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A Novel Smart Vision-Based Sensing System for Structural Health Monitoring: Robust Angle Measurement of Offshore Rotating Machinery with Data-Driven Calibration

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ABSTRACT: To address the critical need for reliable condition monitoring of rotating components (e.g., crane slewing bearings, thrusters) in harsh marine environments characterized by strong electromagnetic interference, salt spray, and persistent vibration, this paper presents a novel smart sensing system for high-precision rotation angle measurement. The proposed intelligent inspection system employs a vision-based principle: a laser spot, projected from a turntable synchronized with the measured shaft, forms a circular trajectory on a fixed Complementary Metal-Oxide-Semiconductor (CMOS) image sensor. A robust machine vision algorithm, integrating an improved Canny-Kirsch operator and a least-squares ellipse fitting method, achieves sub-pixel spot center localization under dynamic conditions. To overcome systematic nonlinearities, a data-driven polynomial compensation model is developed, demonstrating a data-driven calibration approach for enhanced accuracy. Experimental results demonstrate that after compensation, the system achieves a measurement accuracy of 0.9° , with sensitivity, resolution, repeatability error, and hysteresis of 4.25 Counts/ $^\circ$, 0.0017 $^\circ$, 1.83%, and 1.09%, respectively. While matching the precision of traditional encoders, the system exhibits superior immunity to electromagnetic interference and environmental robustness. This work, therefore, presents a practical and smart sensing solution with potential for the structural health monitoring and predictive maintenance of marine infrastructure, contributing to the development of robust sensor systems for industrial applications.

KEYWORDS: Novel smart sensing; structural health monitoring (SHM); vision-based sensor; offshore platform; data-driven modeling; nonlinear compensation

1 Introduction

Marine engineering equipment, including fixed platforms, Floating Production Storage and Offloading units (FPSOs), offshore wind turbines, and various engineering vessels, forms the core infrastructure for national marine resource development and offshore operations. These facilities integrate numerous critical rotating components, such as the slewing bearings of floating cranes, controllable pitch propellers in propulsion systems, fairleads in mooring systems, and various valves and actuators. The precise rotation angles of these components directly reflect their operational status, control accuracy, efficiency optimization, and safety interlocking, serving as core parameters for implementing condition monitoring, fault warning,

and predictive maintenance. Therefore, developing highly reliable, long-term stable rotation angle monitoring technology capable of withstanding harsh marine environments is of paramount importance for ensuring the safe operation of marine equipment, enhancing operational efficiency, and extending service life [1]. Consequently, there is a pressing need for smart sensing technologies and robust structural health monitoring solutions tailored for such demanding applications.

To address this challenge, academia and industry have developed various angle monitoring technologies. Traditional methods primarily rely on contact or electromagnetic sensors, such as photoelectric encoders, resolvers, potentiometers, and magnetic encoders based on the Hall effect or magnetoresistive effect. For instance, high-precision photoelectric encoders convert angular displacement to electrical signals via a grating disk, achieving arc-second level resolution and repeatability in ideal industrial environments. Magnetic encoders detect magnetic field changes using magneto-sensitive elements and are applied in some scenarios due to their non-contact nature [2–5]. For instance, Gu et al. [2] recently reported an angle sensor based on image recognition, demonstrating the potential of vision-based solutions, yet its robustness under extreme ambient light variations requires further improvement. The laser spot tracking method proposed in this study aims to combine the reliability of active vision with the advantages of non-contact measurement, addressing the challenges of environmental robustness and long-term stability faced by the aforementioned solutions in marine engineering applications. However, these technologies exhibit significant limitations in the severe marine environment: the optical system of photoelectric encoders requires extremely high sealing, and the grating disk is easily contaminated by salt spray, leading to signal attenuation or failure; the brushes of potentiometers suffer from mechanical wear, have limited lifespan, and exhibit unstable contact resistance and susceptibility to corrosion in humid, salty environments; the performance of various electromagnetic sensors (including resolvers, Hall sensors, etc.) is highly susceptible to interference from complex, strong electromagnetic fields generated by large motors, frequency converters, and power lines on the platform, causing signal distortion, zero drift, or false triggering, severely compromising reliability [6–8]. Furthermore, traditional slip ring power and signal transmission methods also pose safety hazards such as changing contact resistance, mechanical wear, and spark generation, making them unsuitable for applications requiring long-term maintenance-free operation or involving flammable and explosive risks.

In recent years, with the rapid development of computer vision and image processing technologies, non-contact visual measurement methods have attracted widespread attention in industrial measurement and marine engineering monitoring due to their advantages of rich information, inherent immunity to electromagnetic interference, and flexible deployment, becoming a research frontier [9]. Research primarily focuses on two categories: one is vision-based measurement using natural features, such as monitoring the six-degree-of-freedom motion, overall deformation, or mooring line morphology of large marine structures using binocular or multi-vision systems; another approach utilizes monocular video combined with advanced image processing or deep learning algorithms to extract structural vibration frequencies or displacement responses from fixed camera video streams. These methods have shown potential in laboratory model tests and specific field monitoring scenarios [10–12]. However, existing visual methods still face fundamental challenges for real-time, high-precision, embedded rotation angle monitoring of offshore platform rotating components: Firstly, methods relying on environmental or artificial markers have measurement accuracy and robustness severely constrained by environmental lighting changes, rain, fog, occlusion, and other weather conditions. Feature extraction becomes difficult under low-contrast or uniform backgrounds, failing to meet the engineering demand for stable 24/7 all-weather monitoring. Secondly, most vision systems are designed for general displacement measurement, with complex algorithms, high computational load, and demanding hardware requirements, making miniaturization and integration into space- and power-limited equipment sites difficult. Thirdly, system calibration is complex, and measurement

accuracy is easily affected by camera perspective, perspective distortion, and installation base vibration, making long-term stability hard to guarantee.

Simultaneously, laser-based precision measurement technologies, such as laser interferometers and laser autocollimators, have achieved nanometer-level displacement or sub-arc-second level angle measurement accuracy in metrology and high-end manufacturing. These technologies infer displacement or angle by detecting phase or direction changes of the laser beam, offering clear principles and extremely high accuracy. However, significant obstacles remain in directly applying them to on-site monitoring of rotating equipment in marine engineering: high-precision laser interferometer and autocollimator systems are typically complex, bulky, extremely costly, and highly sensitive to environmental vibration and temperature gradients, with complex calibration and maintenance. While commercial laser triangulation displacement sensors are already productized, their designs mostly target short-distance, small-range, environmentally controlled industrial inspection. In the outdoor harsh environment of offshore platforms with limited space, drastic temperature and humidity changes, and persistent vibration, their long-term stability and reliability have not been fully validated, and they are difficult to directly adapt to the rotation angle measurement mode.

In summary, a core contradiction exists in the field of rotation angle monitoring for offshore platform rotating components: mature, high-precision traditional sensors (photoelectric, magnetic encoders) exhibit clear shortcomings in long-term reliability and environmental adaptability (e.g., susceptibility to EMI, salt spray corrosion, mechanical wear) within the marine environment, while non-contact vision or laser measurement schemes with potential robustness face challenges in practical integration, environmental specificity, and cost-effectiveness for dedicated, embedded monitoring tasks. Therefore, there is an urgent need to develop a smart and intelligent inspection system that combines high measurement accuracy, strong environmental robustness, and ease of integration. This work aims to address this gap by proposing a novel vision-based sensing approach.

