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Implementation and Analysis of LIO-SLAM with IEKF and SC

Group 10

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Abstract

In this study, a system called LiDAR-Inertial Odometry Simultaneous Localization And Mapping (LIO-SLAM) is implemented and analyzed. The system is designed with a well-defined objective of enhancing the path planning and mapping capabilities of robotic systems, especially in ever-changing and evolving environment. LIO-SLAM combines laser sensor technology Light Detection and Ranging (LiDAR) with motion sensor known as Inertial Measurement Unit (IMU) and to get precise data, the Global Positioning System (GPS) is integrated in the system. The implemented system employs Iterative Extended Kalman Filter (IEKF) algorithm for noise mitigation and integrates the Scan Context (SC) framework to achieve a seamless mapping process. The pivotal focus of this work is to create an algorithm powerful to handle and analyze sensor data smoothly, integrating different sensors, and building a software framework that processes this data in real-time. The performance of our system is analyzed using a variety of publicly available datasets, ensuring it works well in any different situations. This report explains the structural composition of the system, the integration processes, addresses encountered challenges, and the implications of the findings for the advancement of robot navigation technology.

Keywords: Light Detection and Ranging (LiDAR), Inertial Measurement Unit (IMU), Global Positioning System (GPS), LiDAR-Inertial Odometry Simultaneous Localization And Mapping (LIO-SLAM), Iterative Extended Kalman Filter (IEKF), Scan Context (SC) Framework

I. Introduction

Autonomous systems, particularly mobile robots and vehicles, require precise and reliable methods for localization and mapping to navigate effectively in dynamic environments. Traditional systems often rely on the data from either LiDAR or IMU, which can lead to limitations in accuracy and performance under various conditions, such as GPS-denied environments. Integrating these technologies can significantly enhance their individual capabilities, offering a more robust solution for real-time applications.

LIO-SLAM, represents a sophisticated approach in this integration, combining the high-resolution spatial data from LiDAR with the temporal accuracy of IMU measurements. This combination allows for precise tracking and mapping even when external signals are unavailable or unreliable. By also integrating GPS data, LIO-SLAM further enhances accuracy, particularly in outdoor environments where GPS signals are available. The IEKF plays a crucial role in merging these data streams, providing a mathematical framework that ensures accurate state estimation and noise mitigation over time. Through the development of algorithms for smooth sensor data handling and real-time processing, as well as integrating the SC framework, this LIO-SLAM framework demonstrates significant improvements in accuracy and efficiency in path planning and mapping, making it highly valuable for applications such as autonomous driving and robotics.

This project aims to develop and evaluate such a LIO-SLAM system tailored to improve autonomous navigation in environments that challenge traditional localization methods. Our methodology involves a multi-faceted approach:

1) **Algorithm Implementation:** We implemented sophisticated algorithms that handle features extraction, state estimation, and mapping, all based on the iterated extended Kalman filter, focusing on the precision of data integration from both LiDAR and IMU.
2) **System Integration:** The seamless integration of components into a unified LIO-SLAM framework is crucial, involving the development of a robust software infrastructure that supports real-time data processing and mapping.
3) **Testing and Evaluation:** Using publicly available datasets, we conducted extensive testing to validate the system, assessing its accuracy, robustness, and overall performance against established metrics.
4) **Sensor Integration:** We ensured the effective synchronization of LiDAR and IMU data through custom sensor drivers and pre-processing routines, aiming to optimize data compatibility and realism in sensor simulation.

II. Related Work

Our project to enhance the LIO-SLAM system is deeply influenced by several groundbreaking studies in the field of SLAM technologies. These studies have provided valuable insights and foundational methods that guide our current research efforts.

A. *LIO-SAM: Tightly-coupled Lidar Inertial Odometry via Smoothing and Mapping [3]*

This paper introduces a novel approach to real-time mobile robot trajectory estimation and mapping. This method skillfully integrates LiDAR, a laser-based distance measurement technology, with IMU, sensors that track motion and orientation, using a factor graph. This integration is particularly effective at addressing issues such as drift, where the robot's perceived location gradually deviates from its actual path. The technique's success across diverse settings has laid a strong foundation for our enhancements to LIO-SLAM.

