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Research on Error Characteristics and Fusion Optimization of MEMS Sensor for Manipulator

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Abstract. With the rapid development of Industry 4.0 and intelligent manufacturing, lightweight collaborative manipulators are increasingly used in precision assembly, intelligent sorting, flexible handling and human-robot collaboration, and their operating accuracy and stability depend heavily on the detection performance of MEMS sensors. However, factors such as ambient temperature fluctuations, mechanical vibration, and long-term accumulated deviation often cause MEMS sensors to experience zero-point drift, data jitter, and detection bias. Moreover, the limitations inherent in single-sensor systems can further amplify operational errors, thereby restricting the precision capabilities of small- and medium-sized manipulators. To address this problem, this paper takes small- and medium-sized collaborative manipulators as the research object, systematically studies the error mechanism and coupling characteristics of MEMS inertial sensors, force sensors and infrared ranging sensors, and proposes an integrated optimization scheme from three dimensions: hardware calibration, algorithmic filtering and multi-sensor fusion. The results show that, compared with the conventional single-sensor detection and mean-filtering scheme, the proposed integrated optimization scheme reduces the static attitude angle error by 62.4%, the dynamic trajectory error by 44.2%, and the compliant grasping force error by 67.6%, while the workpiece slippage and damage rates are both reduced to zero. This significantly improves the manipulator's positioning accuracy, motion stability and compliant operation capability, providing a theoretical basis and technical reference for error optimization and engineering application of MEMS sensing systems in manipulators.

Keywords: Manipulator, MEMS sensor, Error characteristics, Multi-sensor

1. Introduction

With the rapid development of Industry 4.0 and smart manufacturing, collaborative and lightweight industrial robots are increasingly used in precision assembly, intelligent sorting, flexible material handling, and human-robot collaboration. Their operational accuracy and stability depend strongly on the performance of sensing systems. Compared with traditional mechanical and strain-gauge sensors, MEMS sensors offer advantages such as small size, low power consumption, low cost, fast response, and easy integration [1], making them well suited for lightweight robotic arms.

Modern robotic arms commonly employ MEMS inertial sensors, force sensors, and infrared ranging sensors for attitude estimation, force control, and distance detection. However, under

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practical operating conditions, temperature fluctuations, mechanical vibration, and long-term operation can introduce zero-point drift, data noise, and measurement bias. In addition, the limitations of individual sensors can further reduce the accuracy and reliability of robotic perception. Therefore, effective error compensation and multisensor optimization are important for improving the performance of small- and medium-sized robotic arms.

Research on MEMS sensing technologies for robotic applications has developed rapidly. Studies have investigated sensor structural optimization, calibration methods, and noise-reduction algorithms, while techniques such as Kalman filtering and adaptive fusion have been applied to improve robotic pose and motion estimation [2]. However, systematic studies combining multidimensional error analysis, low-cost sensor calibration, operating-condition-adaptive filtering, and multisensor fusion remain relatively limited for small- and medium-sized collaborative robotic arms.

To address these issues, this paper investigates the error characteristics of MEMS inertial, force, and infrared ranging sensors and proposes an integrated optimization scheme combining hardware calibration, adaptive filtering, and multisensor fusion. A MATLAB-based simulation platform is developed to evaluate the proposed method under static positioning, dynamic trajectory tracking, and flexible grasping conditions. The results demonstrate its effectiveness in reducing sensor errors and improving the positioning accuracy, motion stability, and compliant operation capability of robotic arms.

2. Fundamentals of MEMS sensors and error optimization strategies

2.1. Fundamentals of robotic arms and MEMS sensors

Lightweight collaborative robotic arms primarily consist of a mechanical structure, drive modules, a control system, a sensing system, and an end-effector. Their motion accuracy depends not only on the control system but is also closely related to the quality of the sensing data. This paper focuses on small- and medium-sized collaborative robotic arms, with an emphasis on the reliable detection of their state information, such as posture, distance, and gripping force.

MEMS sensors, which rely on micro- and nanofabrication technologies, integrate micro-mechanical structures, sensing units, and signal processing circuits onto a small chip. They are characterized by their compact size, low power consumption, fast response, and relatively low cost, making them well suited for installation in the limited space available in lightweight robotic arms. This paper primarily focuses on MEMS inertial sensors, force sensors, and infrared ranging sensors, which are used for attitude, force, and distance detection, respectively [3], with temperature and humidity data used to assist in temperature-error compensation.

