

AV-SLAM: Autonomous Vehicle Simultaneous Localization and Mapping with Gravity Direction Initialization



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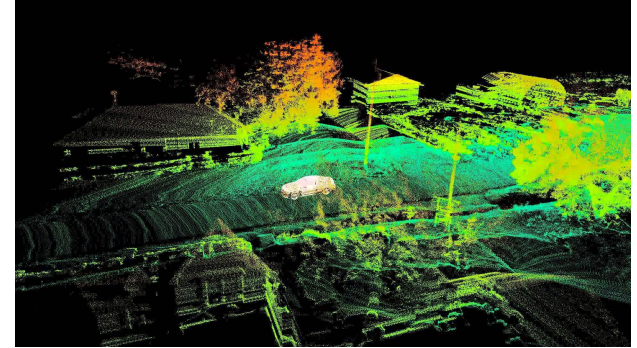
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What is SLAM ?

- Create a map of the environment using sensors
- Localize the vehicle within the map



Inertial Measurement Unit (IMU)



Camera

Stereo Camera / RGB-D Camera



Lidar

Challenges about SLAM



- **IMU initialization**

If **IMU** is being used, then:

- **Robust IMU initialization** for autonomous vehicle scenarios is essential.
- Available methods have been tested only on UAV scenarios.

>>> A gravity direction initialization method is proposed

- **Sensor-failure**

- The accuracy of sensors **can degrade** due to hardware wear.
- Sensors may **stop working completely** because of environmental conditions.

>>> Multiple localization algorithms are proposed to form a single SLAM which have fail-safe modes

MAIN PURPOSE: Developing a fail-safe SLAM algorithm with accurate gravity direction initialization

Proposed SLAM (AV-SLAM)



- Based on Mono-Camera, LIDAR and IMU
- Has 3 sensor setup modes (fail-safe):
 - IMU-Only Localization
 - Camera+LIDAR (RGBD-SLAM)
 - IMU+Camera+LIDAR (VI-SLAM)
- VI-SLAM features a gravity direction initialization algorithm (AGI)

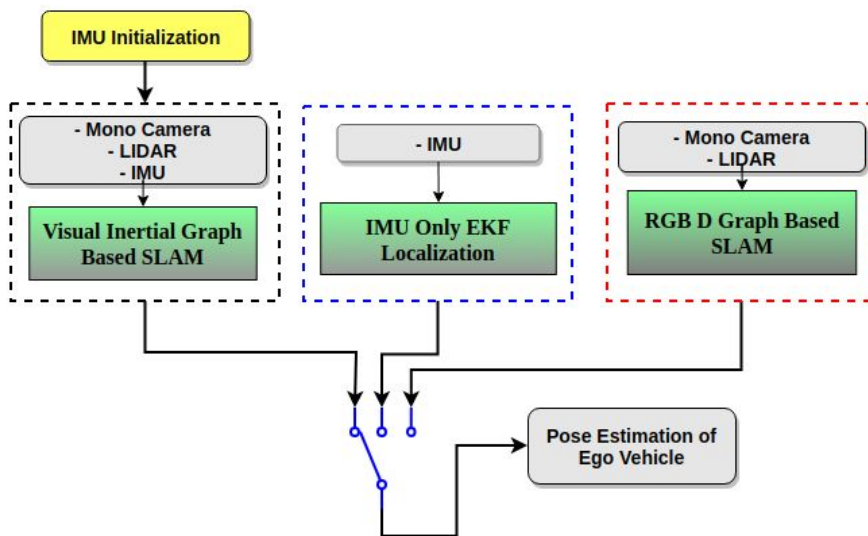


Figure 1: Overall architecture of AV-SLAM

IMU-Only Localization



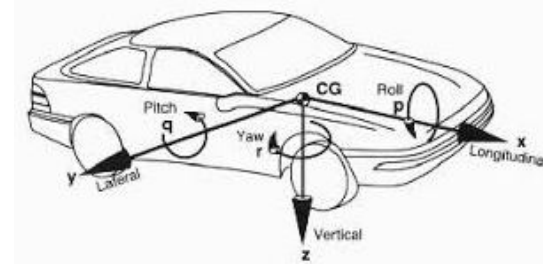
Pseudo-Measurement Concept

Extended Kalman Filter consists of two steps;

- Prediction step
- Update step

In order to proceed the **update step**, **measurement** is needed.

