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Multi-sensor Fusion for High-Precision Robort Arm in Intelligent Manufacturing: A Review

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Abstract. Collaborative robots have seen growing integration into intelligent manufacturing, yet precision challenges in high-demand fields like semiconductor packaging and logistics sorting—stemming from mechanical errors, sensor noise, and control limitations—remain critical. This paper reviews multi-sensor fusion strategies for high-precision robotic arms, focusing on integrating joint encoders, laser trackers, 3D vision systems, and FBG sensors. A hierarchical fusion framework is highlighted, combining data-level calibration (e.g., laser trackers correcting encoder errors), feature-level environment-task mapping (via 3D vision), and decision-level structural health management (using FBG sensors). Case studies demonstrate sub-micron accuracy (±0.5μm) in semiconductor applications by eliminating transmission chain errors and ±0.1mm precision in dynamic logistics sorting through vision-inertial coordination. However, barriers like high hardware costs (core sensors comprising >60% of system costs), multi-data synchronization complexities, and limited upgrade incentives in traditional manufacturing are identified. The study underscores the strategy's potential to meet Industry 4.0 demands for customization and automation, offering a foundational guide for advancing autonomous robotic systems toward smarter, more reliable precision manufacturing solutions via AI-driven models and cost-effective sensor innovations.

Keywords: Multi-sensor Fusion, Collaborative robots, Industrial automation, High-precision robotic arm

1. Introduction

Recent advancements in robotics have enabled greater integration of robots into various aspects of human daily life, covering medical services, search and rescue operations, transportation, agriculture, warehouse management, human-robot interaction (HRI) [1-11]. Among these, collaborative robots have shown greater potential. Initially designed as "tools" for repetitive or physically demanding tasks, such as material handling and surface treatment in automotive production, they have evolved into "collaborative partners" capable of cooperating with humans on complex tasks [12]. For instance, collaborative systems like those developed under the EU SYMPLEXITY project assist in polishing tasks by combining combining automation with human judgment.In general manufacturing, collaborative robots are widely used in assembly, packaging, quality inspection and other processes. Their flexible programmability supports rapid production

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line adjustments, meeting the demands of Industry 4.0 for customization and small-batch production [13]. The logistics sector benefits from the mobility and load capacity of collaborative robots. As their cross-modal interaction and flexible programming improve, collaborative robots are expected to further extend into fields like construction and agriculture.

However, the development of collaborative robots face significant challenges in precision manufacturing. Precision, as the core foundation for the realization of robot functions, directly determines the success or failure of key operations such as grasping, assembly, and welding. Millimeter-level errors can lead to task failures such as component damage and contact failure [14]. Precision errors arising from mechanical design, semsor noise, or control algorithms often compound under complex conditions, reducing overall system efficiency and increasing production costs. This paper reviews the current types of high-precision robotic arms, introduces the sensor fusion technology adopted in this paper to improve the accuracy of robots, as well as the challenges and future prospects of this scheme.

2. Robotic arms in precision manufacturing: classification and performance comparison

2.1. Tandem robotic arms

Tandem Robotic Arm, as an important branch in the field of industrial automation and collaborative robots, its technological development has always revolved around the three core demands of flexibility, safety and intelligence. Early series robotic arms were mainly of rigid structure and relied on high-precision servo motors for drive. They achieved high repeat positioning accuracy (such as 0.1mm) and stable load capacity (typical load range is 500g to 3kg) in scenarios such as automotive manufacturing and welding. However, due to the design limitations of the huge inertia and fixed stiffness, its dynamic response speed and environmental adaptability are restricted to a certain extent. With the breakthroughs in key technologies such as flexible cable drive and variable stiffness joints, modern tandem robotic arms are gradually evolving towards lightweight and biomimetic directions.

2.2. SCARA robot

As a key device in the field of industrial automation, the technological development of SCARA robotic arms has always focused on the core goals of high-precision planar motion and cost efficiency optimization. Since its commercialization in the 1980s, SCARA has established an irreplaceable position in fields such as electronic manufacturing and precision assembly through its unique four-axis structural design. The early products were based on a rigid parallel four-bar structure, focusing on high-speed and high-precision tasks in the horizontal plane. With high repeat positioning accuracy and simplified vertical design, they balanced performance and cost.

2.3. Cartesian coordinate robots

Cartesian coordinate robots are fundamental equipment in the field of industrial automation. Their technological evolution has always been driven by structural simplicity, high load stability and large space coverage capability as the core forces. Since the mid-20th century with the rise of numerical control technology, this type of robot composed of linear movements along the X, Y, and Z axes has become the cornerstone of highly repetitive tasks in production lines due to its modular design. Early Cartesian coordinate robots were mostly used for heavy material handling and basic assembly, relying on mechanical guides and ball screws to achieve millimeter-level positioning accuracy. With

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the popularization of servo control and lightweight materials, its application is gradually extending towards precision and intelligence.

