Master thesis

Vision-Lidar Sensor Data Fusion For Autonomous Vehicles SLAM

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1. Introduction

Autonomous navigation is an essential part of modern robotics and the automotive industry. To enable a robot to cognitively navigate through a known or unknown environment knowledge of its state and its surroundings is necessary. The process of real-time map construction and localisation within it, is called Simultaneous Localisation and Mapping (SLAM).

Monocular SLAM (single camera sensor) has several advantages, with the primary being its affordability. However, the lack of depth information in the two-dimensional image causes scaling issues. The incorporation of a lidar sensor will provide the true distances between the vehicle and the environment, thus eliminating the aforementioned issue.

In this work existing algorithms are evaluated, implemented and fused using an alternative filtering method.

2. Methodology

SLAM algorithms:

- **ORBSLAM:** Monocular SLAM algorithm.
  Implements ORB feature extraction and matching for odometry and trajectory estimation. The three main processes run on different threads allowing timing optimisation. ORBSLAM exploits the same features for all three processes thus avoiding feature depth interpolation which increases robustness and efficiency.

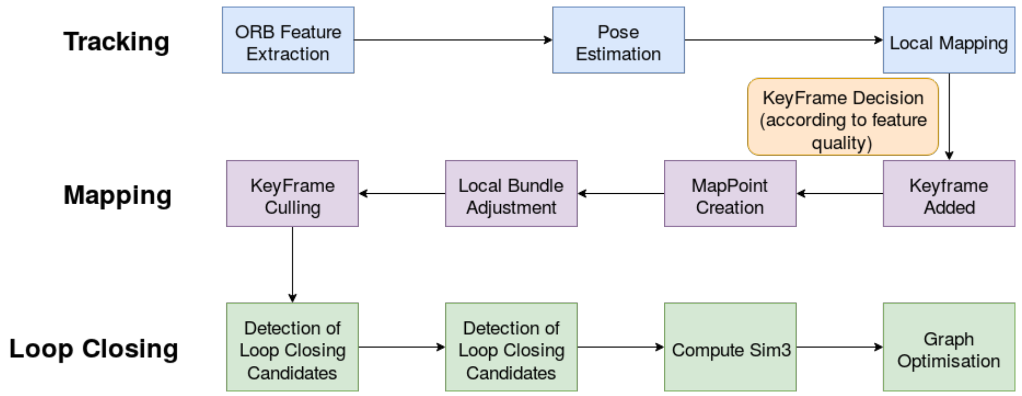

Figure: ORBSLAM algorithm

- **LOAM:** Feature-based SLAM:
  - Divide point cloud gridwise
  - Detect edges and planar areas in each grid
  - Feature Matching of consecutive frames
  - Loop Closing →Drift correction
- **Cartographer:**
  - Local SLAM
    - Submap (grid) creation
    - Submap position through pose estimation
    - Scan Matcher with previous frames
  - Global SLAM
    - Graph SLAM optimisation, Non-linear least squares
    - Scan Matching in batches (20 nodes)
    - Real-time drift correction
    - Sparse Pose Adjustment method

Covariance Intersection Filter: The applied filter considers two uncorrelated sensors A and B and their mean -covariance pairs as $\{\hat{a}, \boldsymbol{A}\}$ and $\{\hat{b}, \boldsymbol{B}\}$
Their correlated covariance is defined as:

$$C^{-1} = \omega A^{-1} + (1-\omega) B^{-1}$$

Assuming the pose estimations of the two sensors are known as x_c and x_l, a fused pose estimation can be calculated as follows:

$$x^* = C(\omega \cdot A^{-1} \cdot x_c + (1-\omega) \cdot B^{-1} \cdot x_l)$$

Factor ω is determined using a determinant minimisation with
$\omega^* =$
$\mathrm{argmin}_\omega \{\det A^{-1} \det A^{-T} \det AC^{\omega}(A)^T\}$

3. Results

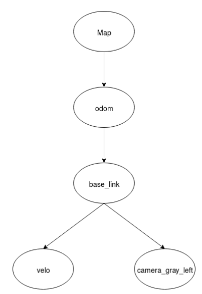

Figure: Simplified Coordinate Frames of vehicle

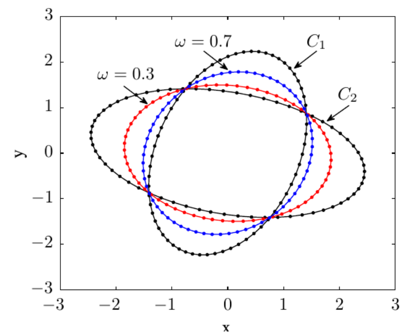

Figure: Fused Covariance and the effect of ω

4. Conclusion

- The Cartographer was selected instead of the LOAM for the lidar data processing
- The ORBSLAM and Cartographer fusion was possible and showed good results
- Covariance Intersection Filter shows adequate results. Further tuning is needed for the covariance correlation

5. Future Development

- The integration of IMU sensor will enable:
  - Improvement in trajectory estimation (Cartographer Front-End)
  - Decrease of optimisation frequency and window
- Acquisition of new Dataset with with Zoé - new cameras, less distortion
- Rigorous testing prior to real life integration