Addressing this need, this paper proposes an intelligent angle sensor based on laser spot image recognition. The core idea is to intelligently transform the precise measurement of rotation angle into a robust visual tracking task of a laser spot's circular trajectory. Specifically, a precision mechanical turntable rigidly connected to the rotating shaft drives the laser emitter to rotate, forming a well-defined spot path on a fixed target surface. A robust spot recognition algorithm, which fuses an improved Canny-Kirsch operator with least-squares ellipse fitting, is developed to achieve stable sub-pixel localization under dynamic conditions. Finally, through pre-calibrated mapping relationships and nonlinear compensation, the pixel position of the spot is converted into the rotation angle value. This method fundamentally avoids electromagnetic interference and mechanical wear while using an active light source to overcome the impact of ambient light changes on feature extraction. The main contributions of this paper are:

- (1) Proposing an integrated sensing scheme that combines a turntable-based mechanical design with vision-based measurement, making it suitable for harsh marine environments.
- (2) Proposing an improved spot center localization algorithm, enhancing detection accuracy and stability under vibration and complex optical backgrounds.
- (3) Validating the system's measurement accuracy, repeatability, and long-term stability under simulated marine environmental conditions through comprehensive experiments, laying a theoretical foundation for its engineering application.
- (4) Demonstrating the feasibility and potential of a data-driven calibration model for enhancing the accuracy of such a vision-based system.

This research aims to provide a reliable and practical fundamental technical means for the intelligent and digital operation and maintenance of rotating machinery in marine engineering equipment.

2 System Design and Method

2.1 Measurement Principle and Overall System Design

Addressing the need for angle monitoring of critical rotating components in complex mechanical systems (e.g., crane slewing mechanisms, controllable pitch propellers, articulated fender structures) on offshore platforms, this paper designs a non-contact angle sensor based on machine vision. Its core lies in transforming the physical quantity of mechanical rotation angle into the continuous trajectory of a high-contrast laser spot on the image plane, achieving angle calculation through high-precision image processing technology. This method fundamentally avoids the reliability degradation caused by brush wear or seal failure of traditional potentiometers or encoders in the high-humidity, salt-spray marine environment, while also eliminating the susceptibility of electromagnetic sensors to strong electromagnetic interference on ships.

2.1.1 Measurement Principle

As shown in Fig. 1, the sensor mainly consists of a rotating part and a fixed part. The core of the rotating part is a precision turntable, whose rotation shaft is rigidly connected to the mechanical shaft of the offshore platform component (e.g., crane slewing bearing shaft) to achieve synchronous rotation. A point laser emitter is mounted on the edge of the turntable. The fixed part includes a high-resolution CMOS image sensor (camera) and its imaging target surface, which are fixed within a housing concentric with the rotation shaft. When the measured shaft drives the turntable to rotate, the laser emitter moves in a circular motion, and its emitted laser beam scans a circular trajectory on the fixed imaging target surface. The image sensor continuously captures spot images, recording a series of pixel coordinates (x_i, y_i) of the spot center in the image coordinate system. These coordinate points should theoretically be distributed on a circle, with each point on the circle corresponding to a unique rotation angle θ_i . By establishing a mapping model between pixel coordinates and rotation angle, real-time, non-contact measurement of the rotation angle is achieved.

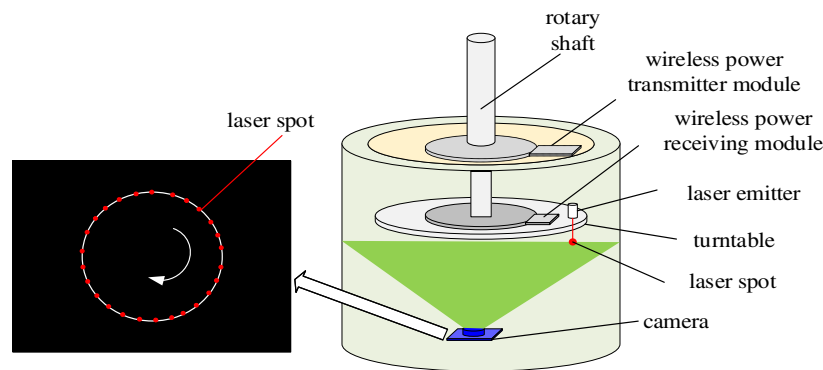


Figure 1: Diagram of the overall structure of the angle sensor.

2.1.2 System Design for Marine Environments

To ensure long-term reliable operation in harsh marine environments, the sensor incorporates specialized design:

- (1) **Mechanical and Sealing Design:** The turntable bearings use high-precision, pre-filled waterproof grease sealed bearings to resist salt spray intrusion. Laser emitter and camera lens windows use optical glass supplemented with O-ring seals. The overall housing protection rating reaches IP67, preventing internal circuits from moisture corrosion.

- (2) **Optical and Imaging Design:** The laser emitter uses a 650 nm wavelength, low-power stabilized point laser module. This wavelength offers good contrast against seawater background and metal structure surfaces. To suppress interference from strong ambient light (especially sunlight) at sea, a narrow bandpass filter (center wavelength 650 nm, bandwidth ± 10 nm) is installed in front of the camera, and the CMOS sensor's High Dynamic Range (HDR) mode is utilized to avoid spot overexposure.
- (3) **Wireless Power and Data Transmission:** To eliminate wear and poor contact risks associated with traditional slip ring power supply on rotating parts, a magnetic resonance-based wireless power module (transmitter at the top and receiver on the turntable in Fig. 1) powers the rotating laser emitter. Processed angle data is transmitted via a low-power wireless module (e.g., Zigbee) fixed on the rotating part to a receiver on the fixed part, then connected to the platform monitoring network.
- (4) **Application Scenario Adaptation:** This sensor can be flexibly installed on various offshore platform rotating mechanisms. For example, installed on the slewing platform of a floating crane to monitor the real-time slewing angle of the boom, preventing interference with surrounding structures; installed on the fairlead shaft of an FPSO mooring line to monitor the payout direction angle of the cable; or used to measure the blade pitch angle of a controllable pitch propeller, providing data for propulsion efficiency optimization.

This design cleverly transforms the complex problem of monitoring marine mechanical motion into a well-controlled visual measurement problem, combining the high reliability of non-contact measurement with the intuitiveness of traditional encoder principles.

2.2 Spot Edge Detection Based on Improved Canny-Kirsch Operator

In the environment of persistent vibration and varying illumination on offshore platforms, obtaining stable and clear spot edges is the primary step to ensure measurement accuracy. Low-frequency vibrations caused by platform engines and wave impact can cause motion blur in spot images, to which edge detection algorithms are highly sensitive. Classical edge detection operators like Sobel and Prewitt use fixed-direction 3×3 gradient templates, responding strongly mainly to horizontal or vertical edges [13–16]. When spot edges become blurred or oriented arbitrarily due to vibration, edges detected by these operators tend to be fractured and discontinuous, severely affecting subsequent center localization accuracy.

The Canny operator, through its multi-stage optimization (Gaussian filtering, gradient calculation, non-maximum suppression, double threshold hysteresis connection), achieves a good balance between noise suppression and edge localization accuracy, widely regarded as an excellent edge detector. However, its gradient calculation typically relies on direction-limited operators like Sobel. The standard Canny operator still faces challenges in edge continuity when processing degraded spot images caused by multi-directional random platform vibration.

