

Multi-Source Error Compensated Localization of Maritime Infrared Targets Using an Earth Ellipsoid Model

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Abstract. Long-range localization of maritime infrared targets is challenging due to Earth's curvature, installation deviations, sensor inaccuracies, and environmental noise. This paper proposes an Earth ellipsoid model-based localization algorithm with a two-stage error compensation mechanism. The algorithm constructs a collinearity equation in the geocentric Cartesian coordinate system to intersect the camera's secondary optical axis with the WGS-84 ellipsoid, obtaining target coordinates. The first stage uses a dual-target-point calibration method to correct installation angle and hardware-induced secondary optical axis pointing errors. The second stage applies an adaptive Kalman filter to dynamically suppress random errors from environmental disturbances. Experiments on shore-based, shipborne, and airborne platforms show that when the observation device is above 80 m sea level, the proposed method achieves a localization accuracy within 5% of the detection range for distant infrared targets. The algorithm effectively compensates multi-source errors, significantly improving positioning precision under complex sea conditions, and is suitable for engineering deployment.

Keywords: Long-range localization; earth ellipsoid model; installation angle error; hardware error; random error.

1. Introduction

Maritime accidents, including vessel collisions, oil spills, and search and rescue (SAR) operations, continue to pose serious threats to maritime safety and navigation efficiency. In 2024 alone, the International Maritime Organization (IMO) reported over 2,800 maritime incidents globally, with economic losses exceeding tens of billions of US dollars [1]. Among the various factors affecting SAR effectiveness, inaccurate target localization remains one of the primary bottlenecks. According to the IMO Annual Report on Maritime Search and Rescue (2025), localization errors account for an estimated 38-45% of total rescue delays in offshore and open-sea operations, directly impacting survival rates of distressed vessels and personnel. This persistent challenge underscores the urgent need for high-precision, long-range maritime positioning technologies.

Existing long-range target localization methods can be broadly divided into four categories: kinematics-based, infrared imaging-based, multi-sensor fusion-based, and geometry-based approaches. Kinematics-based methods rely on motion models, but complex sea conditions cause unpredictable target maneuvers that degrade estimation accuracy [2]. Infrared imaging-based methods suffer from low signal-to-clutter ratio and strong sea clutter interference, making robust feature extraction difficult [3]. Multi-sensor fusion methods integrate GNSS, IMU, and cameras; however, maritime environments often lead to GNSS signal loss, IMU drift, and degraded image quality, complicating data fusion [4]. Geometry-based methods establish geometric relationships between the target, observation point, and reference objects. Compared with the other categories, geometry-based methods are less directly affected by dynamic maritime disturbances and are more suitable for long-range scenarios. Nevertheless, existing geometric methods still face three major challenges: (a) Earth curvature distortion under long-distance observation, (b) installation angle

deviations and sensor hardware errors, and (c) random noise from environmental disturbances such as air turbulence and platform vibration.

To address these challenges, this paper proposes an Earth ellipsoid model-based localization algorithm with a two-stage error compensation mechanism. The main contributions are summarized as follows:

(1) Earth ellipsoid model-based localization. Instead of using a flat-Earth assumption, we construct a collinearity equation for the camera's secondary optical axis in the geocentric Cartesian coordinate system and compute its intersection with the WGS-84 ellipsoid. This effectively eliminates Earth curvature-induced distortions in long-range maritime positioning.

(2) Two-stage error compensation. First, a dual-target-point calibration method corrects installation angle and hardware-induced pointing errors of the secondary optical axis. Second, an adaptive Kalman filter dynamically suppresses random errors caused by environmental noise (air turbulence, platform vibration, etc.).

(3) Multi-platform experimental validation. The proposed method is tested on shore-based (≈ 87 m), shipborne (≈ 22 m), and airborne (125-181 m) platforms over distances up to 9.6 km. Experimental results demonstrate that when the observation device is above 80 m sea level, the localization accuracy is within 5% of the detection range, confirming strong robustness and engineering practicality.

2. Methodology

This section presents the proposed localization framework. Section 2.1 establishes the Earth ellipsoid model-based coordinate transformation from pixel coordinates to WGS-84 geodetic coordinates. Section 2.2 describes the two-stage error compensation mechanism, including dual-target-point calibration for systematic errors and adaptive Kalman filtering for random noise.

