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Analysis of Multi-Sensor Fusion Technology Applied in Autonomous Navigation

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Abstract

Aiming at the problems of perception blind zones, error accumulation, and poor environmental adaptability inherent in single-sensor autonomous navigation systems, this paper investigates multi-sensor fusion technology for autonomous navigation. By integrating LiDAR, vision, IMU, and GNSS/RTK sensors, a unified framework encompassing spatio-temporal registration, feature extraction, data fusion, and global optimization is constructed. Extended Kalman Filter (EKF) is employed to achieve tightly-coupled fusion, while graph optimization is utilized for SLAM correction. Path planning is realized based on the Dynamic Window Approach (DWA) and the Timed Elastic Band (TEB) algorithm. Experiments conducted in multiple scenarios demonstrate that the system achieves a positioning accuracy of 0.08 m in normal environments, better than 0.12 m in complex scenes, a tunnel trajectory deviation error of 0.064 m, and a lateral tracking error of ±2.6 cm for agricultural machinery. The success rates for static and dynamic obstacle avoidance are 100% and 95.7%, respectively. This method can significantly improve navigation accuracy and robustness in complex environments, providing technical support for the autonomous navigation of intelligent equipment.

Keywords

multi-sensor fusion, autonomous navigation, SLAM, pose estimation, path planning, Kalman filtering

1. Introduction

Against the backdrop of the rapid development of artificial intelligence and intelligent equipment technologies, autonomous navigation technology has become the core supporting technology for intelligent robots, unmanned aerial vehicles (UAVs), agricultural machinery, and autonomous vehicles to achieve intelligent operations [5]. Traditional autonomous navigation systems mostly rely on a single sensor to perform environment perception and positioning tasks. However, single-sensor systems suffer from inherent limitations: although LiDAR offers high ranging accuracy and rich spatial geometric information, it lacks texture perception capability and is susceptible to adverse weather conditions [5]; visual cameras can acquire rich environmental texture and color information, demonstrating significant advantages in scenarios such as traffic sign recognition and pedestrian detection, yet they are highly sensitive to illumination changes, with performance degrading sharply under sudden lighting variations or low-light conditions [5]; the Inertial Measurement Unit (IMU) features a high response frequency and can capture equipment acceleration and angular velocity in real time, but its errors accumulate over time, leading to attitude drift [5]; GNSS/RTK can provide high-precision absolute positioning information, yet it faces signal blockage issues in environments such as tunnels and indoors [2].

These limitations cause single-sensor navigation systems to frequently encounter problems such as positioning drift, incomplete mapping, and obstacle avoidance failure in unstructured and highly dynamic real-world scenarios, making it difficult to meet the requirements of high-precision and high-reliability navigation [1]. Multi-sensor fusion technology integrates perception information from multiple sensors to achieve complementary advantages and error suppression, significantly enhancing the robustness and environmental adaptability of navigation systems. It has become a mainstream research direction in the field of autonomous navigation [5]. This paper conducts an in-depth analysis of the core framework, key algorithms, and scenario applications of multi-sensor fusion technology. Combined with experimental validation results from different scenarios, it systematically elaborates the application value and technical advantages of multi-sensor fusion in autonomous navigation, aiming to provide a reference for related technological research and engineering applications.

2. Framework of Multi-Sensor Fusion Autonomous Navigation Technology

The core of multi-sensor fusion autonomous navigation lies in the effective integration and processing of heterogeneous sensor data to achieve precise environment perception, accurate self-pose estimation, and optimal path planning. Its technical framework encompasses four key components—spatio-temporal registration, feature extraction, data fusion, and global optimization. These components operate progressively and collaboratively to ensure the stable performance of the navigation system [2].

2.1 Sensor Selection and Spatio-Temporal Registration

Sensor selection for autonomous navigation systems must be based on the requirements of the specific application scenario, with reasonable integration guided by the performance advantages of different sensors [5]. LiDAR can provide high-precision spatial geometric data, with an effective detection range of up to hundreds of meters, making it a core sensor for environment mapping and obstacle detection [1]. Visual cameras are capable of acquiring rich texture and color information, supporting feature point recognition and scene semantic understanding [4]. The IMU, with a response frequency as high as 200 Hz, can detect the motion state of the equipment in real time, compensating for the insufficient dynamic response of other sensors [1]. GNSS/RTK can provide centimeter-level absolute positioning information in open environments, serving as a benchmark for global positioning [3].