To enhance the algorithm's response capability to edges in arbitrary directions and improve robustness in dynamic marine environments, this paper improves the Canny operator by replacing the traditional gradient calculation method with the Kirsch operator.

$$\begin{bmatrix} 5 & 5 & 5 \\ -3 & 0 & -3 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & 5 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & -3 \end{bmatrix} \begin{bmatrix} -3 & -3 & 5 \\ -3 & 0 & 5 \\ -3 & -3 & 5 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & 5 \\ -3 & 5 & 5 \end{bmatrix} \\
 \begin{bmatrix} -3 & -3 & -3 \\ -3 & 0 & -3 \\ 5 & 5 & 5 \end{bmatrix} \begin{bmatrix} -3 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & 5 & -3 \end{bmatrix} \begin{bmatrix} 5 & -3 & -3 \\ 5 & 0 & -3 \\ 5 & -3 & -3 \end{bmatrix} \begin{bmatrix} 5 & 5 & -3 \\ 5 & 0 & -3 \\ -3 & -3 & 5 \end{bmatrix} \quad (1)$$

The Kirsch operator defines eight 3×3 convolution templates corresponding to eight main directions, as shown in Eq. (1) [17]. Each template corresponds to a specific detection direction. Multi-directional detection helps maintain edge continuity, reduce edge fractures, and improve edge detection quality.

To better illustrate the spot image processing procedure, Fig. 2 presents a specific pixel $P(i, j)$ and the gray values of its eight domains.

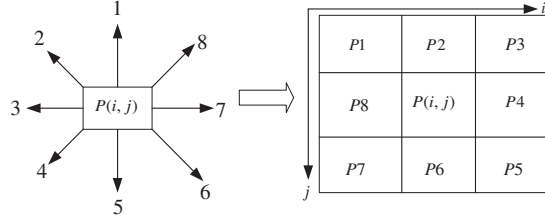


Figure 2: Gray values of $P(i, j)$ and its eight domains.

The gradient value of a pixel point $P(i, j)$ in eight directions is expressed as:

$$\begin{cases} K_1 = 5(P_1 + P_2 + P_3) - 3(P_4 + P_5 + P_6 + P_7 + P_8) \\ K_2 = 5(P_2 + P_3 + P_4) - 3(P_1 + P_5 + P_6 + P_7 + P_8) \\ K_3 = 5(P_3 + P_4 + P_5) - 3(P_1 + P_2 + P_6 + P_7 + P_8) \\ K_4 = 5(P_4 + P_5 + P_6) - 3(P_1 + P_2 + P_3 + P_7 + P_8) \\ K_5 = 5(P_5 + P_6 + P_7) - 3(P_1 + P_2 + P_3 + P_4 + P_8) \\ K_6 = 5(P_6 + P_7 + P_8) - 3(P_1 + P_2 + P_3 + P_4 + P_5) \\ K_7 = 5(P_1 + P_7 + P_8) - 3(P_2 + P_3 + P_4 + P_5 + P_6) \\ K_8 = 5(P_1 + P_2 + P_8) - 3(P_3 + P_4 + P_5 + P_6 + P_7) \end{cases} \quad (2)$$

The calculated maximum value is taken as the gradient value of $P(i, j)$:

$$K_i = \max\{K_1, K_2, K_3, K_4, K_5, K_6, K_7, K_8\} \quad (3)$$

The corresponding edge direction is expressed as:

$$D(i, j) = \{i | K_i \text{ is the maximum value}\} \quad (4)$$

After calculating the gradient magnitudes for eight different directions, the gradient value and edge direction for each pixel in the spot image are obtained. This multi-directional gradient calculation mechanism enables the improved Canny-Kirsch operator to more comprehensively capture intensity changes along the spot contour. Especially when the spot edge is blurred due to vibration, this algorithm can more effectively connect broken edge points.

To verify the feasibility of the improved Canny operator, spot images were collected under both jitter and non-jitter conditions of the angle sensor, and different edge detection algorithms were used for comparison (The simulated vibration was applied using a mechanical shaker to induce low-frequency (1–5 Hz), high-amplitude motion, characteristic of wave-induced platform sway, to test the algorithm's robustness against motion blur.). From Fig. 3, it can be observed that under both jitter and non-jitter conditions, images obtained using the Sobel, Prewitt, and Roberts operators show a small number of scattered spot points. The Canny operator can detect spot edges well, but still shows scattered points under non-jitter conditions and

edge loss under jitter conditions. The improved Canny operator can detect laser edge information well under both jitter and non-jitter conditions. The Kirsch operator is applied prior to Canny detection to enhance edge features, this pre-processing step was chosen for its directional sensitivity, which we hypothesize is beneficial for preserving the edge integrity of the high-contrast laser spot under potential motion blur.

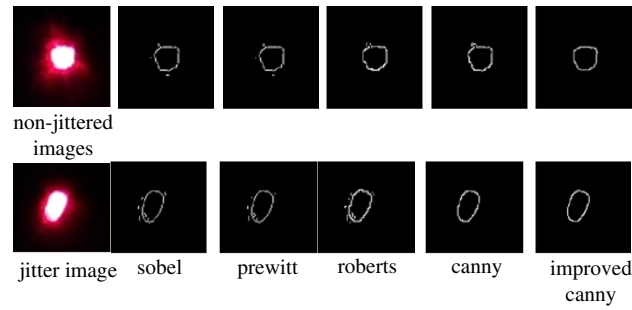


Figure 3: Spot and its edges under jitter and non-jitter conditions.

2.3 Spot Center Localization Based on Least-Squares Ellipse Fitting

Due to the irregularity of offshore platform vibration, the rotating laser spot may appear elliptical on the image sensor due to motion blur. Therefore, using an ellipse model for fitting is more physically realistic and can achieve higher localization accuracy than forcing a circular fit.

After obtaining the binarized spot edge contour point set, this paper employs a direct least-squares ellipse fitting algorithm for center localization. The standard equation of an ellipse is [18]:

$$\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} = 1 \quad (5)$$

where (h, k) are the coordinates of the ellipse center; a and b are the semi-major and semi-minor axes of the ellipse, respectively, as shown in Fig. 4.

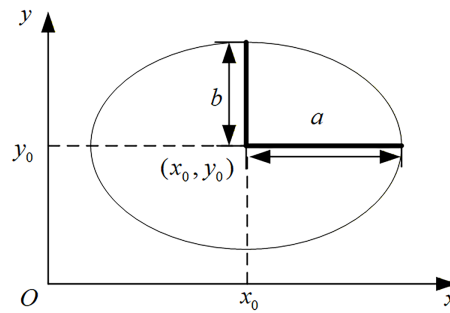


Figure 4: Ellipse schematic diagram.

The goal of the least-squares method is to minimize the sum of squared errors. Let the objective function (error function) S be the sum of squared algebraic distances from data points to the ellipse:

$$S = \sum_{i=1}^n \left[\frac{(x_i - h)^2}{a^2} + \frac{(y_i - k)^2}{b^2} - 1 \right] \quad (6)$$

where (x_i, y_i) represents the coordinates of the i -th data point, and n is the number of data points.