2.1 Earth Ellipsoid Model-Based Localization

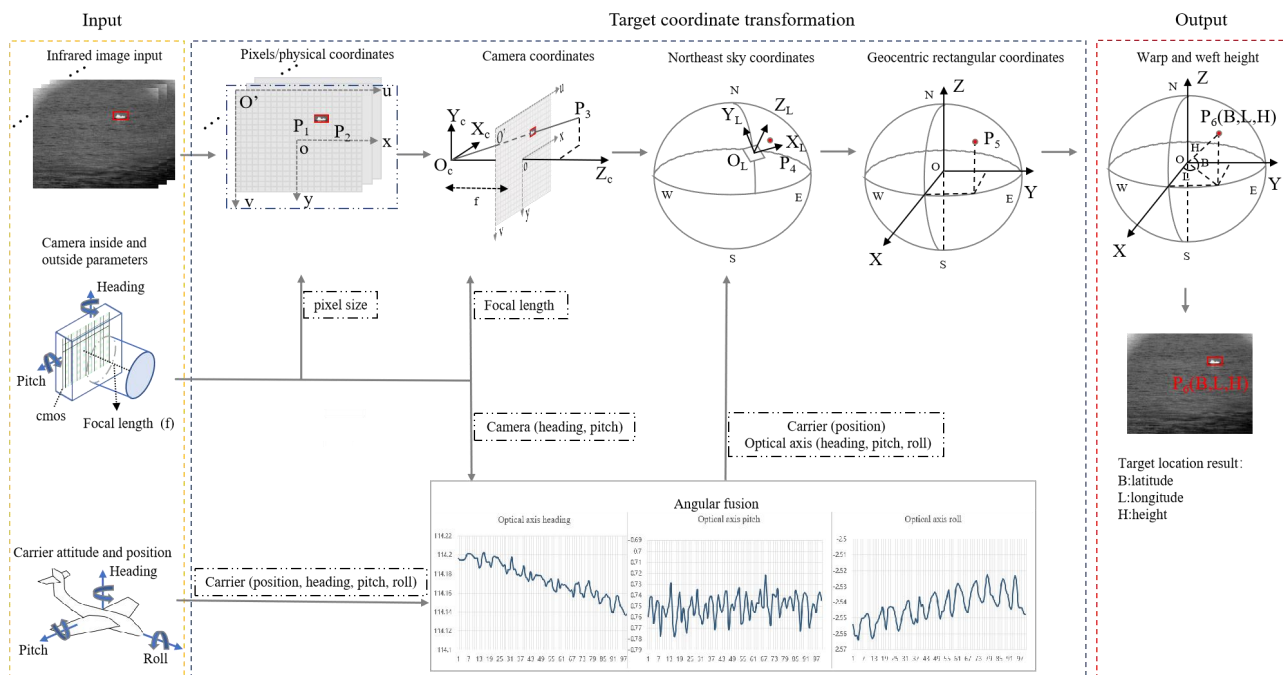


Fig. 1 Algorithm architecture of the Earth ellipsoid model-based localization

To eliminate Earth curvature distortion in long-range maritime positioning, we construct a collinearity equation between the camera's secondary optical axis and the WGS-84 ellipsoid. The system integrates an infrared electro-optical pod and an inertial navigation unit, providing

synchronized data: target pixel coordinates (u, v) , camera intrinsic parameters (focal length f , pixel size dx/dy), camera exterior orientation angles (heading ψ , pitch θ), carrier attitude angles (heading ψ' , pitch θ' , roll ϕ'), and carrier geodetic coordinates (longitude L' , latitude B' , altitude H').

The localization proceeds through five coordinate transformations (Figure 1).

2.1.1 Pixel to Camera Coordinates

The target pixel (u, v) is first converted to the image physical coordinate system (x, y) using the principal point (u_0, v_0) and pixel size:

$$\begin{bmatrix} x \\ y \end{bmatrix} = \begin{bmatrix} (u-u_0)d_x \\ (v-v_0)d_y \end{bmatrix} \quad (1)$$

Then, using perspective projection, the 3D camera coordinates (X_c, Y_c, Z_c) are obtained:

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} = \begin{bmatrix} x \\ y \\ -f \end{bmatrix} \quad (2)$$

2.1.2 Camera to ENU Coordinates

The camera's relative orientation angles are fused with the carrier's absolute attitude to obtain the absolute pointing vector in the East-North-Up (ENU) frame. The rotation matrix R_c for the camera relative to the carrier is:

$$R_c = R_z(\psi)R_y(\theta) \quad (3)$$

and the carrier's rotation matrix R_g in the ENU frame is:

$$R_g = R_z(\psi')R_y(\theta')R_x(\phi') \quad (4)$$

The fused rotation matrix is $M_T = R_g \cdot R_c$. The target coordinates in the ENU frame are:

$$P_{enu} = M_T \begin{bmatrix} X_c \\ Y_c \\ Z_c \end{bmatrix} \quad (5)$$

The Euler angle fusion process follows standard aerospace rotation conventions [5–7].

