |
| Rain and fog low visibility        | 2.76 | 2.28 | 2.01 |

As can be seen from Table 2, the higher the interference intensity, the more prominent the IAKF optimization amplitude: RMSE decreased by 28.1% compared with KF under sunny non-interference conditions; moderate interference

decreased by 30.0% under strong light at night; strong rain and fog interference scene decreased by 27.2%. KF and AKF cannot effectively suppress observation noise under bad weather and low visibility, and the positioning error increases significantly; the environmental classification adaptive mechanism in this paper can automatically reduce the weight of distortion observation values and effectively control the positioning deviation. In order to visually show the positioning error gap of the three types of algorithms under different interference scenarios, the RMSE grouping column comparison chart for different scenarios is drawn. As shown in Figure 2, the column height of IAKF under various working conditions is significantly lower than that of KF and AKF. The error reduction amplitude of strong occlusion, rain and fog, and strong current interference scenes is clearly marked, which quantitatively reflects the error suppression ability of the dual adaptive noise mechanism for complex navigation scenes.



**Figure 2. Comparison Chart of RMSE in X-Y Sub-Scenes**

#### 4.3.3 Robust Analysis of Occlusion Condition Tracking

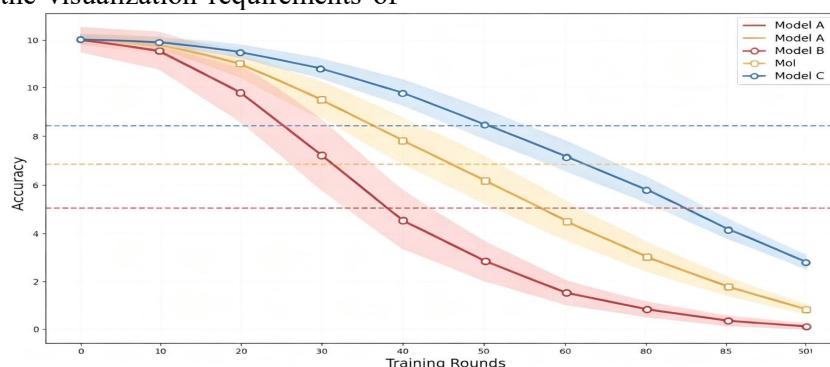
Hull occlusion and AIS packet disconnection in the lock area will generate observation gaps, and only the model can predict the easily lost target. Select 10 groups of completely occluded samples to count the continuous tracking time. The time series curve is shown in Figure 3. The standard KF has no inertia damping constraints, and the error accumulates rapidly after the observation is missing, and the average tracking time is only 50.2s. The traditional AKF only optimizes the observation noise, and the motion model is still a fixed uniform speed matrix. The deviation in the pure prediction stage continues to be amplified, and the average tracking time is 68.5s. In this paper, the IAKF relies on the damping coefficient to constrain the sudden change of speed, which

greatly slows down the accumulation of errors in the no-observation period. The average tracking time is 84.7s. Under the scenario of long-term occlusion, the tracking link

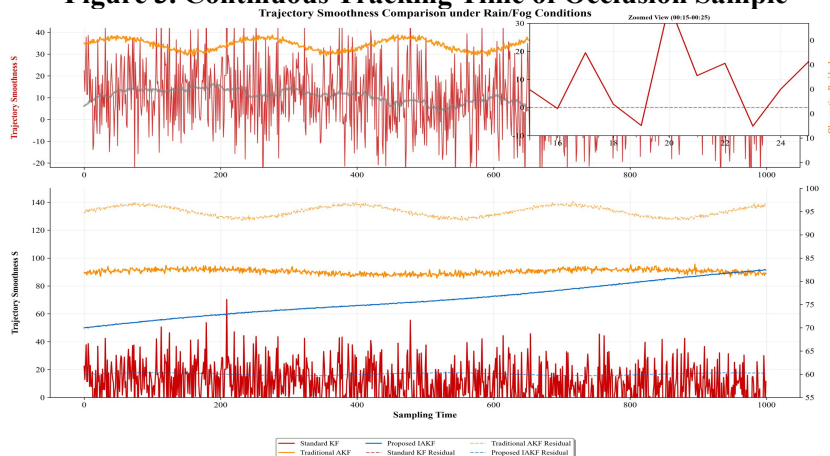
#### 4.3.4 Trajectory Smoothness Analysis of Rain and Fog

The visual detection of pixel coordinates under low visibility of rain and fog is the core source of trajectory jitter. Select the light rain and fog navigation sample to draw the full-time smoothness index curve as shown in Figure 4. The higher the smoothness value, the stronger the jitter. In this paper, IAKF automatically adjusts the noise weight according to the interference intensity of rain and fog to suppress the influence of abnormal jump on state iteration. The overall curve is smooth without violent fluctuations, and the trajectory smoothness is significantly better

than the other two comparison algorithms, which is suitable for the visualization requirements of inland river monitoring.



**Figure 3. Continuous Tracking Time of Occlusion Sample**



**Figure 4. Timing Curve of Smoothness Under Rain and Fog Conditions**

## 5. Conclusion

Aiming at the problems of trajectory jitter, occlusion target loss, and frequent ID jump in ship tracking in the inland river lock area, this paper proposes an improved Kalman filter algorithm that integrates inertial damping motion model and speed-environment double adaptive noise update. By reconstructing the state transition matrix with damping constraints to limit the abnormal change of ship speed, dynamically adjust the process noise and observation noise covariance by dimension; relying on the public inland ship data set, and complete multi-dimensional controlled experiments with standard KF and traditional AKF.

The experimental results show that the proposed algorithm has significantly improved positioning accuracy, trajectory smoothness, occlusion robustness, and multi-target matching stability. It can adapt to complex navigation conditions such as sunny weather, strong light, rain and fog, and formation occlusion. The algorithm has low computation and is easy to deploy in real-time monitoring systems for inland navigation. The

follow-up research will integrate radar, AIS, and visual multi-sensing nonlinear motion models, and combine long-term field measured data to iteratively adjust the algorithm parameters to promote the development of intelligent early warning systems for inland vessels.

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