To find the optimal fitting parameters, partial derivatives of the objective function S with respect to h , k , a , b are taken to obtain the gradient vector ∇S :

$$\nabla S = \begin{bmatrix} \frac{\partial S}{\partial h} \\ \frac{\partial S}{\partial k} \\ \frac{\partial S}{\partial a} \\ \frac{\partial S}{\partial b} \end{bmatrix} = \begin{bmatrix} -2 \sum_{i=1}^n \left[\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} - 1 \right] \frac{x_i - h}{a^2} \\ -2 \sum_{i=1}^n \left[\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} - 1 \right] \frac{y_i - k}{b^2} \\ -2 \sum_{i=1}^n \left[\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} - 1 \right] \frac{(x_i - h)^2}{a^3} \\ -2 \sum_{i=1}^n \left[\frac{(x-h)^2}{a^2} + \frac{(y-k)^2}{b^2} - 1 \right] \frac{(y_i - k)^2}{b^3} \end{bmatrix} \quad (7)$$

Here, the gradient components $\frac{\partial S}{\partial h}$ and $\frac{\partial S}{\partial k}$ signify the sensitivity of the fitting error to shifts in the ellipse center, while $\frac{\partial S}{\partial a}$ and $\frac{\partial S}{\partial b}$ correspond to sensitivity against changes in its axes lengths. The descent algorithm adjusts parameters against this gradient to minimize S .

In the gradient descent method, parameters are updated in the direction of the gradient. The update amount $\Delta \partial$ for each iteration is calculated as:

$$\Delta \partial = -\varepsilon \nabla S \quad (8)$$

where ε is the learning rate, controlling the magnitude of parameter updates per iteration. In this paper, $\varepsilon = 0.001$.

The update formulas for h , k , a , b are respectively:

$$\begin{cases} \Delta h = -\eta \frac{\partial S}{\partial h} \\ \Delta k = -\eta \frac{\partial S}{\partial k} \\ \Delta a = -\eta \frac{\partial S}{\partial a} \\ \Delta b = -\eta \frac{\partial S}{\partial b} \end{cases} \quad (9)$$

After each iteration, parameters are updated as:

$$\begin{cases} h = h - \Delta h \\ k = k - \Delta k \\ a = a - \Delta a \\ b = b - \Delta b \end{cases} \quad (10)$$

Through multiple iterations, parameters h , k , a , b gradually approach optimal values, achieving spot center point localization.

To verify the feasibility and applicability of the least-squares-based ellipse fitting algorithm, spot images under different backgrounds were collected: ideal spot on a smooth surface background, unsaturated spot, stepped spot, and spot on a curved background, as shown in [Fig. 5](#).

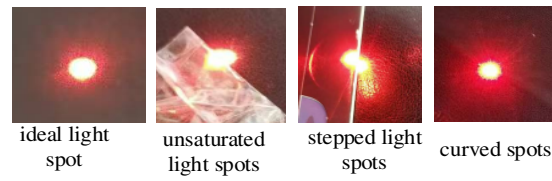


Figure 5: Spot images with different backgrounds.

Then, the gray centroid method, edge detection method, Hough transform method, and least-squares-based ellipse fitting algorithm were used to calculate the center point coordinates of spot images under different backgrounds [19–21]. Results are shown in Table 1.

Table 1: Spot center point coordinate detection results.

Positioning Algorithms	Ideal Light Spot	Unsaturated Light Spots	Stepped Light Spots	Curved Spots
Gray centroid method	(40.8, 43.8)	(40.3, 42.9)	(45.9, 47.9)	(40.9, 42.3)
Edge detection method	(44.2, 41.2)	(36.9, 45.20)	(36.6, 43.3)	(42.7, 40.9)
Hough transform	(44.2, 31.4)	(41.3, 47.3)	(58.6, 18.9)	(37.2, 25.6)
Ellipse-fitting algorithm based on least squares	(41.3, 43.7)	(41.9, 44.1)	(42, 43.4)	(42.7, 42.9)

Note: All coordinate values are in pixels.

From the table, it can be seen that the center coordinates obtained by different algorithms are inconsistent. When the spot shape changes, the coordinates calculated by the gray centroid method, edge detection method, and Hough transform method differ significantly from those of the ideal spot, while the variation of the least-squares-based ellipse fitting algorithm is smaller, indicating greater stability.

Since spot coordinates are two-dimensional data while rotation angle is one-dimensional, to have one angle correspond to one output value, the square root of the spot center pixel coordinates is taken as the output for that point:

$$H_i = \sqrt{x_i^2 + y_i^2} \quad (11)$$

where H_i is the output value (in pixels) of the spot center point. Before the experiment, the theoretical spot center pixel coordinates are unknown, resulting in a certain difference between the theoretical and measured values. Therefore, the residual is introduced to represent their difference:

$$\Delta H = H_i - H' \quad (12)$$

where H' is the average value (in pixels) of the spot center points. The standard error is then calculated using the Bessel formula [22]:

$$\delta = \sqrt{\frac{\sum_{i=1}^n \Delta \chi^2}{n-1}} \quad (13)$$

where n represents the number of measurements (taken as 10 in this paper). Table 2 compares different localization algorithms for ideal spot localization.

Table 2: Comparison of ideal spot center point positioning algorithms.

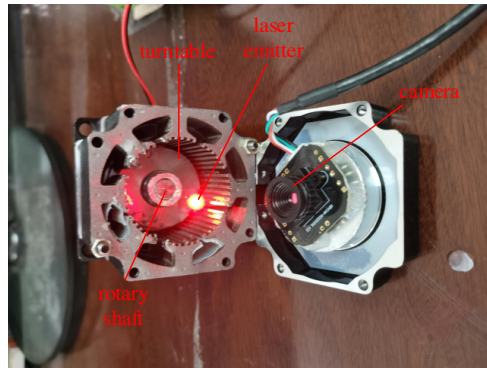
Algorithm	Gray Centroid Method	Edge Detection Method	Hough Transform	Ellipse-Fitting Algorithm Based on Least Squares
Standard deviation	1.84	2.47	6.76	0.64
Average time/s	0.37	1.55	3.88	0.41

From the table, it is observed that the standard deviation and average computation time of the gray centroid method and the least-squares-based ellipse fitting algorithm are lower than the other two methods. Although the least-squares-based ellipse fitting algorithm takes slightly more time than the gray centroid method, its standard error is smaller, indicating that choosing the least-squares-based ellipse fitting algorithm is more suitable.

Beyond motion blur, the algorithm's performance under other marine image degradations was considered. The high contrast of the active laser spot and the intensity thresholding in the Canny step provide inherent robustness against moderate Gaussian noise. Sporadic, pixel-sized occlusions (e.g., from water droplets) are mitigated by the least-squares fitting process, which averages over many edge points. However, sustained, large occlusions covering a significant portion of the spot would require fault-detection logic, a consideration for future software enhancement.

2.4 Image Data Acquisition, System Calibration, and Nonlinear Compensation

To obtain the measured spot coordinates of the designed angle sensor, an experimental platform was set up as shown in Fig. 6.

**Figure 6:** Experimental platform.

A dial with scale is placed at the top of the sensor. Rotating the shaft according to the dial's markings for one full rotation yields the spot motion trajectory, as shown in Fig. 7.

The pixel coordinates corresponding to each rotation angle are calculated, and the square root of these coordinates is taken to obtain the spot coordinate square root H_i , which is then mapped one-to-one with the angle. Fig. 8 shows experimental data obtained after five measurements.

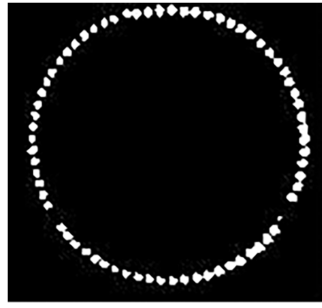


Figure 7: Spot motion trajectory after one rotation.