2.1.3 ENU to ECEF and Ellipsoid Intersection

The ENU coordinates are transformed to the Earth-Centered Earth-Fixed (ECEF) frame using the carrier's geodetic coordinates. The collinearity equation of the camera-target secondary optical axis in ECEF is:

$$\frac{X-X_c}{X_t-X_c} = \frac{Y-Y_c}{Y_t-Y_c} = \frac{Z-Z_c}{Z_t-Z_c} \quad (6)$$

where (X_c, Y_c, Z_c) is the camera optical center, and (X_t, Y_t, Z_t) is any point on the optical axis. The WGS-84 ellipsoid model is:

$$\frac{X^2+Y^2}{R_e^2} + \frac{Z^2}{R_p^2} = 1 \quad (7)$$

with equatorial radius $R_e=6378.137\text{km}$ and polar radius $R_p=6356.752\text{km}$. Solving (6) and (7) yields two intersection points; the one closer to the camera is selected as the target's ECEF coordinates[8,9]. Finally, the ECEF coordinates are converted to WGS-84 longitude, latitude, and altitude using standard formulas.

2.2 Two-Stage Error Compensation

The localization accuracy is primarily affected by two types of errors: (i) systematic pointing errors of the camera-target secondary optical axis, caused by installation angle misalignment and hardware sensor inaccuracies; (ii) random errors induced by environmental noise (air turbulence, platform vibration, thermal fluctuations). We propose a two-stage compensation mechanism.

2.2.1 Dual-Target-Point Calibration for Systematic Errors

The pointing error of the secondary optical axis is denoted as $(\Delta\psi, \Delta\theta, \Delta\phi)$. To calibrate these errors, two reference targets with precisely known coordinates (measured by differential GPS) are placed within the camera's field of view. Figure 2 illustrates the complete calibration procedure.

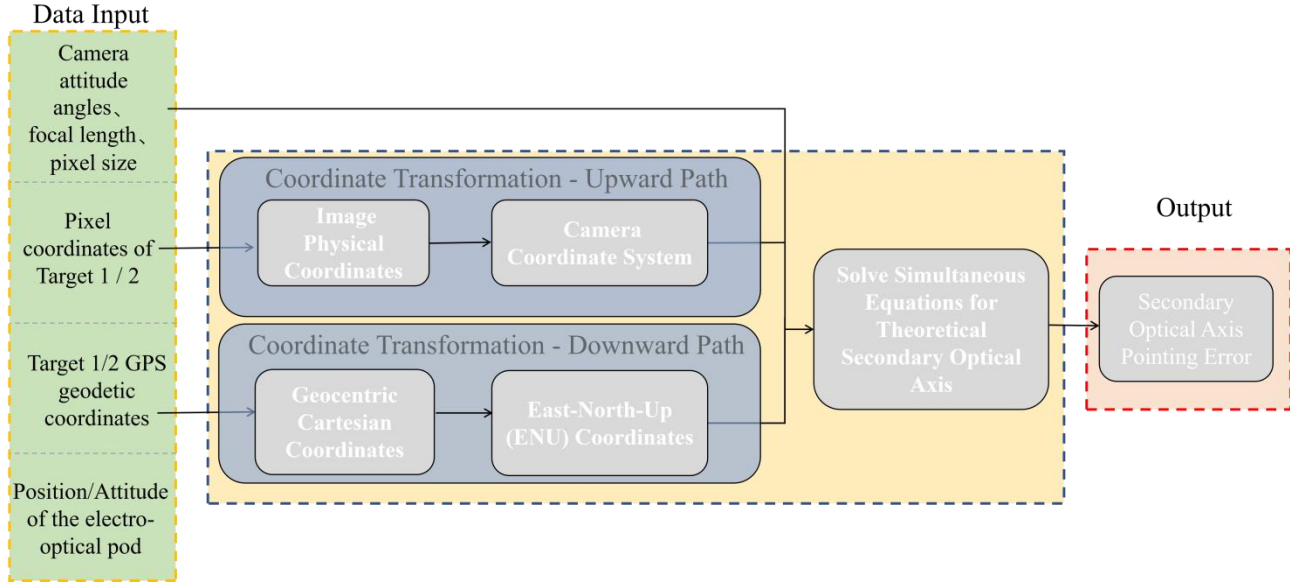


Fig. 2 Flowchart of the dual-target-point calibration method for secondary optical axis pointing error