Building on this, improvements in loop closure methods for LiDAR odometry and mapping have shown significant advancements in recognizing revisited areas quickly and accurately using detailed point cloud data. Loop closure is crucial for correcting any cumulative mapping errors by identifying when the robot returns to a previously visited spot. Enhancing this aspect within LIO-SLAM is key to ensuring the maps produced are both precise and dependable, particularly in complex or challenging environments.

B. *LOAM: Lidar Odometry and Mapping in Real-time [5]*

The pioneering work done in this paper has been instrumental in setting new standards for real-time mapping capabilities. By effectively combining LiDAR and IMU data, LOAM minimized the perception errors during navigation, mainly using IMU data to refine the LiDAR scans. Although its integration of data was not as comprehensive as later developments, LOAM's approach to real-time data processing has heavily influenced our strategies, demonstrating the feasibility of achieving low-error mapping in real-time environments.

By leveraging these critical insights from the aforementioned studies, our project aims to further develop the computational efficiency and adaptability of the LIO-SLAM system. We are focused on ensuring that our system not only maintains high accuracy and robustness as environmental conditions change but also becomes a reliable tool for real-time navigation and mapping.

III. Problem Statement

Autonomous systems operating in dynamic or GPS-denied environments require precise and reliable localization and mapping, a task complicated by the technical challenges of integrating LiDAR with IMU in LIO-SLAM. This integration faces hurdles such as computational complexity in merging data streams using the IEKF, maintaining accuracy amidst environmental and sensor noise, and ensuring system scalability and adaptability.

A. *Objective*

The primary goal of this project is to design and implement a LIO-SLAM that significantly enhances precision in real-time mapping and localization, especially tailored for dynamic environments. This system seeks to merge high-resolution spatial data from LiDAR with precise temporal data from IMU and also incorporating it with the GPS data via an IEKF and SC, a process aimed at refining state estimations to improve position and movement accuracy.

B. *State Representation*

Robot State Vector: The core of our methodology is defined by the robot state vector x, represented as:

$$x = [R^T, p^T, v^T, b^T]^T \tag{1}$$

where R denotes the rotation matrix, p the position vector, v velocity, and b the IMU bias. This configuration is essential for processing and interpreting the sensor data through algorithms that are grounded in the iterated extended Kalman filter, ensuring precise system state estimation.

C. *Algorithmic Framework*

This simulation involves critical tasks such as feature extraction, motion estimation, and mapping. The utilization of the iterated extended Kalman filter is vital for effectively combining LiDAR and data from IMU, maintaining the accuracy of the system's state estimation. Our objective is to accurately replicate the dynamics of LIO-SLAM, providing insights into its algorithmic structure and identifying opportunities for refinement and advancement.

D. *Observation Model*

Observations z link the robot's state vector to features within the environment, modeled as:

$$z = h(x, m) + w \tag{2}$$

where h is a non-linear function representing how features are perceived from the robot's current state, and w denotes the noise associated with these observations. This model is crucial for integrating sensor data into the mapping process and enhancing the robot's ability to navigate and understand its environment.

E. LIO SLAM Algorithm

A pivotal stage in our methodology is the systematic integration of sensor data. Pre-processing algorithms are engineered to calibrate and temporally align the sensor outputs. The fidelity of the sensor data is preserved through calibration matrices and time-synchronization protocols, preparing the data for effective integration into the Kalman filter. The process consists of two main steps:

