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CS 4610
Spring 2025

UAV Autonomous Navigation in Indoor and GPS-Denied Environments: Literature Review 1

Summary

The work A Simultaneous Control, Localization, and Mapping System for UAVs in GPS-Denied Environments." by Rodrigo Munguia et al.[1] presents a general solution to the SCLAM problem with a visual-based technique, meaning that the UAV is equipped with a monocular camera as its main sensor. Future work may include testing the proposed technique in an actual environment, outside of simulations, implementing the technique in low-lighting environments using tools such as LiDAR, as well as combining the proposed technique with collision avoidance algorithms. Additionally, various implementations for described subsystems can be explored.

Main Content

This paper presents a literature review of the work "A Simultaneous Control, Localization, and Mapping System for UAVs in GPS-Denied Environments." by Rodrigo Munguia et al.[1], thereby referred to as "the work." It aims to explore the techniques described in the work and create a vision of future research on the matter, including future improvements, further and extended testing, as well as their application to other, related problems.

In GPS-denied environments, UAV technology has relied on onboard sensors and various technologies such as SLAM to address this issue. While SLAM provides a solution for tracking the UAV's position while mapping the surrounding environment, it doesn't address the simultaneous and autonomous control of the UAV. Such autonomous control has been difficult to achieve while maintaining the localization and mapping functionality of SLAM. This is caused by factors such as the SLAM system's ability to handle sensor noise and uncertainties in the environment mapping. If errors occur in obtained estimates, they are prone to propagating into control algorithms. This can, in turn, cause instability, collisions, and poor trajectory adherence.[1]

Another aspect of the SLAM system to consider is its high computational intensity, which might cause delays in delivering estimates to other subsystems.[1]

The term SCLAM (Simultaneous Control, Localization, and Mapping) refers to techniques for "concurrently integrating control tasks with localization and mapping tasks"." 1 The paper analyzed in this work aims to address a novel vision-based approach to SCLAM designed for UAV operation in GPS-denied environments. The paper addresses challenges such as real-time processing, autonomous exploration, home return, and the closing-the-loop problem.

The work focuses on enabling a UAV with a monocular camera as its main sensor to perform autonomous exploration missions in GPS-denied environments. The mission involves following a predefined flight plan with commands like take-off, flying to specific points, exploring areas, returning home, and landing. The key contribution is a novel system architecture that is flexible and adaptable, allowing for the use of alternative techniques in its subsystems. The work details high- and low-level control algorithms while referencing a previous study for the SLAM subsystem. Additionally, it introduces a new technique to help the UAV return to its home position despite accumulated pose estimation errors, addressing a common challenge in GPS-denied environments.[1]

In SCLAM methods, the SLAM subsystem's estimated pose is directly used by the autonomous control subsystem as if it were ground truth. This means any errors in the SLAM-estimated position lead to discrepancies between the robot's desired and actual positions. However, when a loop closure occurs, the SLAM system corrects the estimated position, allowing the control subsystem to detect and adjust for the robot's drift position.[1]

The key differences between SLAM and SCLAM lie in their integration with control systems and error handling. In SLAM, the robot is typically guided along a predefined trajectory under the assumption of perfect control, but the estimated trajectory drifts from the actual path due to integration errors. This drift is corrected during loop closure, where the robot revisits a previously mapped area, and the SLAM algorithm reduces accumulated errors. Performance is evaluated by comparing the estimated trajectory to the predefined path. In contrast, SCLAM directly feeds the SLAM subsystem's estimated pose into the autonomous control subsystem, treating it as ground truth. This means errors in the SLAM-estimated position cause discrepancies between the desired and actual robot positions. However, during loop closure, the SLAM system corrects the estimated position, enabling the control subsystem to identify and adjust for the robot's drifted position. Thus, SLAM focuses on trajectory estimation and error correction, while SCLAM integrates SLAM estimates into real-time autonomous control for dynamic adjustments.[1]

The SLAM system utilized in the work combines the strengths of filter-based and optimization-based methods in a visual-based SLAM framework. This hybrid approach integrates their complementary features: the filter-based subsystem handles continuous local SLAM processes, while the optimization-based subsystem maintains a consistent global map. By running these components concurrently in separate processes, the system achieves greater modularity, robustness, and redundancy.[1] [12] The work focuses on novel techniques when it comes to the UAV's control system, which is designed to work with a visual camera as the robot's main sensor.[1] The exact algorithms and calculations can be explored in the work. Source code is available at https://github.com/rodrigo-munguia/SCLAM-UAVs.

The virtual experiment results demonstrate that the proposed SCLAM system successfully enables a multi-rotor UAV, utilizing a monocular camera as its primary sensor, to execute fully autonomous exploration missions in GPS-denied environments. These missions encompass takeoff, navigation to a target location, exploration of the surroundings, and returning to the home position for landing. Unlike other related approaches that primarily evaluate specific estimation-control frameworks, this proposal presents a comprehensive SCLAM architecture designed to address autonomous exploration challenges from a broader perspective. Notably, the subsystems within this architecture can be implemented using various control and estimation techniques.

Future research could explore different control, estimation, and trajectory generation methods for implementing the system's subsystems. This includes alternative control algorithms to enable spiral or circular movements, as well as methods that enhance speed or responsiveness. While virtual experiments provide valuable insights into the SCLAM system's potential in real-world applications, future work should also focus on validating these findings in real-world environments, following the approach used for the SLAM subsystem in the author's previous research.

Other techniques have been explored to solve the SCLAM problem. Shen et al.[2] provide a comprehensive survey on visual SLAM techniques for UAVs and emphasize tightly coupled visual-inertial navigation systems (VINS) for autonomous navigation. They propose a system combining visual and inertial data to enhance UAV navigation. Forster et al.[3] introduce a visual-inertial SLAM system with an efficient control algorithm for precise navigation in cluttered spaces. Zhang and Scaramuzza[4] integrate visual SLAM with model predictive control for improved path planning and collision avoidance. Faessler et al.[5] incorporate monocular SLAM with nonlinear model predictive control (NMPC) to enable agile drone flight. Li et al.[6] developed a monocular SLAM system optimized for MAVs, focusing on computational efficiency. Mei et al.[7] enhance visual SLAM for outdoor UAVs, addressing lighting variations. Liu et al.[8] and Kaufmann et al.[9] integrate adaptive control strategies for dynamic environments, while Bachrach et al.[10] develop a system for stable indoor and outdoor UAV operation. Sun et al.[11] apply reinforcement learning to optimize SLAM and control integration, improving real-time UAV navigation.[1]

Sources

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