As shown in the figure, the theoretical rotation matrix M_T of the secondary optical axis is first derived from the known target coordinates. Simultaneously, the measured rotation matrix M'_T is obtained from the raw sensor outputs. The error rotation matrix R_{err} satisfies $M'_T = R_{err} \cdot M_T$. By solving the system of equations using the two target points, the error angles are estimated and then compensated in subsequent localizations[10]. Experimental calibration results (Table 1) show that after compensation, the relative positioning error is reduced from over 1.2% to below 1.0% at a distance of approximately 2 km.

Table 1. Comparison of compensation results for the pointing deviation of the camera-target secondary optical axis

Data Sequence Number	Pointing Deviation of Camera-Target Secondary Optical Axis/ $^{\circ}$	After Correction Target Computation Longitude/ $^{\circ}$ E	After Correction Target Computation Latitude/ $^{\circ}$ E	Error/m	Distance /m	Before Correction Positioning Accuracy/%	After Correction Positioning Accuracy/%
1	(5.27, 0.39, 0.462)	121.588087	38.865478	20.6	2103	1.21	0.98
2		121.585027	38.865872	26.061	2190	1.35	1.19

2.2.2 Adaptive Kalman Filter for Random Errors

In addition to systematic pointing errors, random noise induced by environmental disturbances-such as airflow turbulence, platform vibration, and thermal fluctuations-causes high-frequency jitter in the measured attitude angles of both the camera and the carrier. This jitter propagates through the coordinate transformation pipeline and introduces uncertainty in the final localization results. Conventional Kalman filtering assumes known statistics of process and measurement noise, which is not satisfied in complex maritime environments. We therefore employ an adaptive Kalman filter that dynamically estimates noise covariances in real time[11,12].

State space model. The state vector is defined as:

$$x(k) = [\psi, \omega_{\psi}, \theta, \omega_{\theta}, \psi', \omega_{\psi}', \theta', \omega_{\theta}', \phi, \omega_{\phi}]^T \quad (8)$$

where ψ and θ are the camera heading and pitch, (ψ', θ', ϕ') are the carrier heading, pitch, and roll, and ω denotes the corresponding angular velocities. The state transition is modeled as a first-order Markov process with constant angular velocity:

$$x(k) = A \cdot x(k-1) + w(k) \quad (9)$$

where A is the block-diagonal state transition matrix and $w(k)$ is process noise. The measurement vector consists of the directly observed angles:

$$y(k) = [\psi, \theta, \psi', \theta', \phi']^T = H \cdot x(k) + v(k) \quad (10)$$

with H being the measurement matrix and $v(k)$ the measurement noise.

Adaptive noise estimation. To handle unknown and time-varying noise statistics, the filter updates the process noise covariance $Q(k)$ and measurement noise covariance $R(k)$ using a sliding window of residuals. The residual at time k is defined as $r(k) = y(k) - H \cdot \hat{x}(k|k-1)$. Within a window of size $W=20$, the sample covariance of residuals is computed and used to adaptively adjust $R(k)$ and $Q(k)$ via covariance matching. This adaptive mechanism prevents filter divergence and maintains optimal performance under varying sea conditions.

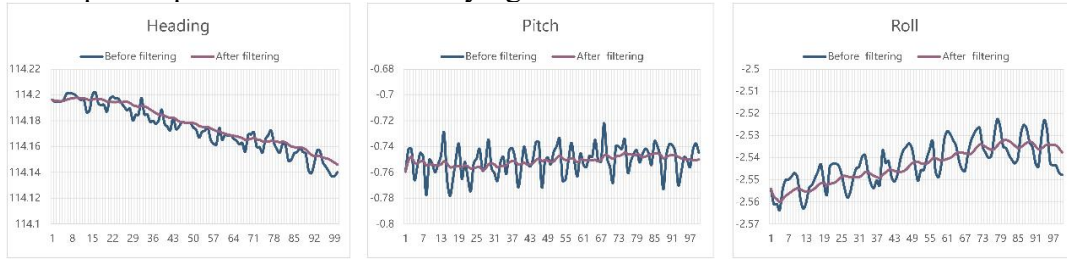


Fig. 3 Comparison of camera heading angle before and after adaptive Kalman filtering