Robotic arm perception systems can employ either single-sensor detection or multi-sensor fusion. A single-sensor system is simple in structure but is susceptible to drift, vibration, and environmental changes; multi-sensor fusion, on the other hand, leverages the complementary information from different sensors to cross-calibrate attitude, distance, and force data, thereby laying the foundation for subsequent error optimization and closed-loop control.

2.2. Major errors and general optimization approach

Based on the actual operation of robotic arms, the primary sources of error in MEMS sensors include zero-point drift, temperature drift, random noise caused by mechanical vibrations, and interference from external acceleration on inertial measurement results during dynamic motion [4].

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Among these, zero-point and temperature drifts cause static attitude deviations to increase over time, while external acceleration and random noise during motion reduce the stability and accuracy of attitude estimates. Existing research has shown that the impact of errors in MEMS inertial sensors under dynamic conditions can be effectively reduced through sensor bias calibration, as well as methods such as filtering and fusion.

2.3. Hardware calibration and operating condition-adaptive filtering

At the hardware level, the system primarily addresses three types of disturbances: zero-point, temperature, and vibration [5]. After the robotic arm is powered on, it remains idle without a load for 3 seconds to automatically capture the initial output and calculate the zero-point offset, thereby achieving rapid zeroing. At the same time, temperature sensor data are used to establish a temperature-error compensation model, which is then applied in real time to inertial and force-sensing measurements to reduce errors caused by ambient temperature variations. The sensors are mounted using a combination of silicone shock absorption and rigid mounting, which ensures installation stability while attenuating high-frequency vibrations and impacts.

At the algorithmic level, differentiated filtering strategies are employed based on the operational state. Complementary filtering is used during static or low-speed fine-tuning to smooth attitude and force detection data with lower computational overhead; Kalman filtering is employed during high-speed motion, dynamic grasping, and reciprocating trajectory operations to suppress random noise and dynamic jitter through state estimation [6]. Compared to uniformly using mean filtering, this approach of selecting filtering methods based on operating conditions strikes a balance between the computational cost of the embedded platform and the accuracy of dynamic detection.

2.4. Improvements in multisensor fusion

After basic calibration and filtering, data from three sensor types—inertial, force-sensing, and infrared ranging—are further fused in a hierarchical manner. The inertial sensors provide basic attitude and motion trajectories; infrared ranging data are used to correct spatial position deviations and help compensate for long-term error accumulation, while also supporting obstacle distance estimation; force sensors are used to detect changes in the force applied to the end-effector and to adjust the gripping force and motion posture based on the force status, thereby identifying potential workpiece slippage [7-9].

The multisensor data are processed through weighted fusion and outlier removal, allowing measurements from different sensors to be cross-validated. The resulting processing chain can be summarized as "acquisition—calibration—filtering—fusion—control." This approach retains the original low-cost hardware configuration while integrating hardware compensation, adaptive filtering, and multisensor fusion.

3. Simulation/experimental validation and results analysis

3.1. Simulation platform and parameter settings

To verify the effectiveness of the hardware calibration, algorithmic filtering and multi-sensor fusion optimisation schemes described in this paper, a MATLAB-based simulation system for a small- to medium-sized six-axis collaborative robotic arm was developed to reproduce representative operating conditions. At the core of the experimental platform are an MPU6050 MEMS six-axis

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inertial sensor [10], a miniature MEMS piezoresistive force sensor, an infrared distance sensor and an accompanying temperature and humidity sensor module, all adapted to the motion parameters of a desktop-class, lightweight six-axis robotic arm.

The simulation and experimental parameters were standardized as follows: sensor sampling frequency of 100 Hz, standard robotic arm movement speed of 0.2 m/s, maximum operating radius of 0.5 m, and standard operating temperature range of 0°C to 45°C; Artificial errors simulating real-world operating conditions were introduced, including gyroscope zero drift of 0.05°/s, accelerometer noise of ±0.02 g, a temperature drift coefficient of 0.001°/(s·°C), and high-frequency mechanical vibration noise. Two sets of control systems were established for the experiment: the control group employed a traditional single-sensor detection and mean-value filtering scheme, while the experimental group utilized the hardware calibration, hierarchical filtering, and multi-sensor fusion optimization scheme described in this paper. All experimental conditions and parameters were kept consistent to ensure the fairness and rigor of the comparison.