2.4. Parallel robotic arms

The parallel manipulator is characterized by a closed-loop multi-branch chain structure as its core feature, and its technological development focuses on high dynamic response, ultra-high rigidity and precise motion control. Since Delta robots pioneered the three-degree-of-freedom parallel configuration, such robotic arms have developed unique advantages in high-speed and high-precision scenarios by synergistically driving the moving platform through multiple drive side chains. The early design was based on lightweight alloys and ball hinges to achieve micron-level accuracy and ultra-high-speed movement capabilities. With the upgrading of materials and algorithms, modern parallel robotic arms have gradually expanded to multiple degrees of freedom (such as the six-degree-of-freedom Stewart platform) and integrated intelligent control logic to support high-end industrial and scientific research demands.

3. Sensor technologies for precision enhancement

3.1. Joint encoders

In the parallel manipulator based on multi-sensor fusion, Joint encoders are the core position sensing components. The main function of joint encoders is to accurately measure the rotation Angle or displacement of each joint in real time to provide basic position feedback data for the control system. These data support the closed-loop control of the robotic arm, assist the controller in achieving precise planning and tracking of the end trajectory, and at the same time provide original position information for kinematic solutions, dynamic modeling, and multi-sensor data fusion.

3.2. Laser tracker

In the parallel robotic arm system based on multi-sensor fusion, Laser tracker is the core device for achieving high-precision external position measurement. It mainly acquires the three-dimensional position and attitude information of the end effector of the robotic arm in real time by emitting laser and receiving the target reflection signal. Its main function is to provide a global absolute positioning reference, compensate for the cumulative errors and structural deformation deviations of internal sensors such as joint encoders, support the dynamic calibration and error compensation of end trajectories, and is particularly suitable for high-precision processing and assembly tasks.

3.3. 3D vision system

In the parallel robotic arm system based on multi-sensor fusion, the 3D vision system is the core external sensor for environmental perception and target positioning. It acquires three-dimensional point cloud data through technologies such as depth cameras and structured light, and analyzes the spatial position, attitude and geometric features of the object. Its function is to provide external visual information for the robotic arm, support target recognition, dynamic positioning and path planning, and make up for the limitation that the internal sensors only know the joint positions.

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3.4. FBG sensors

In the parallel robotic arm system based on multi-sensor fusion, FBG sensors are the core sensors for structural health monitoring and physical quantity perception. Through the wavelength modulation characteristics of fiber Bragg gratings, they monitor parameters such as strain and temperature of key components of the robotic arm (such as connecting rods and spherical bearing joints) in real time. Its function is to provide feedback on the internal structural state, identify deformation, fatigue damage or thermal errors, support error compensation, life prediction and fault early warning, and is especially suitable for high-speed and heavy-load working conditions.

4. Multi-sensor fusion strategies in robotic systems

In a parallel robotic arm system, the integration of joint encoders, laser trackers, 3D vision systems and fiber Bragg grating sensors (FBG) constructs a hierarchical multi-sensor framework, achieving high-precision positioning, environmental adaptation and structural health perception.

The joint encoder provides high-frequency joint angle feedback, but suffers from kinematic cumulative errors and mechanical deformation. The laser tracker, with sub-millimeter global accuracy, acts as an external reference. By fusing tracker data at the data level, encoder readings are corrected in real time via inverse kinematics, compensating for structural flexibilities and joint clearances. This significantly improves precision, e.g., in aviation component assembly, positioning error is reduced by 82% compared to the single-sensor system. The 3D vision system reconstructs target poses via point clouds, linking internal joint space to external task space.Visual features (e.g., object centroids, surface normals) are fused with encoder and tracker data to construct a unified coordinate model. In scenarios like disordered object grasping, the visual system adjusts end-effector trajectories dynamically based on fused pose estimation, compensating for object pose shifts and mechanical errors. This strategy increases the success rate of unstructured crawling by 65% over the single vision or encoder solution. FBG sensors monitor the structural status of the robotic arm (connecting rod strain, joint temperature) with micro-strain-level sensitivity, and its anti-electromagnetic interference capability is suitable for industrial environments. Decision-level fusion combines the structural health indicators (stress concentration, coefficient of thermal expansion) of FBG with positioning and visual data to achieve adaptive control: When abnormal strain of the connecting rod is detected under high load, the control system dynamically adjusts the trajectory planning (reducing acceleration or joint load distribution), and simultaneously verifies the positioning accuracy through the tracker. When the strain exceeds the limit (such as exceeding the threshold by 15%), a fault response is triggered, and the end is safely moved away from the obstacle in combination with visual feedback.

Hierarchical Fusion Architecture: The fusion framework is divided into three layers: (1) Perception layer: Each sensor (encoder measures joint Angle, FBG measures strain, vision measures target pose, tracker measures global position) collects raw data with high spatiotemporal resolution (encoder/FBG 1kHz, tracker 0.1mm); (2) Processing layer: Calibrate the encoder error with a tracker for data-level fusion; Feature-level fusion integrates visual point clouds and kinematic models to generate task instructions; FBG data identifies structural anomalies through machine learning (such as LSTM); (3) Control layer: Decision-level fusion and comprehensive correction of position, task objectives and structural status, generating adaptive control signals to ensure the balance accuracy, dynamic response and safety of the robotic arm.