Filtering results. Figure 3 compares the camera heading angle before and after adaptive Kalman filtering. The raw signal exhibits significant high-frequency jitter due to environmental noise, while the filtered output is substantially smoother with reduced fluctuations. The standard deviation of the heading angle decreases from 0.092° to 0.031° after filtering, confirming the effectiveness of the adaptive filter in suppressing random errors. By mitigating random attitude jitter, the adaptive Kalman filter enhances the stability and reliability of the subsequent coordinate transformation, contributing directly to improved overall localization accuracy.

3. Experimental Validation

Experiments were conducted on three maritime platforms: a shore-based platform (≈ 87 m altitude), a shipborne platform (≈ 22 m), and an airborne platform (125-181 m). A high-precision differential GPS (accuracy better than 0.3 m) provided ground truth for the target vessel. Detection distances ranged from 0.7 km to 9.6 km. The infrared electro-optical pod system synchronously captured target images, camera attitude angles, carrier attitude angles, and carrier geodetic coordinates.

3.1 Shore-Based Platform Results

Figure 4 shows infrared images of the target vessel captured by the shore-based platform at distances of 1.8 km, 3.2 km, and 8.6 km. After applying both stages of error compensation (dual-target-point calibration + adaptive Kalman filter), the relative positioning errors were 1.1%, 2.6%, and 4.7%, respectively (Table 2). All errors were within 5% of the detection range.

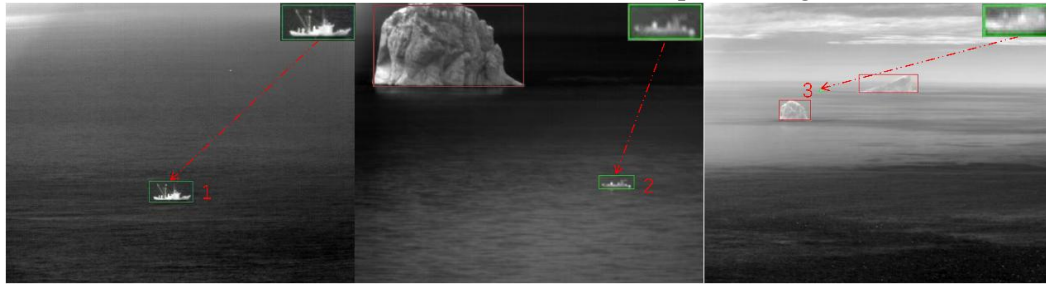


Fig. 4 Infrared images of the target vessel at short-range, medium-range, and long-range distances (shore-based platform)

Table 2. Positioning results on shore-based platform.

Data Sequence Number	Target Computation Longitude/°E	Target Computation Latitude/°N	Target Measurement Longitude/°E	Target Measurement Latitude/°N	Error/m	Distance/m	Positioning Accuracy /%
1	121.634724	38.848504	121.634552	38.848701	20.24	1840	1.1
2	121.630726	38.837152	121.629758	38.837272	83.98	3230	2.6
3	121.599726	38.795887	121.595105	38.795641	404.48	8606	4.7

3.2 Shipborne Platform Results

Figure 5 presents infrared images captured by the shipborne platform (≈ 22 m altitude) under the interferences of sea surface sway, hull vibration, and near-sea multipath effects. The relative errors at 3.2 km, 4.6 km, and 9.6 km were 1.6%, 2.8%, and 4.78%, respectively (Table 3), demonstrating strong anti-interference capability.