It is assumed that while a car is travelling, its **lateral** and **upward** velocities are 'zero'.



$$\mathbf{z} = \begin{bmatrix} \text{IMU } \mathbf{v}_t^{lat}; \text{IMU } \mathbf{v}_t^{up} \end{bmatrix} = \mathbf{0}$$

Figure 2: Roll, pitch and yaw directions

RGBD-SLAM



- Graph-SLAM that involves **Mono-Camera + LIDAR.**
- Scales of visual keypoints are estimated from LIDAR-interpolated depth image
- Create new 3D map points with unmatched ORB features
- Manage keyframes

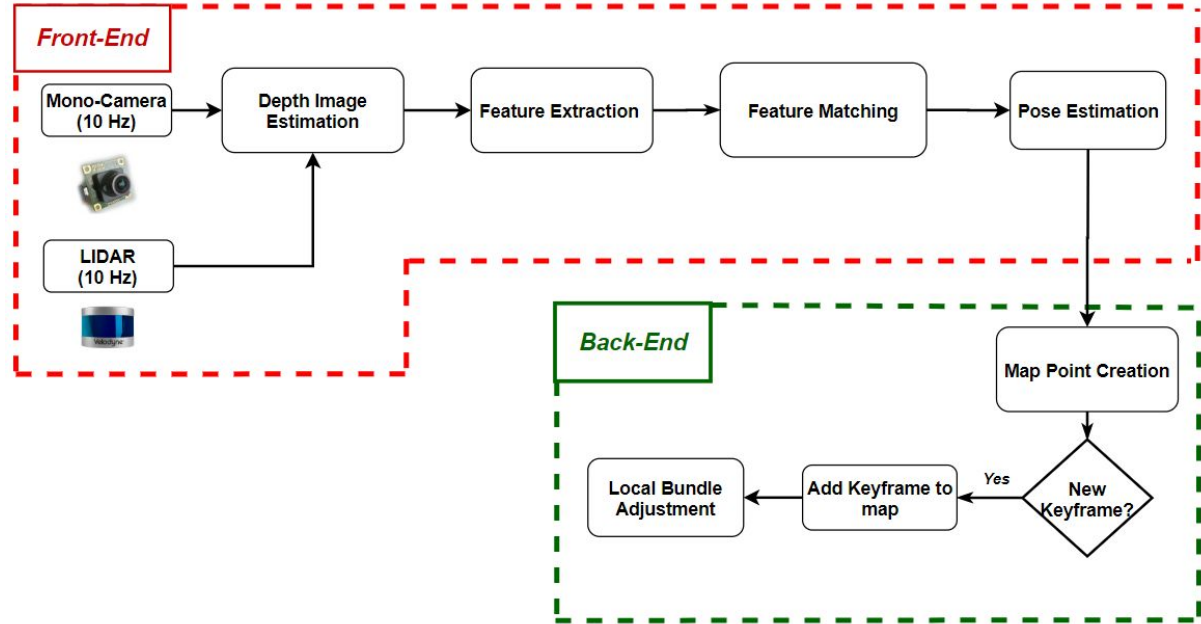


Figure 3: High-level architecture of RGBD-SLAM

Visual-Inertial SLAM (VI-SLAM)



- Involves fusing RGBD-SLAM with IMU measurements
- Features a gravity direction initialization method