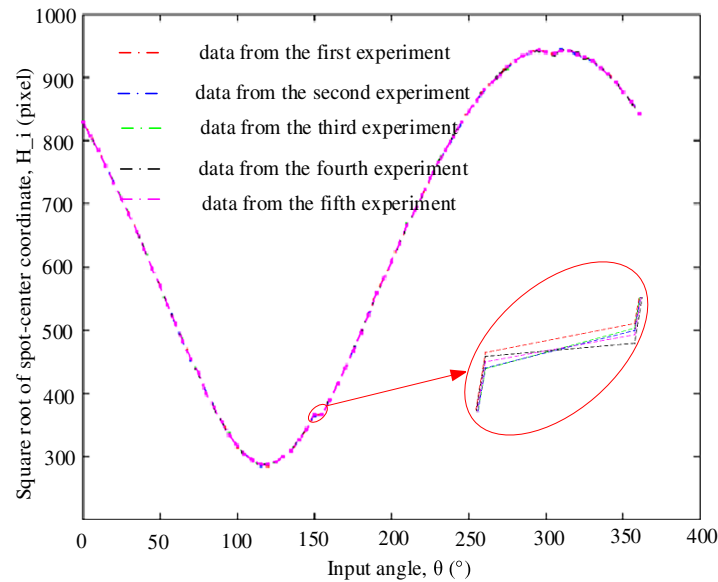


Figure 8: Input angle—coordinate square root curve.

From the figure, it can be seen that the input angle and the square root of the spot center coordinates exhibit nonlinear characteristics, which would lead to inaccurate measurement results. Therefore, to improve measurement accuracy, this nonlinear relationship needs to be compensated.

3 Nonlinear Error Analysis and Compensation

When applying vision-based angle sensors to monitor rotating machinery on offshore platforms, besides the accuracy of image processing algorithms, the overall measurement accuracy of the sensing system is also constrained by systematic errors introduced by factors such as mechanical installation, optical distortion, and environmental interference. Among these, nonlinear error is a key factor affecting the final measurement accuracy. This section aims to analyze in detail the sources of nonlinear error in this sensor system and establish compensation models based on two classic curve fitting methods—Fourier fitting and Polynomial fitting to significantly improve the measurement accuracy and stability of the sensor in simulated marine environments.

3.1 Nonlinear Error Source Analysis and Modeling

The ideal relationship between the sensor output (spot center coordinate square root $H_i = \sqrt{x_i^2 + y_i^2}$) and the input rotation angle (θ_i) should be linear. However, as shown in Fig. 8, the measured data show obvious periodic fluctuations and non-ideal linearity. This nonlinear deviation mainly stems from the following aspects, which are particularly prominent in real marine engineering environments:

- (1) **Mechanical and Installation Errors:** Non-ideal orthogonality between the turntable rotation axis and the image sensor optical axis, laser emitter mounting eccentricity, and bearing clearance introduce periodic sinusoidal or cosine form errors within one mechanical rotation. Such errors are inherent to the system, and their frequency is related to the rotation frequency. Specifically, non-orthogonality between axes introduces a first-order harmonic error, while laser eccentricity contributes to a once-per-revolution circular error in the spot path.
- (2) **Optical System Errors:** Radial and tangential distortion of the camera lens cause nonlinear shifts in image point positions. Although high-quality industrial lenses are used, such distortion cannot be completely eliminated across the entire field of view, especially in edge regions. Although calibrated, residual lens distortion causes a non-linear mapping between physical and image coordinates, especially at the field edges.
- (3) **Environmental Interference:** Vibration and ambient light changes in simulated experiments, as well as temperature gradients and humidity changes faced in real marine environments, may cause fluctuations in laser output power and changes in CMOS sensor dark current, introducing random and slow drift errors into the signal. Vibration primarily induces motion blur, affecting edge detection precision. Temperature gradients can alter the laser diode's output and the sensor's responsivity. While the narrowband filter mitigates ambient light, extreme direct sunlight could lead to local sensor saturation (blooming), distorting the spot shape. The designed algorithms (e.g., ellipse fitting) and hardware (HDR mode) provide a degree of robustness against these effects.

To quantify and compensate for these errors, precise mathematical modeling is first required. Fourier series, due to its strong ability to describe periodic signals, is first used to analyze and fit the initial nonlinear output curve. Any periodic function can be expressed as a sum of a series of sine and cosine functions. Assuming the sensor's original output data $f(x)$ is periodic, it can be expanded into a Fourier series [23]:

$$f(x) = \frac{a_0}{2} + \sum_{n=1}^{\infty} [a_n \cos(nx) + b_n \sin(nx)] \quad (14)$$

where a_0 is the DC component; a_n and b_n are Fourier coefficients; n is the frequency (Hz). Fourier coefficients a_n and b_n are calculated by integrating the original data:

$$\begin{cases} a_n = \frac{1}{T} \int_T f(x) \cos(nx) dx \\ b_n = \frac{1}{T} \int_T f(x) \sin(nx) dx \end{cases} \quad (15)$$

where T is the length of the data period (s).

By minimizing the residual sum of squares, the optimal Fourier coefficients a_n and b_n can be determined. The residual sum of squares is defined as:

$$S = \sum_{i=1}^N \left\{ f(x_i) - \frac{a_0}{2} - \sum_{n=1}^{\infty} [a_n \cos(nx_i) + b_n \sin(nx_i)] \right\}^2 \quad (16)$$

where N is the number of data points.

Through multiple MATLAB simulations, it was found that when the number of fitting terms is 5, the coefficient of determination reaches 0.9999. Increasing the number of terms leads to overfitting. Fig. 9 shows a comparison between the original curve and the fitted curve.

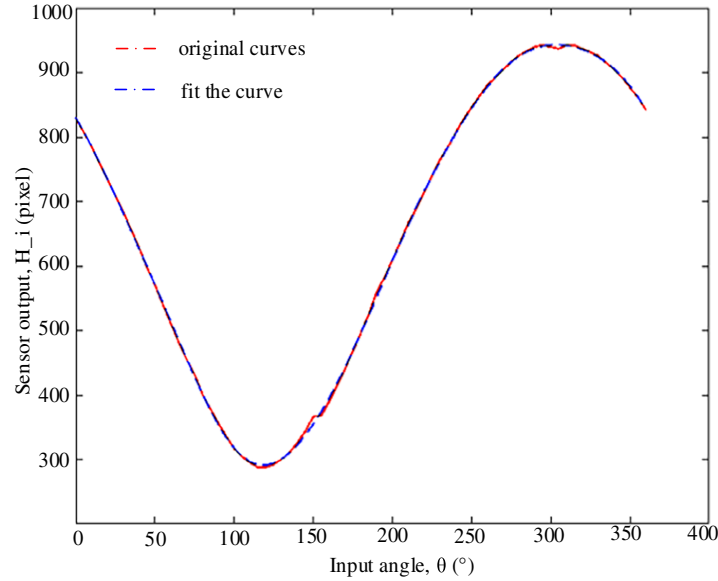


Figure 9: Comparison between the original curve and the fitting curve.