3.2. Comparative experimental design

To evaluate the overall performance of the proposed optimization scheme, this paper conducts three comparative experiments under three representative operating conditions—static, dynamic, and practical operation—for the robotic arm, in order to quantitatively evaluate the optimization results.

Experiment 1: Static Positioning Accuracy Experiment. The robotic arm was maintained at a fixed position, and pose data were continuously collected for 30 seconds. The angular offsets and data fluctuation ranges of the control group and the experimental group were compared to verify the effectiveness of the optimization scheme in suppressing zero-point drift and static noise.

Experiment 2: Dynamic Trajectory Motion Error Experiment. The robotic arm was controlled to follow a continuous sinusoidal reciprocating trajectory to simulate dynamic industrial operating conditions. The trajectory deviation and standard deviation of dynamic pose errors were recorded for the two approaches to evaluate the effectiveness of hierarchical filtering in suppressing vibration-induced noise and cumulative errors during dynamic motion.

Experiment 3: Flexible Gripping Stability Experiment. A standard fragile-workpiece gripping task was set up, and the gripping experiment was repeated 20 times. The gripping force measurement errors, workpiece slippage failure rates, and workpiece breakage rates for the two approaches were recorded to verify the effectiveness of the multi-sensor fusion approach in enhancing the robotic arm's flexible gripping performance.

3.3. Experimental results and analysis

After completing the three sets of experiments, statistical analysis of the experimental data was performed using three quantitative metrics: maximum absolute error (MAE), mean squared error (MSE), and standard deviation of error. The differences in performance before and after optimization were visually compared using data tables and waveform diagrams. The summarized results of the quantitative comparison for the three sets of experiments are shown in Table 1.

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Table 1. Summary of quantitative results from the three comparative experiments

Experimental Projects	Indicators	Control Group	Experimental Group	Degree of Improvement
Experiment 1: Static Positioning (30 s)	Posture Angle MAE (°)	0.744	0.280	62.4%↓
	MSE	0.701	0.122	—
	STD (°)	0.384	0.350	—
Experiment 2: Dynamic Trajectory (20 s)	Position MAE (m)	0.0180	0.0100	44.2%↓
	MSE	4.4×10^{-4}	1.6×10^{-4}	—
	STD (m)	0.0108	0.0125	—
Experiment 3: Flexible Grasping (20 repetitions)	Clamping Force MAE (N)	0.358	0.116	67.6%↓
	Slip Error Rate	20.0%	0.0%	—
	Damage Rate	5.0%	0.0%	—