1) Prediction Step: This step projects the future state using the state transition function f, considering the control input u_k, to form the state prediction $\hat{x}_{k|k-1}$. The uncertainty of this prediction is encapsulated by the covariance matrix P:

$$\hat{x}_{k|k-1} = f(\hat{x}_{k-1|k-1}, u_k) \tag{3}$$

$$P_{k|k-1} = F_k P_{k-1|k-1} F_k^\top + Q_k \tag{4}$$

2) Update Step: Refining the state estimate with the latest measurement y_k, where the Kalman gain K_k determines the extent of the adjustment based on the prediction and the measurement:

$$K_k = P_{k|k-1} H_k^T (H_k P_{k|k-1} H_k^T + R_k)^{-1} \tag{5}$$

$$\hat{x}_{k|k} = \hat{x}_{k|k-1} + K_k(y_k - h(\hat{x}_{k|k-1})) \tag{6}$$

$$P_{k|k} = (I - K_k H_k) P_{k|k-1} \tag{7}$$

Iterative refinement of the Kalman Filter enhances system performance by optimizing its parameters, systematically reducing the Root Mean Square Error (RMSE), and thus improving localization accuracy:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\hat{\mathbf{p}}_i - \mathbf{p}_i)^2} \tag{8}$$

where $\hat{p}_i$ is the estimated position and p_i is the true position. The iterative process of the Kalman Filter is key to achieving a robust LIO-SLAM system, fine-tuning parameters and validating against ground truth to enhance accuracy and performance.

IV. Results and Observations

A. Datasets

In the development of our LIO-SLAM system, we utilized datasets including

1) KITTI Odometry
2) Ouster OS1-128
3) Livox-Horizon
4) KA-Urban

B. Setup

With the datasets in hand, we implemented the FAST LIO-SLAM code with loop closure, utilizing the IEKF. This integration aimed to capitalize on the rapid processing capabilities of FAST LIO-SLAM while enhancing precision with the IEKF, thereby improving overall performance. Meticulous adjustments were made to the FAST LIO-SLAM architecture, specifically embedding the IEKF within the loop closure mechanism to bolster the system's real-time error correction capabilities. This strategic enhancement ensured that the LIO-SLAM system maintained its operational speed and significantly increased both precision and reliability, especially in complex urban environments.

Our framework revolves around harnessing input data from IMU and LiDAR sensors, then effectively mapping these data points. For mapping LiDAR points and achieving a refined map output, we employ a combination of state estimation algorithms, IEKF and SC framework. Subsequently, we validate the correctness of state updates and aim for a Root Mean Square Error (RMSE) approaching zero. If discrepancies arise, the algorithm iterates through residual computation again to converge the state closer to ground truth (as in fig. 1). Within the mapping process, we utilize the Iterative Closest Point (ICP) algorithm and SC framework to identify loop closures.

Additionally, we integrate GPS data into the mapping process to enhance the accuracy of the IMU-derived path by leveraging GPS information for adaptation.

C. Observation

1) Loop Closure: The experiments focusing only on loop closure (as shown in Fig. 2) revealed a big difference between using LIO-SLAM with and without loop closures. Without loop closures, the path drifts a lot in places already visited by sensors, making it less reliable. But when we include loop closures, the path still drifts a bit, but much less comparatively. Fig. 3 demonstrates how loops are detected using the ICP algorithm with the state poses.