The corresponding fitted curve is:

$$\begin{aligned}
 f(x) = & 749.0565 + 164.9623 \cos(0.0173x) - 277.5539 \sin(0.0173x) \\
 & + 0.0173x \cos(0.0346x) + 23.8473 \sin(0.0346x) - 3.6014x \cos(0.0519x) \\
 & + 1.1915x \sin(0.0519x) - 0.2077x \cos(0.0692x) - 2.3398x \sin(0.0692x) \\
 & + 1.6092x \cos(0.0865x) - 1.6448x \sin(0.0865x)
 \end{aligned} \quad (17)$$

For each data point, the nonlinear error e_i is the difference between the actual output $f(x_i)$ and the theoretical output $f'(x_i)$ (fitted value) [24]:

$$e_i = |f(x_i) - f'(x_i)| \quad (18)$$

The average nonlinear error is obtained by calculating the sum of nonlinear errors for all data points and dividing by the number of data points:

$$\bar{e} = \frac{\sum_{i=1}^N e_i}{N} \quad (19)$$

The standard deviation of the nonlinear error is then calculated to evaluate the fluctuation of the nonlinear error:

$$\sigma_e = \sqrt{\frac{\sum_{i=1}^N (e_i - \bar{e})^2}{N - 1}} \quad (20)$$

As shown in Fig. 10, based on experimental data, the average nonlinear error of the angle sensor is calculated to be 1.96, with a standard deviation of 1.97. This indicates that the deviation between the sensor output and the true angle value has significant fluctuation, and the nonlinear error is unstable, mainly influenced by mechanical errors and environmental interference.

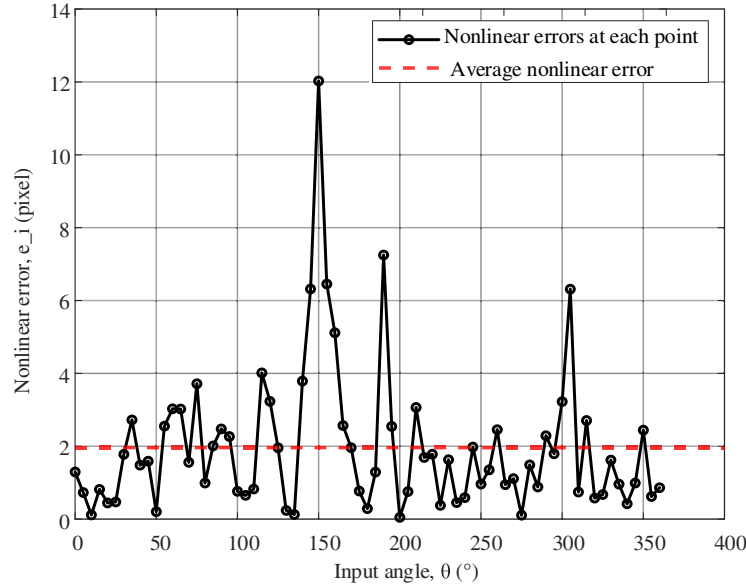


Figure 10: The curve of nonlinear errors.

3.2 Nonlinear Compensation Based on Polynomial Curve Fitting

Although Fourier fitting can accurately describe nonlinear characteristics, its model form is complex, making real-time inversion (i.e., obtaining input θ from output H) difficult in embedded systems. For sensor calibration and real-time compensation, establishing a concise, invertible mapping model from input angle x to ideal linear output y is more practical. Polynomial curve fitting is widely used in sensor nonlinear correction due to its simple model and computational efficiency.

To enable intelligent sensor calibration, a data-driven modeling approach is employed. Specifically, polynomial curve fitting is utilized due to its simple model and computational efficiency. Polynomial curve fitting is a mathematical tool used to find a curve that best fits a set of observed data. This curve can describe relationships between data, predict unknown data points, or extract signals from noise. By selecting an appropriate function form (e.g., linear, polynomial, exponential, logarithmic) and using optimization techniques like least squares to determine function parameters, the curve is made to approximate all data points as closely as possible, achieving data smoothing, trend analysis, or error correction.

We adopt an n -th degree polynomial to establish the relationship between the input angle x (unit: °) and the expected, compensated output $y(x)$ (i.e., the theoretical linear value of the spot coordinate square root, unit: pixel) [25]:

$$y(x) = a_0 + a_1x + a_2x^2 + \dots + a_nx^n \quad (21)$$

where $y(x)$ is the sensor output (spot coordinate square root); x is the actual input angle; $a_0, a_1, \dots, a_n$ are polynomial coefficients. The least squares method is used to find the optimal polynomial coefficients. The error function is:

$$E = \sum_i^m [y_i - y(x_i)]^2 \quad (22)$$

where m is the number of data points; y_i is the actual output of the i -th data point; $y(x_i)$ is the polynomial model's predicted output at the i -th data point.

The least squares method is used to estimate polynomial model parameters $a_0, a_1, \dots, a_n$. A matrix A and a vector b are created, where:

$$A = \begin{bmatrix} x_1^n & x_1^{n-1} & \cdots & x_1^1 & x_1^0 \\ x_2^n & x_2^{n-1} & \cdots & x_2^1 & x_2^0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ x_N^n & x_N^{n-1} & \cdots & x_N^1 & x_N^0 \end{bmatrix} \quad (23)$$

$$b = \begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_N \end{bmatrix} \quad (24)$$

Each element A_{ij} in matrix A corresponds to the j -th power of x_i , and vector b contains the actual output values.

The linear system of equations $Aa = b$ is solved using least squares, where $a = [a_n, a_{n-1}, \dots, a_1, a_0]^T$. This is achieved by solving for the inverse matrix $(A^T A)^{-1}$ of $A^T A$, then multiplying by A^T to obtain the parameter vector a :

$$a = (A^T A)^{-1} A^T b \quad (25)$$

The estimated parameters $a_0, a_1, \dots, a_n$ are then used to calculate the compensated output $y(x)$.

3.3 Compensation Effect Evaluation and Application Analysis in Smart Monitoring

The compensated data are shown in Table 3.

Table 3: Nonlinear compensation results and their fitting values.

$\theta/(^{\circ})$	0	5	10	15	20	...	345	350	355	360
F1	928.79	907.40	884.77	859.15	833.93	...	992.29	976.32	961.41	942.30
F2	930.24	906.52	882.77	858.81	834.42	...	993.21	979.42	962.32	940.4
F3	931.91	905.34	881.09	857.76	834.31	...	990.57	976.18	960.6	944.23
$ \Delta F $	2.75	1.45	2.46	1.85	0.65	...	1.85	2.46	1.45	2.75

In the table: θ represents the calibration angle value; F_1 is the measured value of the spot coordinate square root; F_2 is the spot coordinate square root after nonlinear compensation; F_3 is the fitted value of F_2 ; ΔF is the difference between F_3 and F_2 .

According to Eqs. (18)–(20), after nonlinear compensation, the sensor's average nonlinear error is 1.13, and the standard deviation is 1.24, reduced by 0.83 and 0.73, respectively compared to before compensation. This indicates that the sensor's output data is more accurate after compensation, significantly improving measurement accuracy and stability.

For marine engineering applications, this nonlinear compensation holds significant value:

- (1) **Improving Long-Term Monitoring Reliability:** Rotation angle monitoring of offshore platform machinery often requires continuous operation for months or even years. Systematic nonlinear errors, if not compensated, can accumulate over time, causing unacceptable drift in angle readings. The compensation model can effectively suppress this systematic bias, ensuring long-term data reliability.
- (2) **Enhancing Environmental Adaptability:** Although the compensation model is calibrated in the laboratory, its core purpose is to correct the inherent nonlinearity determined by mechanical installation and the optical system. Once calibrated, this model is relatively insensitive to output “shift” or “scale” changes caused by slow-varying environmental factors like temperature and humidity. Major slow-varying errors can be addressed through periodic zero-point calibration, while rapidly changing vibration noise is filtered out by the aforementioned image processing algorithms. This ensures output stability of the sensor in the variable marine environment.
- (3) **Meeting High-Precision Control Requirements:** Many offshore platform rotating mechanisms, such as thruster rudder angles in dynamic positioning systems and automatic control systems for cranes, require angle feedback with high accuracy and linearity. After compensation, the linearity of the sensor output is greatly improved, better meeting the input requirements of closed-loop control systems.