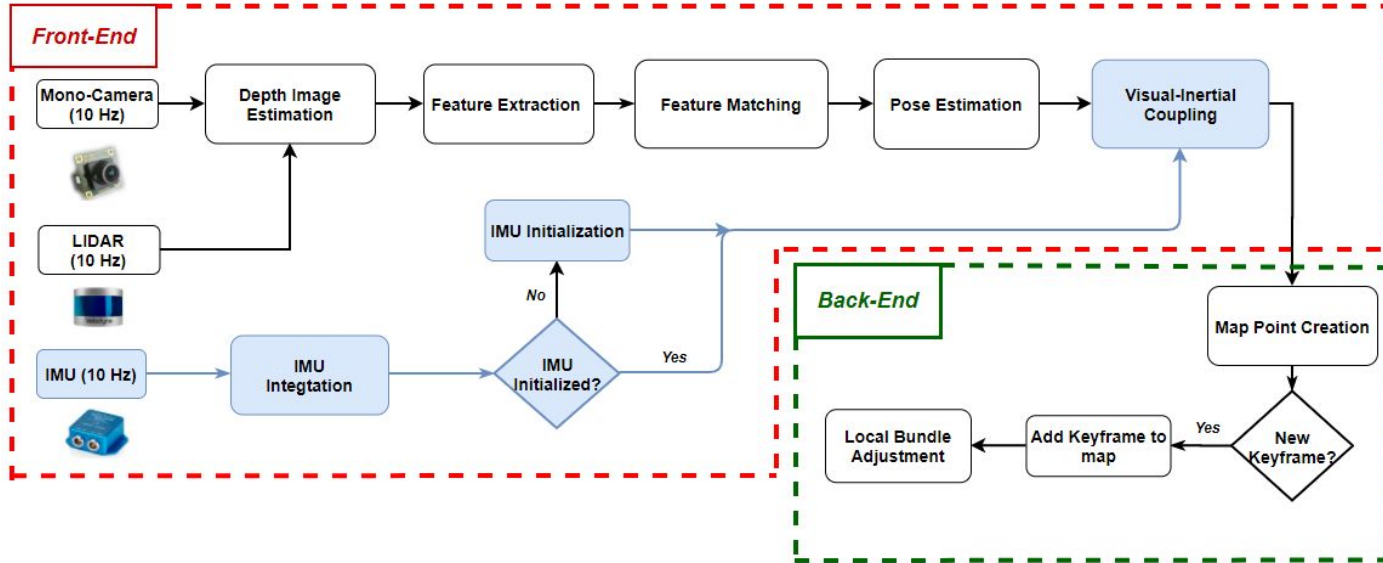


Figure 4: High-level architecture of VI-SLAM

VI-SLAM: Fusing Visual and Inertial Pose Estimations



- Visual and IMU pose estimation are loosely coupled
- Equally weighting between Visual and IMU estimations

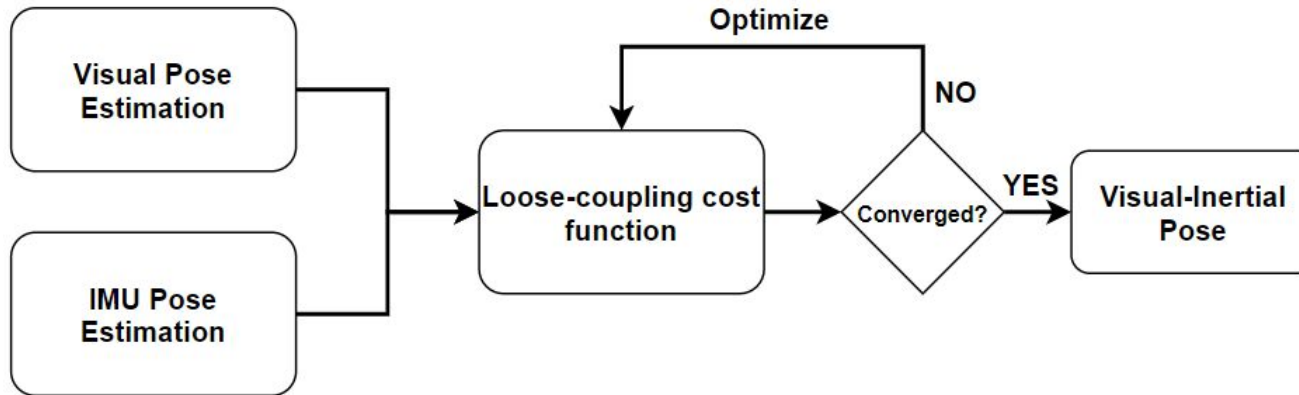


Figure 5: Coupling mechanism of VI-SLAM

VI-SLAM: Proposed Gravity Direction Initialization (AGI)



1. Calculate roll and pitch angles using the estimated gravitational accelerations at each timestep.
2. The moving average of roll and pitch angles are calculated.