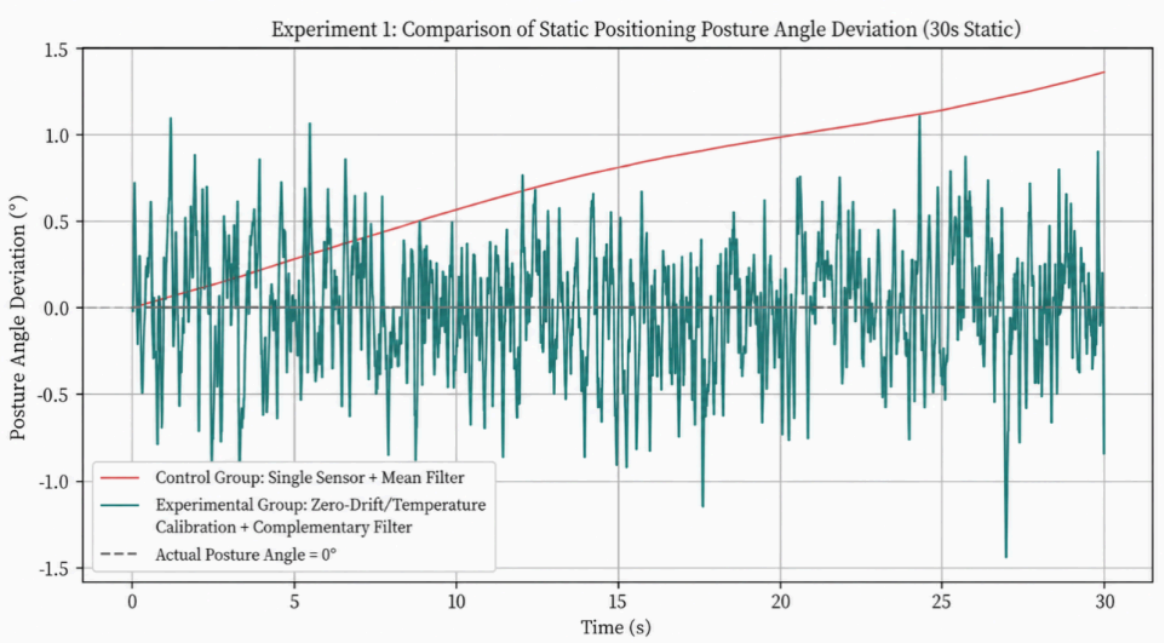

Figure 1. Experiment 1: comparison of static positioning attitude angle deviations (30-second standstill)

The results of the static positioning experiment showed that, during the 30-second idle period, the control group (single sensor + mean filtering) exhibited a maximum absolute error (MaxAE) of 0.744°, a mean squared error (MSE) of 0.701, and an error standard deviation of 0.384°. Furthermore, because zero-point drift and temperature drift were not eliminated, the error continued to increase over time, reaching approximately 1.4° by the end of the 30-second period; In the experimental group (zero-point/temperature calibration + complementary filtering), the MAE of the

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attitude angle decreased to 0.280°, the MSE decreased to 0.122, and the standard deviation was 0.350°. The MAE was reduced by 62.4%. The hardware zero-point calibration and temperature compensation strategy effectively suppressed static drift errors and significantly improved the static positioning stability of the robotic arm (as shown in Figure 1).

