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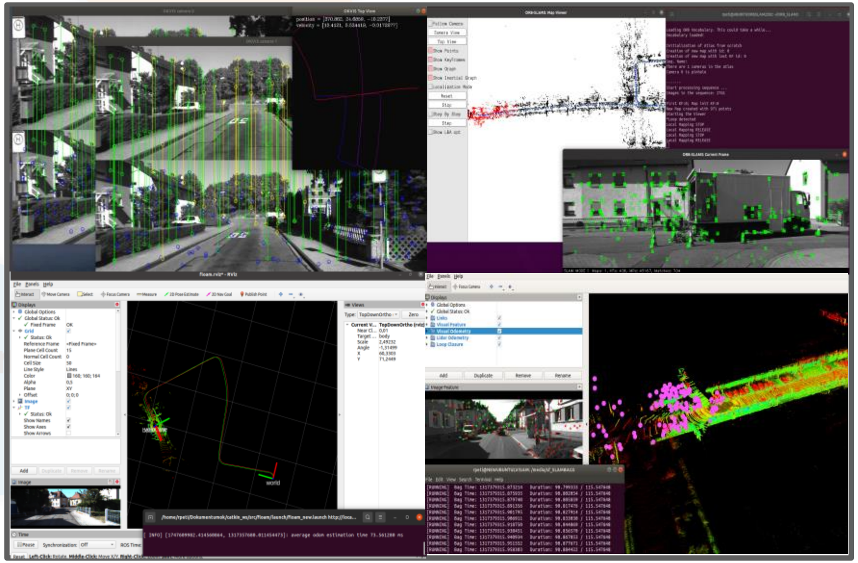
Project type: Thesis project

Topic: Quantitative comparison of Simultaneous Localization And Mapping (SLAM) algorithms

Supervisor: Dr. László Schäffer

- SLAM solutions differing in both sensor utilization and algorithmic approach
  - EKF-SLAM: monocular, Kalman filter
  - MSCKF: stereo + IMU, Kalman filter
  - OKVIS, ORB-SLAM3: stereo + IMU, opt.-based
  - ORB-SLAM3: stereo/RGB-D + IMU, opt.-based
  - F-LOAM: LiDAR, opt.-based
  - LVI-SAM: sensor fusion approach, opt.-based
- Qualitative analysis from publication
- Quantitative testing via open−source code
- Summarized pros & cons of each algorithm
- The implementation of the algorithms was necessary, as accuracy results were not available for a common sequence.
- The algorithms were executed within virtual machines deployed on a laptop



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Experiments

- Each algorithm deployed in a separate virtual machine**,** *due to OS and package version differences*
- KITTI dataset sequences 05 and 07 selected
  - Length: 2223 m and 695 m
  - Includes loop closure points
- 6 algorithms reviewed, 5 implemented, 4 evaluated on KITTI
- 5 runs per sequence to mitigate non-deterministic effects
- We examined the following:
  - *Average Position Error* – the average of all recorded position errors, in meters
  - *Average Rotation Error* – the average of all recorded rotational errors, in degrees
  - *Average Final Position Error* – the average of the final position errors, in meters
  - *Average Final Orientation Error* – the average of the final orientation errors, in degrees
  - *Maximum Position Error* – the largest recorded position error, in meters

Results & future work

- ORB-SLAM3
  - Best accuracy, improvement potential: include IMU to reduce sensor-related errors or GPS based map correction
- LVI-SAM
  - Good performance but suffers from critical failures
  - Needs robust failure handling and loop closure validation
- F-LOAM
  - LiDAR-only approach with moderate accuracy
  - Accuracy can be improved with IMU integration
- OKVIS
  - High error, especially endpoint position
  - Lack of loop closure affects pose accuracy
  - Recommend: implement loop closure detection and pose correction
- MSCKF SLAM requires parameter tuning for better estimation quality

KITTI sequence 5

Algorithm	Average Position Error ±STD [m]	Average Rotation Error ±STD [°]	Average Final Position Error ±STD [m]	Average Final Rotation Error ±STD [°]	Maximum Position Error [m]
ORB-SLAM3	**1.62 ± 0.40**	**0.35 ± 0.21**	**2.58 ± 0.29**	**0.19 ± 0.04**	**4.87**
LVI-SAM	6.16 ± 0.09	1.44 ± 0.06	8.93 ± 0.08	1.48 ± 0.02	16.50
F-LOAM	8.99 ± 0.16	2.03 ± 0.08	21.41 ± 0.14	3.72 ± 0.04	21.67
OKVIS	12.45 ± 1.54	3.42 ± 0.74	31.52 ± 4.75	7.17 ± 1.20	42.52

KITTI sequence 7

Algorithm	Average Position Error ±STD [m]	Average Rotation Error ±STD [°]	Average Final Position Error ±STD [m]	Average Final Rotation Error ±STD [°]	Maximum Position Error [m]
ORB-SLAM3	**0.72 ± 0.06**	**0.29 ± 0.05**	**0.11 ± 0.003**	0.27 ± 0.01	**1.45**
LVI-SAM	2.51 ± 0.03	0.99 ± 0.04	1.82 ± 0.15	2.71 ± 0.47	3.34
F-LOAM	2.61 ± 0.36	0.80 ± 0.08	1.40 ± 0.21	**0.18 ± 0.13**	6.50
OKVIS	3.46 ± 0.74	1.64 ± 0.66	5.12 ± 0.69	3.46 ± 0.79	6.94

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