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5. Application cases and future directions

5.1. Semiconductor manufacturing and packaging (positioning accuracy ±0.5μm)

In semiconductor manufacturing and packaging, robot systems must achieve nano-level positioning accuracy, control of structural deformation and transmission chain error, and adaptation to clean environments. In this application, the laser tracker serves as an absolute reference to directly measure the end coordinates, calibrate the deviation of the joint encoder in real time, and eliminate errors such as gear clearance and thermal expansion. The FBG strain sensor is embedded in key components to monitor stress and temperature deformation and warn of the risk of position drift. The joint encoder provides high-frequency feedback on the joint Angle, complementing the laser tracker with "high-frequency control + low-frequency correction." This multi-sensor strategy enables non-contact absolute measurement, bypassing errors introduced by the transmission chain. In addition, distributed strain monitoring allows for pre-compensates for thermal and mechanical deformation. As a result, the system achieves sub-micron stable positioning, and meets the "zero defect" assembly requirements of semiconductors.

5.2. Intelligent logistics sorting (positioning accuracy ±0.1mm)

In intelligent logistics sorting scenarios, robotic arms must dynamically identify occlessed targets, adapt to changes in lighting, suppress high-speed vibrations, and achieve millimeter-level sorting. In this context, the 3D vision system reconstructs three-dimensional scenes, identifies occluded targets and calculates their poses, generating obstacle avoidance paths. The IMU monitors the vibration at the end, compensates for inertial shock, and stabilizes the visual positioning data. The joint encoder provides joint Angle input to assist the visual servo control in calculating the drive signal.

The visual system resolves disordered target recognition, the IMU enhances dynamic stability, the encoder ensures basic accuracy, and forms a "visual guidance-inertial stability-position closed loop" architecture. The sorting efficiency is 800 times per hour, and the positioning error is stable within ±0.1mm.

6. Barriers to deployment and industrial adoption

At present, multi-sensor fusion schemes face three main challenges in engineering applications. Firstly, the hardware cost barrier is relatively high. The cost of core equipment such as laser trackers and fiber demodulators accounts for more than 60% of the total system cost, significantly raising the threshold for technology implementation. The current situation where such precision measurement equipment relies on imports further intensifies the cost pressure and restricts the adoption of technology by small and medium-sized enterprises.

Secondly, the technical complexity of multi-source data fusion is relatively high. There are significant temporal asynchronicity and spatial coordinate differences among various sensors (such as the low-frequency global coordinates of the laser tracker, the high-frequency joint angles of the joint encoder, and the structural strain signals of the FBG sensor). Time synchronization and unified coordinate conversion need to be achieved through complex algorithms such as extended Kalman filtering. Such algorithms have strict requirements for developers' mathematical modeling ability and engineering debugging experience, forming a relatively high technical development threshold.

The third issue is the insufficient impetus for upgrading in traditional manufacturing industries. Currently, the demand for positioning accuracy in most conventional manufacturing scenarios is

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only ±50μm, and the existing single-sensor solutions can already meet the production requirements. However, for the sub-micron-level solutions required in high-precision fields such as semiconductor packaging, the cost input brought about by performance improvement and the actual production capacity benefits are difficult to form an effective balance, resulting in enterprises lacking the internal driving force to proactively upgrade sensor systems. These factors jointly restrict the large-scale application of multi-sensor fusion technology in the industrial field.

7. Conclusion

This paper systematically investigates multi-sensor fusion strategies for parallel robotic arms in precision manufacturing, focusing on the integration of joint encoders, laser trackers, 3D vision systems, and FBG sensors.The core findings demonstrate that hierarchical fusion—encompassing data-level calibration, feature-level environment-task mapping, and decision-level structural health management—significantly enhances robotic precision, adaptability, and reliability. For instance, in semiconductor manufacturing, the fusion of laser trackers (absolute positioning) and FBG sensors (strain monitoring) achieves ±0.5μm accuracy by eliminating transmission chain errors and predicting structural deformations.In logistics sorting, 3D vision systems coupled with IMUs and joint encoders enable ±0.1mm precision in dynamic.

However, the proposed framework faces notable limitations. Firstly, the high cost of core hardware (e.g., laser trackers and fiber demodulators accounting for >60% of system costs) restricts accessibility, particularly for small-to-medium enterprises. Secondly, the complexity of multi-sensor synchronization and coordinate alignment—requiring advanced algorithms like EKF—creates a high technical barrier. Lastly, traditional manufacturing industries' reliance on low-precision (±50μm) single-sensor solutions diminishes incentives for upgrading, despite the evident performance gains in high-precision sectors.

Future research should prioritize two directions.First, developing cost-effective alternatives, such as miniaturized laser trackers or AI-driven sensor fusion models that reduce hardware dependency, could democratize the technology.Second, optimizing real-time fusion algorithms via edge computing or deep learning(e.g., transformer-based models for multi-modal data) may streamline synchronization and enhance robustness.By addressing these gaps, multi-sensor fusion can unlock broader industrial adoption, driving the next generation of autonomous, intelligent robotic systems.

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