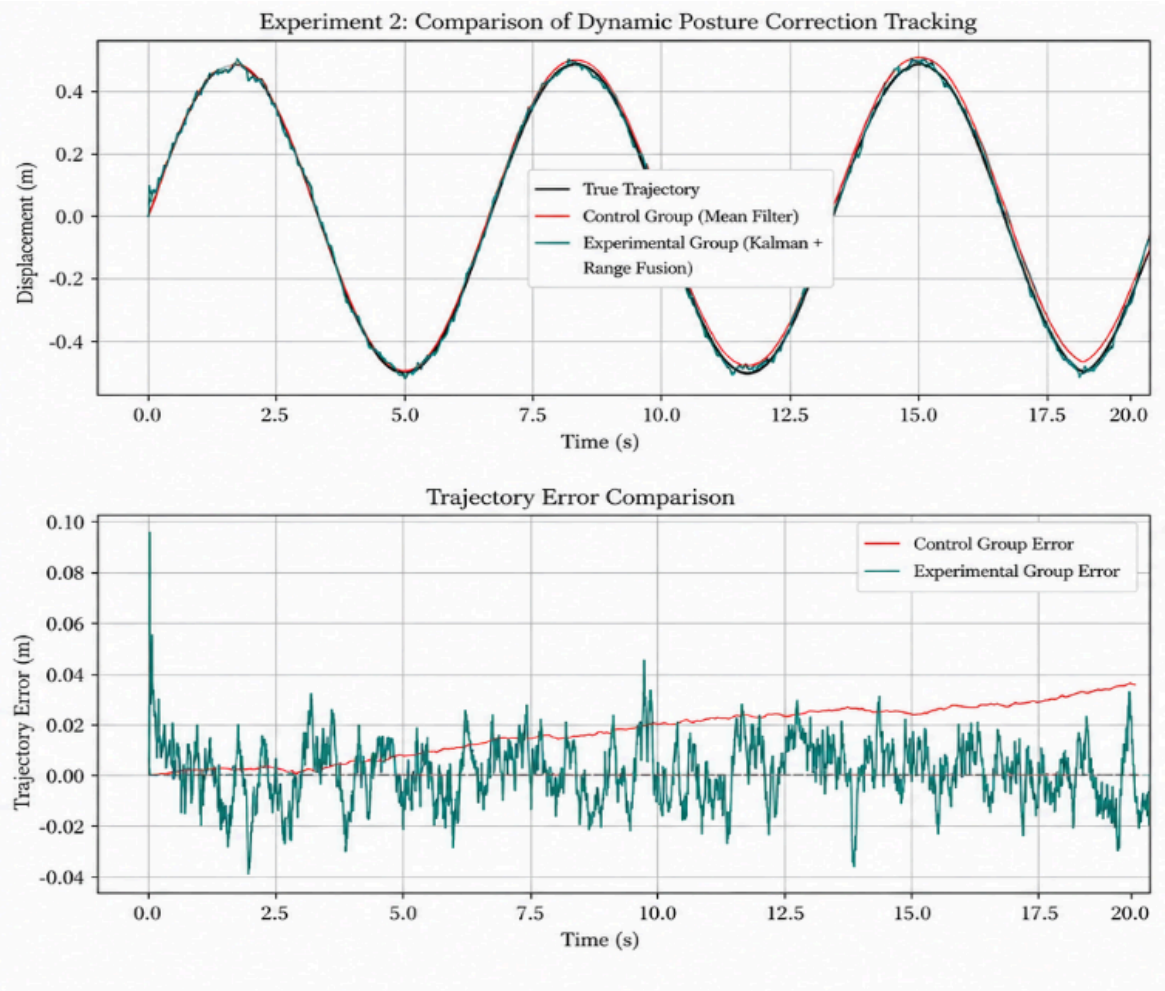

Figure 2. Experiment 2: comparison of dynamic sine wave reciprocating trajectory tracking

The results of the dynamic trajectory experiments showed that, for the control group (mean filtering), the trajectory deviation had a mean absolute error (MAE) of 0.018 m, a mean squared error (MSE) of 4.4×10^{-4}, and a standard deviation of 0.011 m; furthermore, the deviation continued to accumulate and monotonically increase over time. For the experimental group (Kalman filtering + range fusion), the trajectory deviation MAE decreased to 0.010 m, the MSE decreased to 1.6×10^{-4}, and the standard deviation was 0.013 m. The trajectory deviation was reduced by 44.2%. The dynamic noise reduction provided by the Kalman filter, combined with real-time correction of ranging data, effectively counteracted mechanical vibration interference, suppressed dynamic cumulative errors, and improved the accuracy and smoothness of the robotic arm's high-speed motion trajectory (as shown in Figure 2).

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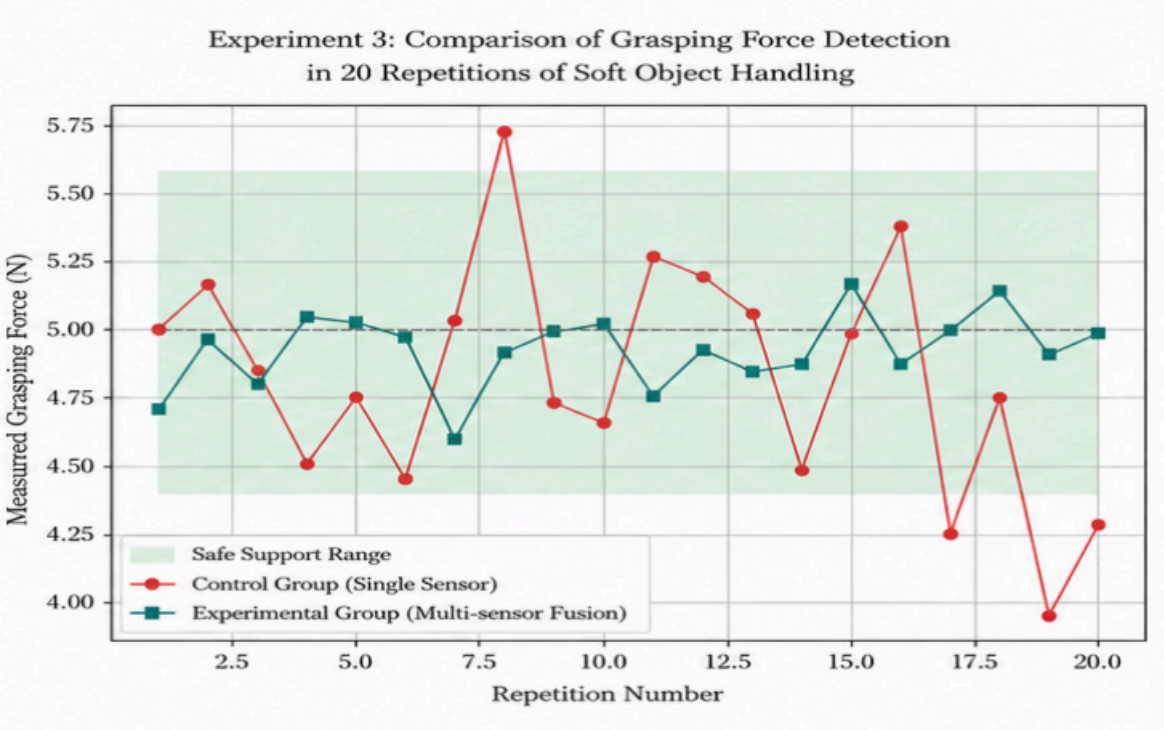