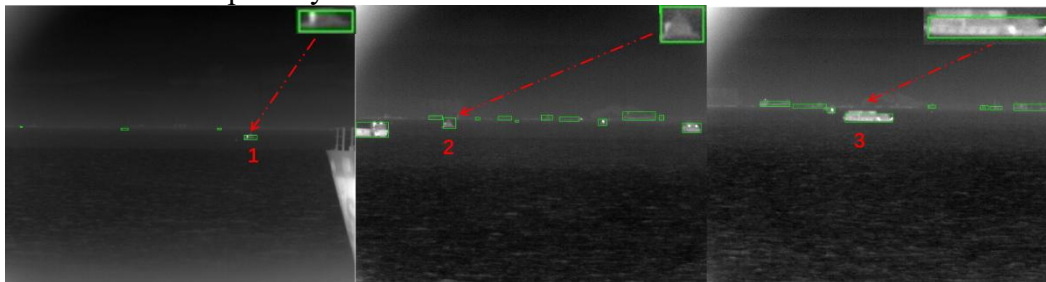


Fig. 5 Infrared images of the target vessel captured by the shipborne equipment under short-range, medium-range, and long-range conditions

Table 3. Positioning results on shipborne platform

Data Sequence Number	Target Computation Longitude/°E	Target Computation Latitude/°N	Target Measurement Longitude/°E	Target Measurement Latitude/°N	Error/m	Distance /m	Positioning Accuracy /%
1	113.820043	22.527544	113.82006201	22.527078	51.6	3200	1.6
2	113.806256	22.534660	113.80650523	22.533468	130	4580	2.8
3	113.765640	22.565952	113.76641038	22.56185246	460	9630	4.78

3.3 Airborne Platform Results

Figure 6 shows infrared images captured by the airborne platform (altitude 125-181 m). The higher observation altitude provided the best performance, effectively avoiding near-sea surface interference. At distances of 0.7 km, 2.8 km, and 4.0 km, the relative errors were 1.2%, 2.17%, and 2.54%, respectively (Table 4). At the maximum distance of 4.0 km, the relative error was only 2.54%, confirming the effectiveness of the proposed method on dynamic platforms.

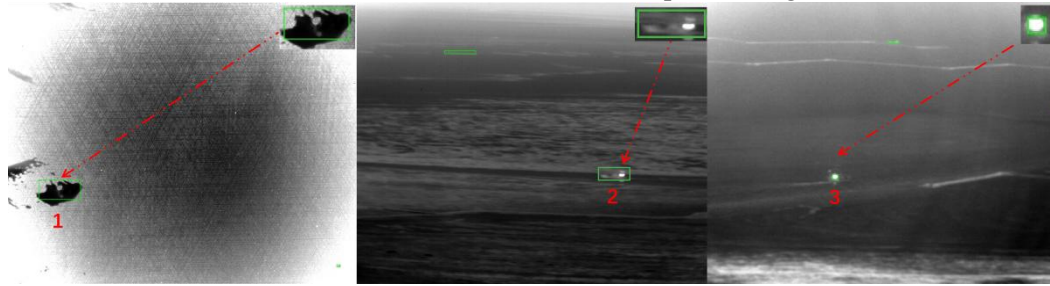


Fig. 6 Infrared images of the target vessel captured by the airborne equipment under short-range, medium-range, and long-range conditions

Table 4. Positioning results on airborne platform

Data Sequence Number	Target Computation Longitude/°E	Target Computation Latitude/°N	Target Measurement Longitude/°E	Target Measurement Latitude/°N	Error/m	Distance /m	Positioning Accuracy /%
1	118.956505	37.595118	118.956547	37.595195	9	730	1.2
2	118.960920	37.583933	118.960187	37.589448	62	2850	2.17
3	118.971405	37.584361	118.970397	37.584762	102	4010	2.54

4. Conclusions

This paper proposed an Earth ellipsoid model-based localization algorithm with a two-stage error compensation mechanism for long-range maritime infrared targets. The main conclusions are summarized as follows.

(1) The Earth ellipsoid model effectively eliminates Earth curvature distortion, which is the fundamental limitation of flat-Earth assumptions in long-range positioning.

(2) The dual-target-point calibration method corrects systematic pointing errors of the camera-target secondary optical axis, reducing the relative positioning error from over 1.2% to below 1.0% at a distance of 2 km.

(3) The adaptive Kalman filter dynamically suppresses random noise caused by environmental disturbances, reducing the standard deviation of attitude angles from 0.092° to 0.031° .

(4) Experimental validation on three platforms (shore-based, shipborne, airborne) over distances up to 9.6 km demonstrated that when the observation device is above 80 m sea level, the localization accuracy is within 5% of the detection range, meeting the requirements of practical maritime applications.

Future work will focus on extending the method to ultra-long distances ($>10\text{km}$) by incorporating multi-sensor fusion (e.g., radar and infrared) and deploying edge computing for real-time processing on resource-constrained platforms.

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