Gravity direction ← Converged values of roll and pitch angles

Dataset 09: Estimated Gravity Direction

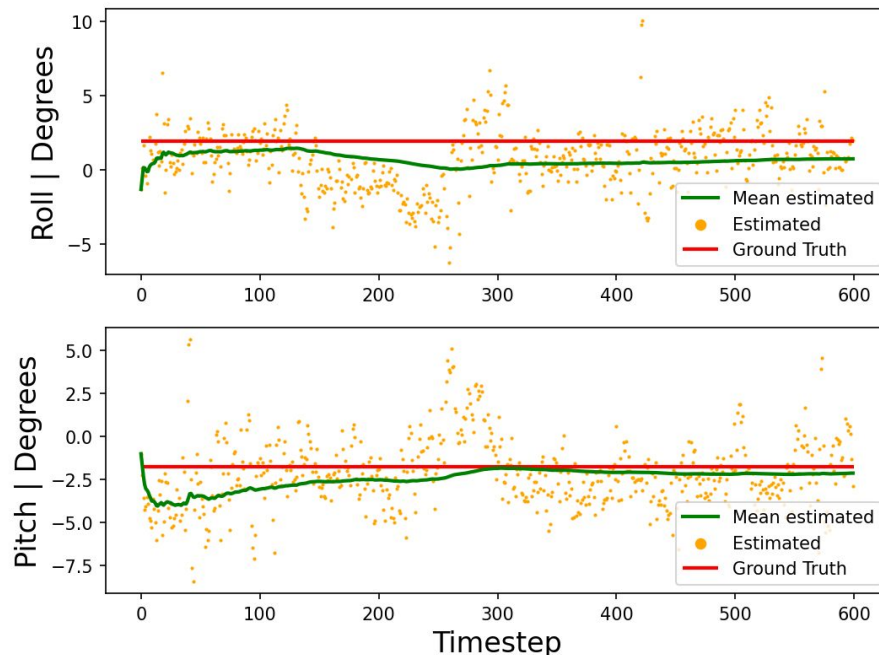


Figure 8: Convergence plot of gravity direction initialization

Results: Translational RPE Comparison



Table 1: Percentage Translational RPE of proposed and state-of-the-art SLAM algorithms on KITTI sequences

Seq No	% RPE _{trans}						
	IMU-Only (Proposed)	RGBD- SLAM (Proposed)	VI-SLAM (Proposed)	LOAM	ORB- SLAM2	Cube- SLAM	PL-SLAM
00	362	1.62	2.03	0.78	0.7	1.97	2.38
01	14.0	31.1	32.1	1.43	1.39	-	3.23
02	91.5	1.25	1.19	0.92	0.76	2.48	2.2
04	2.23	0.9	1.16	0.71	0.55	1.12	1.57
05	24.2	1.53	1.31	0.57	0.37	1.64	1.67
06	6.65	1.69	1.36	0.65	0.43	2.26	2.02
07	3.95	2.01	1.21	0.63	0.45	1.63	1.57
08	22.7	1.78	1.3	1.12	1.06	2.05	2.42
09	11.1	1.05	0.65	0.77	0.83	1.66	1.49
10	11.9	1.04	0.75	0.79	0.55	1.46	1.61

Results: Gravity Direction Initialization



- Abs. error <1 degree in datasets 02, 07, 08, 09 and 10
- Low std deviation across multiple runs
- Sampling: 10Hz
- Compared with VINS-Mono's method and a baseline method (Roll and pitch are initialized to 0 deg)

Table 2: Absolute error of gravity direction initialization methods

Seq No	Roll - Abs Error (deg)			Pitch - Abs Error (deg)		
	Baseline	AGI (Proposed)	VINS-Mono	Baseline	AGI (Proposed)	VINS-Mono
00	2.41	0.8 ± 0.03	0.57 ± 0.1	1.27	2.38 ± 0.05	1.06 ± 0.02
01	0.73	1.07 ± 0.95	9.6 ± 0.06	3.01	6.78 ± 0.45	4.44 ± 0.03
02	0.9	0.68 ± 0.01	0.19 ± 0.01	0.23	0.34 ± 0.05	0.19 ± 0.08
04	2.44	3.22 ± 0.06	-	0.66	1.3 ± 0.08	-
05	1.87	3.85 ± 0.01	-	1.22	0.09 ± 0.02	-
06	2.65	5.3 ± 0.01	5.42 ± 0.02	0.55	1.38 ± 0.22	0.93 ± 0.01
07	1.29	0.38 ± 0.06	3.35 ± 0.2	0.64	0.93 ± 0.06	0.73 ± 0.01
08	2.95	0.49 ± 0.14	8.52 ± 0.3	1.37	0.52 ± 0.04	1.5 ± 0.02
09	1.92	1.46 ± 0.05	0.94 ± 0.05	1.76	0.1 ± 0.01	1.83 ± 0.01
10	1.4	0.82 ± 0.03	-	3.22	0.33 ± 0.05	-

Table 3: Timesteps required to initialize gravity direction

Seq No	#Timesteps to Initialization	
	AGI (Proposed)	VINS-Mono
00	169 ± 48	741 ± 2
01	599 ± 62	170 ± 3
02	343 ± 2	186 ± 60
04	243 ± 38	-
05	279 ± 28	-
06	202 ± 29	78 ± 8
07	211 ± 22	125 ± 2
08	174 ± 23	154 ± 4
09	325 ± 0	177 ± 1
10	211 ± 0	-

Conclusion



We developed:

- A SLAM algorithm comprising of 3 localization algorithms
- Ability to work when IMU fails or when Camera and LIDAR fail
- A gravity direction initialization method and tested it on raw KITTI datasets

1. AV-SLAM ensures relative translation error of **<2.03%** for low to medium speed ego-vehicle scenarios (speed **<38km/h**) when all sensors are available
2. The proposed SLAM framework with AGI method without loop closure modules outperforms state-of-the-art methods with loop closure modules on some datasets.
3. The proposed VI-SLAM with AGI algorithm provides fast, accurate and repeatable initialization on some datasets.



QUESTIONS & ANSWERS



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