This section reveals the periodic characteristics of the system's nonlinear error through Fourier analysis and successfully applies polynomial least-squares fitting to establish an efficient nonlinear compensation model. Experiments prove that this model can effectively suppress systematic nonlinear errors, enabling the sensor's comprehensive performance to meet the urgent need for high-precision, high-stability condition monitoring of critical rotating components in the field of marine engineering.

4 Experimental Analysis and Marine Environmental Adaptability Verification

To comprehensively evaluate the performance of the image recognition-based angle sensor designed in this paper under simulated marine engineering environments, systematic experimental analysis is conducted. The experiments aim to verify the sensor's basic performance indicators, quantify its measurement accuracy, compare it with existing technologies, and finally discuss its applicability and potential advantages in real offshore platform rotating component monitoring scenarios.

Experimental setup and conditions: All performance tests were conducted in a laboratory environment. To evaluate the system's robustness under conditions simulating key marine stressors, the prototype was subjected to controlled disturbances during specific tests: (i) Vibration: The test bench was mounted on a shaker to introduce low-frequency (1–5 Hz) motion blur, simulating wave-induced platform sway. (ii) Lighting: Variable ambient light intensity was used to test the effectiveness of the optical filter and HDR mode. (iii) Repetition: All static performance tests (sensitivity, resolution, repeatability, hysteresis) were repeated five times to ensure statistical reliability. The core measurement setup, as shown in Fig. 6, consisted of a high-precision indexing head (reference), the prototype sensor, and a data acquisition system.

4.1 Performance Testing and Marine Engineering Applicability Analysis

The sensor's core performance indicators, such as sensitivity, resolution, repeatability, and hysteresis, directly determine the reliability and effectiveness of its monitoring data in harsh marine environments. These indicators are evaluated based on the principles of relevant test standards from organizations like the International Electrotechnical Commission (IEC) for marine and offshore environmental measurement equipment. Based on the reference angle provided by a high-precision indexing head and the output signal

(spot center coordinate square root H_i) collected by the sensor, key performance parameters are calculated as follows:

(1) Sensitivity

Sensitivity reflects the sensor's ability to respond to minute changes in input angle, crucial for monitoring subtle changes or early fault indicator of offshore platform rotating machinery (e.g., steering gear, crane slewing mechanisms). It is defined as the ratio of output change to input change. Taking the change value at $0 \sim 1^\circ$ as an example [26]:

$$S_i = \lim_{\Delta\theta_i \rightarrow 0} \frac{\Delta H_i}{\Delta\theta_i} = \frac{925.83 - 930.08}{1 - 0} = 4.25 \text{ Counts}/^\circ \quad (26)$$

where $\Delta\theta_i$ represents the input angle change at measurement point i ; ΔH_i is the corresponding change in output value. This sensitivity is directly related to the radius of the laser spot's circular path on the image sensor; a larger radius would yield a higher sensitivity. The negative sign indicates the output decreases as the input increases, with an absolute value of 4.25 Counts/ $^\circ$. Higher sensitivity indicates the sensor can effectively capture small angle change of rotating components, meeting the needs of high-precision control and condition monitoring.

(2) Resolution

Resolution determines the smallest angle change the sensor can be detected, key to evaluating its ability to detect subtle motion or vibration. Testing across the sensor's full range, by gradually reducing the input angle change until an identifiable change in the output signal is observed, determines the minimum resolvable angle [26]:

$$R = \max |\Delta\theta_{i,min}| = |-0.0017| = 0.0017^\circ \quad (27)$$

where $\Delta\theta_{i,min}$ represents the minimum input change at measurement point i that causes a change in the output quantity; $\max |\Delta\theta_{i,min}|$ is defined as the minimum change in the input quantity that can be detected in the output over the entire operating range. This resolution (approximately 6.12 arc s) is sufficient to monitor the steady-state working angles and subtle vibration of most offshore platform rotating machinery, superior to many traditional potentiometer-type sensors.

(3) Repeatability Error

Repeatability error measures the consistency between results obtained from consecutive measurements of the same input quantity under the same measurement conditions. For marine applications requiring long-term, stable monitoring, low repeatability error implies higher data credibility. The calculation formula is [27]:

$$E = \frac{H_{\max}}{Y_{FS}} \times 100\% = \frac{12}{655} \times 100\% = 1.83\% \quad (28)$$

where $H_{\max}$ is the maximum output error; Y_{FS} is the sensor's maximum output value across the entire range. This error mainly originates from random factors, such as image sensor noise, subtle hysteresis in mechanical structure, and ambient light fluctuations.

(4) Hysteresis Error

Hysteresis error reflects the difference in output values for the same input angle between the forward (angle increasing) and reverse (angle decreasing) travel. Marine platform equipment like steering gears and

valve actuators often require reciprocating motion, making low hysteresis essential for ensuring bidirectional control accuracy. The calculation formula is [27]:

$$E = \frac{\Delta H_{\max}}{Y_{FS}} \times 100\% = \frac{7.16}{655} \times 100\% = 1.09\% \quad (29)$$

where $\Delta H_{\max}$ is the maximum difference between forward and reverse measurement output values. This error mainly originates from friction and gap in the mechanical turntable bearings.

The above calculation results show that the designed sensor has high sensitivity (4.25 Counts/°) and high resolution (0.0017°), capable of responding to minute angle changes. Repeatability error (1.83%) and hysteresis error (1.09%) are within acceptable ranges but indicate directions for further optimization, such as using higher precision bearings and optimizing mechanical structure to reduce friction. Overall, these basic performance indicators demonstrate that the sensor principle is suitable for high-precision angle measurement applications, laying a foundation for its application in the field of marine engineering.

4.2 Measurement Error Analysis and Discussion on Marine Environmental Influencing Factors

While the IP67 housing and optical filter mitigate common issues, extreme field conditions like persistent salt crust formation on the lens or rapid thermal cycling could influence long-term stability. For extended maritime deployment, future iterations could integrate passive solutions like hydrophobic coatings or active measures such as a protective purge system to maintain optical clarity. The system's software could also include diagnostic routines to flag image quality degradation.

To verify the sensor's absolute measurement accuracy, the output of a calibrated high-precision Hall effect angle sensor (accuracy better than 0.05°) is used as the reference true value. Within the full range of 0° to 360°, 360 sets of comparative data were collected at equal intervals. Some experimental data are shown in Table 4.

Table 4: Partially describes the test data.

Serial Number	Hall Angle Sensor Angle/(°)	The Angle Sensor Designed in This Paper/(°)	Difference/(°)
1	1.0	1.9	0.9
2	2.3	3.0	0.7
3	3.5	4.3	0.8
⋮	⋮	⋮	⋮
358	358.2	357.7	0.5
359	359.6	358.5	1.1
360	360.0	359.4	0.6
Measurement accuracy			0.9

Based on all 360 sets of data, the root mean square error (RMSE) between this sensor's measurement results and the reference values is calculated to be 0.9°, which is defined as the sensor's measurement accuracy. This 0.9° measurement accuracy is mainly limited by the following factors in the current prototype, which are particularly important in real marine environments:

- (1) **Mechanical Installation and Machining Precision:** Mechanical errors such as non-ideal orthogonality between the turntable rotation axis and the image sensor optical axis, laser emitter mounting

eccentricity, and bearing radial runout are the main sources of systematic error. In marine vibration environments, these mechanical clearances may worsen, affecting long-term stability.