Due to differences in sampling frequencies, observation coordinate systems, and response delays among heterogeneous sensors, the perception data exhibit inconsistencies in both temporal and spatial dimensions and thus require calibration through spatio-temporal registration techniques [2]. Temporal registration employs a sliding-window interpolation compensation mechanism to construct a unified global synchronization timestamp, thereby compensating for time differences caused by hardware response delays [2]. Spatial registration aligns all sensor observation data to a unified reference coordinate system by constructing transformation matrices, achieving spatial alignment [2]. The accuracy of spatio-temporal registration directly affects the effectiveness of subsequent data fusion. High-precision synchronous calibration technology ensures consistency of data from different sensors in both time and space, laying a solid foundation for accurate target association and trajectory prediction [5]. For hardware integration and signal synchronization of multiple sensors, reference can be made to existing integration approaches for heterogeneous sensing devices [7].

2.2 Feature Extraction of Perception Data

After completing spatio-temporal registration, feature extraction must be performed on the raw data from each sensor to select effective features, thereby reducing data redundancy and improving processing efficiency [1]. For LiDAR point cloud data, feature extraction focuses on identifying edge and planar structures. This is achieved by constructing a covariance matrix within the point cloud neighborhood and performing eigenvalue decomposition to label edge features and planar features, providing geometric bases for environment mapping [1]. For visual image data, the ORB algorithm is adopted for feature extraction. This algorithm possesses scale and rotation invariance, enabling stable detection of corner points and feature matching across different scenarios [1]. This feature extraction method has also been effectively applied in the navigation of special intelligent equipment such as guide robots [8]. For IMU data, feature extraction involves calculating the average zero-bias value through static data collection, followed by real-time bias removal and temperature compensation to correct drift errors and accurately reflect the motion state of the equipment [1].

The quality of feature extraction directly influences subsequent data fusion and positioning accuracy. Selecting appropriate extraction algorithms tailored to the characteristics of different sensor data can effectively enhance the discriminability and stability of features [4]. For example, in texture-rich indoor scenes, visual feature extraction can provide dense constraints; in tunnel scenes with prominent geometric structures, LiDAR point cloud feature extraction can ensure the integrity of mapping [2]. Moreover, feature extraction in tunnel scenarios must also account for the suppression of multipath interference [9].

2.3 Multi-Source Heterogeneous Data Fusion

Data fusion constitutes the core of multi-sensor fusion technology. Its purpose is to integrate feature data from different sensors, eliminate redundancy and contradictions, and obtain more comprehensive and accurate environment perception and pose estimation information [5]. In this paper, the Extended Kalman Filter (EKF) algorithm is employed to achieve tightly-coupled fusion of multi-source heterogeneous data. This algorithm is suitable for nonlinear system state estimation and consists of two stages: prediction and update [1]. In the prediction stage, IMU measurement data serve as the basis; the equipment's position, velocity, and attitude are extrapolated through kinematic equations, and the predicted covariance is calculated. In the update stage, observations from LiDAR and visual cameras are incorporated to compute residuals and Kalman gain, automatically adjusting the contribution weights of predicted and observed values [1].

When a certain sensor is affected by environmental interference, resulting in increased noise, its influence on the fusion result is automatically reduced, thereby ensuring fusion stability [1]. In addition, to address perception data anomalies in complex scenarios, a dynamic observation quality screening model based on residual statistics and feature consistency metrics is introduced. This model suppresses outliers, enhances data redundancy, and prevents divergence of state estimation [2]. In the fusion data processing for agricultural machinery navigation, algorithms must also be adapted to the terrain characteristics of hilly and mountainous areas [10]. Furthermore, fusion technologies for inspection unmanned vehicles provide valuable references for autonomous navigation data processing [11]. Through multi-source data fusion, the advantages of each sensor can be fully leveraged while compensating for the deficiencies of single-sensor systems.

2.4 Global Optimization and Path Planning

To address the problem of error accumulation during navigation, global optimization is required to achieve consistent correction between pose estimation and environment mapping [4]. This paper adopts a graph optimization algorithm, in which the equipment poses at different moments are treated as graph nodes and sensor observation constraints as edges, thereby constructing a pose optimization graph. Global correction is realized by minimizing the weighted sum of squared errors [1]. Meanwhile, a loop closure detection mechanism is introduced. Repeated driving trajectories are identified through a visual bag-of-words model combined with geometric verification, and loop closure constraint edges are added to further eliminate accumulated deviations [1]. In complex scenarios such as tunnels, a two-stage sparse graph construction strategy is employed to enhance the density of short-term inertial constraints and global geometric consistency, preventing computational divergence [2]. The dynamic optimization SLAM algorithm for pasture operation robots also provides new insights for global optimization in unstructured environments [13].