Figure 3. Experiment 3: comparison of gripping force measurements over 20 repetitions

The results of the flexible grasping experiments showed that, in 20 repeated grasping trials, the control group (single force sensor) had a mean absolute error (MAE) of 0.358 N for grip force detection, a workpiece slippage failure rate of 20.0%, and a damage rate of 5.0%; in the experimental group (multi-sensor fusion), the MAE for gripping force detection decreased to 0.116 N—a reduction of 67.6%—while both the workpiece slippage failure rate and breakage rate dropped to 0%. The multi-sensor fusion approach achieved coordinated control of posture, distance, and force data, effectively addressing the issues of insufficient detection accuracy and poor adaptability to operating conditions associated with single-force control, and significantly enhancing the robotic arm's capability for flexible and precise operations (as shown in Figure 3).

The comprehensive experimental results showed (summarized in Table 1) that the integrated optimization scheme proposed in this paper achieved a 62.4% reduction in attitude angle MAE, a 44.2% reduction in dynamic trajectory MAE, and a 67.6% reduction in gripping force MAE across the three sets of experiments. Both the workpiece slippage and damage rates were reduced to 0%, comprehensively improving the detection performance of the MEMS sensors, effectively addressing core issues such as drift, noise, and environmental interference, and significantly enhancing the robotic arm's positioning accuracy, motion stability, and operational safety. The experiments also showed that the proposed optimization scheme was evaluated only under standard operating conditions (0–45°C, 0.2 m/s, 0.5 m operating radius). Its adaptability under complex conditions—such as heavy loads, ultra-high speeds, and extreme high or low temperatures—remains to be further verified, and the algorithm's noise reduction and error compensation effects require further optimization.

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4. Conclusion

This paper investigated the error characteristics of MEMS sensors in small- and medium-sized collaborative robotic arms and proposed an integrated optimization scheme combining hardware calibration, adaptive filtering, and multisensor fusion. The scheme uses zero-point and temperature compensation to reduce systematic errors, complementary and Kalman filtering to suppress noise under different operating conditions, and hierarchical fusion of inertial, force, and infrared ranging data to improve sensing reliability.

Simulation results showed that, compared with conventional single-sensor detection and mean filtering, the proposed method reduced the static attitude-angle MAE by 62.4%, the dynamic trajectory MAE by 44.2%, and the gripping-force MAE by 67.6%. Both the workpiece slippage failure rate and damage rate were reduced to 0%, demonstrating improved positioning accuracy, motion stability, and compliant grasping performance.

The main contribution of this study is the integration of hardware calibration, operating-condition-adaptive filtering, and multisensor fusion into a low-cost optimization framework for lightweight robotic arms. The proposed approach improves sensor reliability without changing the original hardware configuration and provides differentiated processing for static and dynamic operating conditions.

However, the proposed method was validated only through simulation under standard conditions of 0–45°C, 0.2 m/s movement speed, and a 0.5 m operating radius. Its robustness under heavy loads, higher speeds, and extreme temperatures requires further experimental verification. Future work could also investigate adaptive filtering and intelligent error-compensation methods, as well as extend the multisensor fusion framework to multi-robot and human-robot collaborative scenarios.

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