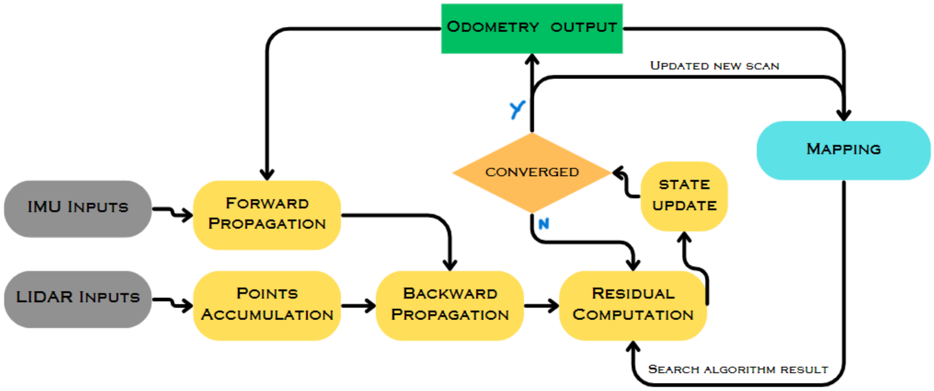
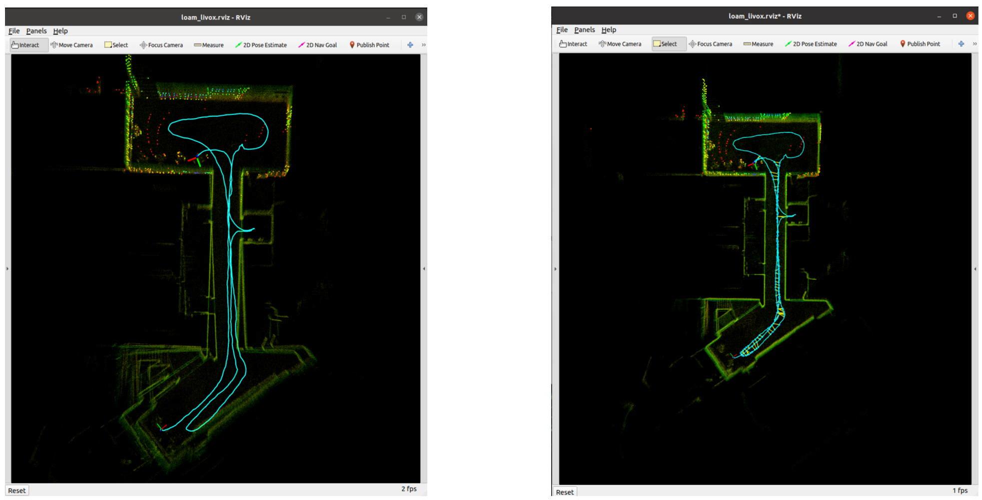
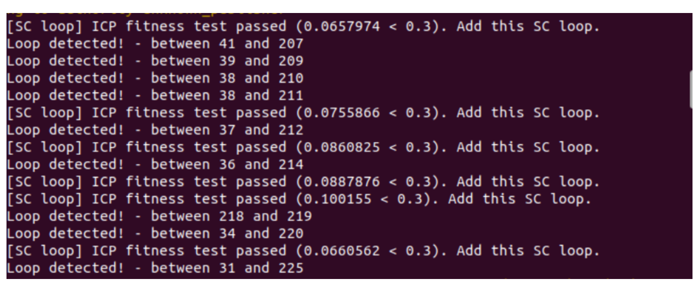


Fig. 1: Our Framework



(a) Without Loop Closure (b) With Loop Closure

Fig. 2: Visualization of the LIO-SLAM path estimation process



```
[SC loop] ICP fitness test passed (0.0657974 < 0.3). Add this SC loop.
Loop detected! - between 41 and 207
Loop detected! - between 39 and 209
Loop detected! - between 38 and 210
Loop detected! - between 38 and 211
[SC loop] ICP fitness test passed (0.0755866 < 0.3). Add this SC loop.
Loop detected! - between 37 and 212
[SC loop] ICP fitness test passed (0.0860825 < 0.3). Add this SC loop.
Loop detected! - between 36 and 214
[SC loop] ICP fitness test passed (0.0887876 < 0.3). Add this SC loop.
[SC loop] ICP fitness test passed (0.100155 < 0.3). Add this SC loop.
Loop detected! - between 218 and 219
Loop detected! - between 34 and 220
[SC loop] ICP fitness test passed (0.0660562 < 0.3). Add this SC loop.
Loop detected! - between 31 and 225
```

Fig. 3: Initial loop closure detection highlighting the potential overlap in the SLAM path.