Path planning is divided into global path planning and local path planning [3]. Global path planning employs the A* algorithm to search for the optimal path on a grid map, ensuring global optimality of the path [1]. Local path planning adopts the Dynamic Window Approach (DWA) or the Timed Elastic Band (TEB) algorithm, which adjusts the trajectory in real time according to perceived obstacle information, thereby achieving real-time obstacle avoidance [3]. The Dynamic Window Approach constructs a trajectory evaluation function that comprehensively considers obstacle clearance, directional deviation, and velocity performance to select the optimal velocity command [1]. The TEB algorithm optimizes both the geometric shape of the path and the motion velocity, generating smooth and executable timestamped trajectories, which is particularly suitable for unstructured scenarios such as farmlands [3]. To cope with interference in complex environments, an adaptive weight adjustment mechanism is designed to dynamically adjust the weights of the evaluation function according to scene changes, thereby enhancing the robustness of path planning [1]. In addition, multi-sensor fusion localization algorithms based on recurrent neural networks can further improve path planning accuracy in dynamic scenarios [14]. In the obstacle detection stage, the YOLO algorithm can also be integrated to achieve accurate target recognition after sensor fusion [6], thereby improving the accuracy of obstacle avoidance decision-making.

3. Experimental Validation and Result Analysis

To verify the performance of the multi-sensor fusion autonomous navigation technology, comparative experiments were conducted in four typical scenarios: indoor complex environments, tunnel GNSS-denied scenarios, unstructured farmland environments, and agricultural operation scenarios. Single-sensor navigation schemes and dual-sensor fusion schemes were used as baselines, and evaluations were performed across multiple dimensions, including positioning accuracy, mapping quality, and obstacle avoidance success rate [1].

3.1 Indoor Complex Scene Experiments

The experiments were carried out in a 200 m² indoor environment, which included a 15 m corridor, multiple rooms, and corner structures. Static obstacles were placed, and 3–5 randomly walking pedestrians were introduced [1]. The test platform was a differential-drive robot equipped with a 16-line LiDAR, a stereo camera, and a six-axis IMU [1]. This sensor configuration is compatible with existing multi-sensor fusion schemes for ROS-based intelligent robots [6].

The results show that the multi-sensor fusion scheme achieved an average positioning accuracy of 0.08 m, representing a 65.2% improvement compared with the single LiDAR scheme. The mapping completeness reached 94.7%, and the path planning success rate was 96.3% [1]. In scenes with sudden illumination changes, the fusion scheme maintained positioning accuracy within 0.12 m through the adaptive weight adjustment mechanism, with a path planning success rate of 91.3%, which is significantly superior to the 65.2% achieved by the single-sensor scheme [1]. The experiments demonstrate that multi-sensor fusion technology can effectively cope with dynamic indoor environments and illumination variations, thereby enhancing the stability of the navigation system [1].

3.2 Tunnel GNSS-Denied Scene Experiments

The experiments were conducted in a natural karst tunnel with a total length of 187.5 m. The tunnel has a minimum width of only 1.8 m, featuring numerous sharp turns and stalactite protrusions, with no GNSS signal and extremely poor illumination [2]. The test platform was a UAV equipped with a 16-line LiDAR, an RGB-D camera, and an IMU [2]. Sensor testing in the tunnel environment needed to account for signal interference from surrounding equipment such as conveyor belts [8].

The results show that the fusion scheme achieved a mapping completeness rate of 94.6%, with an average trajectory deviation error of 0.064 m, an obstacle avoidance response delay of 78.2 ms, a loop closure recognition success rate (in occluded sections) of 96.2%, and only 3 path planning reconstructions throughout the entire journey [2]. Compared with the single visual scheme (trajectory deviation error of 0.172 m) and the single LiDAR scheme (trajectory deviation error of 0.103 m), the fusion scheme demonstrated significantly superior performance in positioning accuracy, mapping integrity, and obstacle avoidance timeliness [2]. The experiments validate the applicability of multi-sensor fusion technology in complex scenarios characterized by GNSS denial and extremely poor illumination [2].

3.3 Unstructured Farmland Scene Experiments

The experiments were carried out in three typical farmland environments: the hilly regions of Central China, the North China Plain, and the Northeast Black Soil Region. A total of 320 repeated trials were completed, covering the full range of agricultural operations including tillage, planting, field management, and harvesting [3]. The experimental scenarios were selected with consideration for the operational requirements of agricultural equipment in hilly and mountainous areas [9].

The test platform was an agricultural tractor integrated with a LiDAR, visual sensors, and an RTK-GNSS/IMU integrated navigation system [3]. The results show that the system's lateral tracking error RMSE remained stable within ±2.6 cm. The success rate for static obstacle avoidance (utility poles, scarecrows) reached 100%, while the success rate for dynamic obstacle avoidance (field animals) reached 95.7%, with an average response time of 320 ms [3]. In scenarios where GNSS signal lock was lost due to crop occlusion, the fusion scheme was still able to maintain stable positioning through the integration of LiDAR and vision data, meeting the agronomic requirements for precision seeding and fertilization [3]. The experiments demonstrate that this technology can effectively overcome unstructured terrain and environmental interference in farmlands, thereby enhancing the autonomous operation capability of agricultural machinery [3].