- (2) **Environmental Temperature Influence:** Temperature changes cause thermal expansion and contraction of metal mechanical structures, altering the optical arm length (distance from laser emitter to imaging surface), and may affect the pixel response of the CMOS image sensor, leading to output drift. Large daily and seasonal temperature variations on offshore platforms make temperature drift compensation a necessary issue for future engineering.
- (3) **Ambient Light and Vibration Interference:** Although narrowband filters and active laser source are used, strong direct sunlight or periodic shadows under extreme conditions may still affect image contrast. Additionally, persistent low-frequency vibration of the platform may cause slight blurring of spot images. Although the algorithm has certain robustness, accuracy may decline under extreme vibration.

To further validate the feasibility of this approach, the average absolute error (MAE), root mean square error (RMSE), maximum error (Max Error), and standard deviation (STD) of the sensor were calculated as 0.9000, 0.9182, 1.3000, 0.9195, and 0.9000, respectively. Histograms or residual curves were plotted, as shown in Fig. 11.

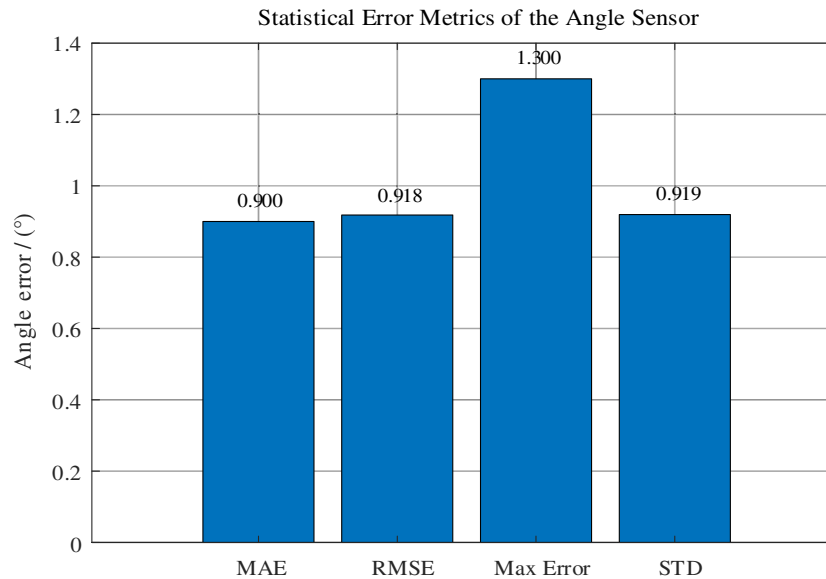


Figure 11: Comparison of various errors of the angle sensor.

A discussion on measurement uncertainty contextualizes the reported performance. The overall uncertainty stems from Type A (random) components, such as noise in image localization under vibration, reflected in the repeatability error, and Type B (systematic) components, including residual nonlinearity after compensation and reference sensor accuracy, reflected in the measurement accuracy. The propagation of pixel coordinate errors through the polynomial mapping model was inherent in the calibration process. For long-term reliability in harsh environments—a critical concern for offshore applications—the system’s design addresses key failure modes: IP67 sealing prevents moisture ingress, corrosion-resistant materials are used, and wireless transmission eliminates slip-ring wear. Future work will involve a rigorous uncertainty budget analysis and long-term field trials to fully quantify measurement reliability, informed by uncertainty quantification frameworks established for vision-based structural measurement systems [28].

4.3 Comparative Analysis with Existing Angle Sensing Technologies

Comparing the sensor designed in this paper with other angle sensors reported in recent literature helps objectively position its technical level. Comparison results are shown in Table 5, focusing on the core indicator of measurement accuracy.

As shown in Table 5, the smart angle sensing system proposed in this paper achieves a measurement accuracy of 0.900° , which is superior to the image-recognition-based sensor in Reference [2] and the magnetic-induction sensor in Reference [29], although it is slightly lower than the optical-fiber angle sensors in References [30,31]. However, from the perspective of comprehensive engineering applicability, the proposed sensor exhibits a more balanced performance profile.

Compared with magnetic-induction sensors, the proposed vision-based scheme has stronger immunity to electromagnetic interference, which is particularly beneficial for offshore machinery operating near motors, power cables, and frequency converters. Compared with optical-fiber angle sensors, although the present prototype shows slightly lower measurement accuracy, it avoids the relatively complex optical-fiber coupling and signal-conditioning structure, and maintains favorable robustness in harsh marine environments through non-contact laser-spot measurement, sealed structural design, and image-based signal extraction. Compared with the image-recognition-based sensor in Reference [2], the proposed system further improves measurement accuracy while preserving the inherent advantages of visual sensing, such as non-contact operation and high electromagnetic compatibility.

Therefore, the proposed smart angle sensing system is not only competitive in terms of measurement accuracy, but also shows clear advantages in electromagnetic interference resistance, environmental robustness, and long-term monitoring suitability, making it a promising solution for angle monitoring of offshore rotating machinery.

Table 5: Performance comparison of various angular sensors.

Source of Angle Sensor	Sensing Principle	Measurement Accuracy	Cost	Power Consumption	EMI Immunity	Installation Convenience	Maintenance	Environmental Robustness
Reference [2]	Image-recognition-based angle sensor	2.624°	Medium	Medium	High	Medium	Medium	Medium
Reference [30]	Optical-fiber angle sensor	0.269°	High	Low	High	Medium	Low	High
Reference [31]	Optical-fiber angle sensor	0.677°	High	Low	High	Medium	Low	High
Reference [29]	Magnetic-induction angle sensor	2.000°	Low	Low	Medium	High	Low	Medium
Smart angle sensing system proposed in this paper	Laser-spot vision-based angle sensor with data-driven calibration	0.900°	Medium	Medium	High	Medium	Low-Medium	High
Source of angle sensor	Sensing principle	Measurement accuracy	Cost	Power consumption	EMI immunity	Installation convenience	Maintenance	Environmental robustness

5 Conclusion

This study presented a novel vision-based sensing system for robust angle measurement of offshore rotating machinery. The work can be concluded with the following three points:

(1) **Achieved Performance and Contributions:** An integrated smart sensing scheme was proposed, transforming angular measurement into a laser spot tracking task. A robust image processing pipeline combining an enhanced Canny-Kirsch operator and ellipse fitting was developed. Through data-driven

polynomial compensation, the system achieved a measurement accuracy of 0.9° with good sensitivity, resolution, and repeatability under laboratory-tested conditions.

(2) **Comparative Advantages:** The system's primary advantage is its inherent immunity to electromagnetic interference and reduced susceptibility to environmental factors like humidity compared to traditional contact-based or electromagnetic encoders, addressing key reliability concerns in marine settings.

(3) **Limitations and Future Work:** The main limitation is the validation under simulated rather than real, long-term offshore field conditions. Future work will therefore focus on: (i) extended field trials on operational platforms to validate long-term reliability and robustness; (ii) further investigation of performance under extreme, combined environmental stressors; and (iii) miniaturization and power optimization for wider deployment.

The proposed system demonstrates a promising and practical approach for the structural health monitoring of critical marine infrastructure.

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Abbreviations

The following abbreviations are used in this manuscript:

SHM	Structural Health Monitoring
CMOS	Complementary Metal-Oxide-Semiconductor
FPSOs	Floating Production Storage and Offloading units
HDR	High Dynamic Range
IEC	International Electrotechnical Commission

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