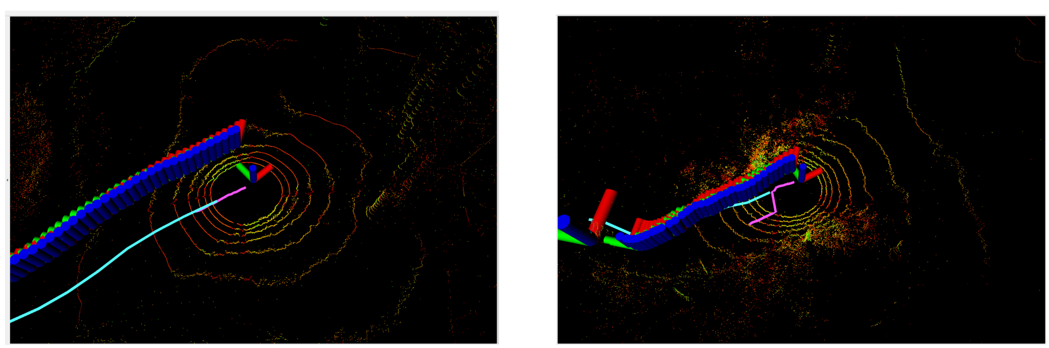
2) Map with IEKF and SC Framework: The experiments carried out on the Garden dataset (as depicted in Fig. 4) show that incorporating the IEKF and SC framework greatly enhances the smoothness of both the mapped points and the path compared to solely using LIO-SAM. This fusion framework also aids in handling loop closures, effectively mitigating significant drift in both the path and the map. Moreover, this framework offers the flexibility to exclude feature and edge points from mapping, leading to faster computation. However, this choice presents a trade-off between precision and speed in mapping.

3) GPS Fusion: The experiment conducted on the Park dataset, collected by Yewei Huang (which includes GPS data), depicted in Fig. 5, highlights a substantial drift or error in the IMU's path estimate when compared to GPS (Fig. 5a). However, this drift is effectively mitigated by correcting the IMU odometry path data with the GPS odometry path data, resulting in an RMSE of the paths approaching zero (as in Fig. 5b).

In addition to rectifying path discrepancies, this integration of GPS data offers several advantages:

Fig. 4: Detailed view of the Fusion Framework within the map environment of Garden Dataset

1) Enhanced Accuracy: By aligning IMU-derived paths with GPS data, the overall accuracy of the path estimation is significantly improved.
2) Robustness: Combining IMU and GPS data provides a more robust navigation solution, particularly in challenging environments where individual sensors may exhibit limitations or inaccuracies.
3) Consistency: The correction process ensures consistency between the IMU and GPS-derived paths, leading to a more coherent and reliable navigation output.
4) Real-Time Correction: The ability to dynamically correct IMU odometry with GPS data facilitates real-time adjustments, allowing for more accurate and responsive navigation in dynamic environments.
5) Reduced Drift: By leveraging GPS data to correct IMU-derived paths, the framework effectively reduces drift, leading to more precise and reliable navigation outcomes over extended periods



(a) GPS path (axes) and IMU path getting mapped

(b) IMU path correcting according to GPS path

Fig. 5: Visualization of the LIO-SLAM with GPS fusion using Park dataset

V. Conclusion

In this report, our study implemented and evaluated the LIO-SLAM with the novel iterated extended Kalman Filter and SC framework for different public datasets. We focused on implementing a method in the LIO-SLAM technology which can seamlessly integrate LiDAR and IMU data for mapping and assessed its performance in different environments. Additionally, our work optimized the system's performance and also proved that the accuracy of mapping can be improved by employing the IEKF and SC framework, the robustness has been increased with the integration of GPS to the system.

Significant effort was dedicated to experimenting with diverse optimization algorithms and analyzing their performance. Comparisons with recent research provided insights into LIO-SLAM advancements. We acknowledged persistent challenges and highlighted potential future developments. Our study contributes to understanding LIO-SLAM's performance in different environments. The analysis conducted against benchmark approaches offer valuable insights and indicate future research directions for improving the algorithm's effectiveness.

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