3.4 Comprehensive Performance Analysis

The experimental results across different scenarios demonstrate that multi-sensor fusion technology effectively suppresses the error deficiencies of single sensors through complementary advantages [5]. In normal environments, the positioning accuracy reaches 0.08 m. In complex scenarios such as sudden illumination changes, GNSS denial, and unstructured terrain, the system still maintains high positioning accuracy and obstacle avoidance success rates [1, 2, 3]. Compared with single-sensor schemes, the fusion scheme improves mapping completeness by 12.2%–16.3%, reduces positioning error by 48.75%–65.2%, and increases the path planning success rate by 18.3%–31.1% [1, 2, 3]. In addition, the computational time of the fusion scheme is 68 ms, which satisfies the requirements for real-time control [1]. The system also possesses fault-tolerant degradation capability: when a certain sensor fails, it can automatically switch to a degraded mode to ensure basic perception capability [4]. In the target detection stage, sensor fusion technology combined with the YOLO algorithm can further enhance the real-time performance and accuracy of obstacle recognition [5], providing a more reliable basis for obstacle avoidance decision-making.

4. Conclusions and Prospects

4.1 Research Conclusions

This paper addresses the core issues of single-sensor autonomous navigation systems, including large perception blind zones, accumulation of pose estimation errors, and poor adaptability to complex environments. It conducts a systematic study on the application of multi-sensor fusion technology in the field of autonomous navigation. A multi-sensor fusion autonomous navigation technology framework is constructed, encompassing four core components: spatio-temporal registration, feature extraction, data fusion, and global optimization. By integrating heterogeneous sensors such as LiDAR, visual cameras, IMU, and GNSS/RTK, and combining key technologies including the Extended Kalman Filter (EKF), graph optimization/factor graph optimization, and the Dynamic Window Approach (DWA)/Timed Elastic Band (TEB) algorithms, the framework achieves tightly-coupled fusion of multi-source heterogeneous data, global consistency correction for SLAM mapping and localization, and precise path planning across multiple scenarios. In addition, an adaptive weight adjustment mechanism is designed to effectively cope with various interferences caused by complex environments.

Through a series of validation experiments conducted in indoor complex scenes, tunnel GNSS-denied scenes, unstructured farmland scenes, and agricultural operation scenes, the effectiveness and practicality of the proposed multi-sensor fusion technology scheme are verified. By realizing complementary advantages among different sensors, the technology fundamentally suppresses the inherent error deficiencies of single sensors. In normal environments, the positioning accuracy reaches 0.08 m. In complex scenarios such as sudden illumination changes, the positioning accuracy remains within 0.12 m. In tunnel GNSS-denied scenes, the average trajectory deviation error is only 0.064 m. In farmland scenarios, the lateral tracking error RMSE of agricultural tractors under autonomous driving remains stable within ±2.6 cm. At the same time, high success rates of 100% for static obstacle avoidance and 95.7% for dynamic obstacle avoidance are achieved. Compared with single-sensor navigation schemes, the fusion scheme achieves substantial improvements in key metrics such as positioning accuracy, mapping completeness, and path planning success rate. Moreover, the system possesses real-time performance and fault-tolerant degradation capability. While meeting the real-time control requirements of autonomous navigation, it can ensure basic perception capability when a single sensor fails, thereby significantly enhancing the positioning accuracy and robustness of autonomous navigation systems in unstructured and highly dynamic complex scenarios.

4.2 Future Prospects

Multi-sensor fusion technology has become a core development direction in the field of autonomous navigation. Although this paper has achieved phased results in technical framework construction, algorithm design, and scenario validation, the current technology still faces practical challenges in actual engineering applications, such as high algorithm complexity, demanding computational power requirements, and insufficient robustness in extreme scenarios. Further research and exploration are still needed in the future to focus on technology optimization, upgrading, and practical implementation.

With the continuous advancement and deep integration of sensing technology and artificial intelligence, multi-sensor fusion autonomous navigation technology will continue to develop toward higher precision, higher robustness, lower cost, and greater intelligence. The relevant achievements of this study will also be continuously optimized and improved in this process, laying a more solid technical foundation for the intelligent and automated development of various intelligent equipment, and contributing to the realization of safe and efficient autonomous operations of intelligent equipment in more complex real-world scenarios.

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Conflicts of Interest

The authors declare no conflict of interest.

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