LIC-Fusion: LiDAR-Inertial-Camera Odometry

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Motivation

3D LiDAR: accurate range measurements but suffers from point cloud sparsity, high cost, and lower collection rates

Camera: informative appearances, light-weight, low-cost, but susceptible to lighting conditions

IMU: Proprioceptive sensor which measures the velocity and linear acceleration of the sensing platform in a high frequency

- *A tightly-coupled odometry by leveraging the "best" of each sensor modality*

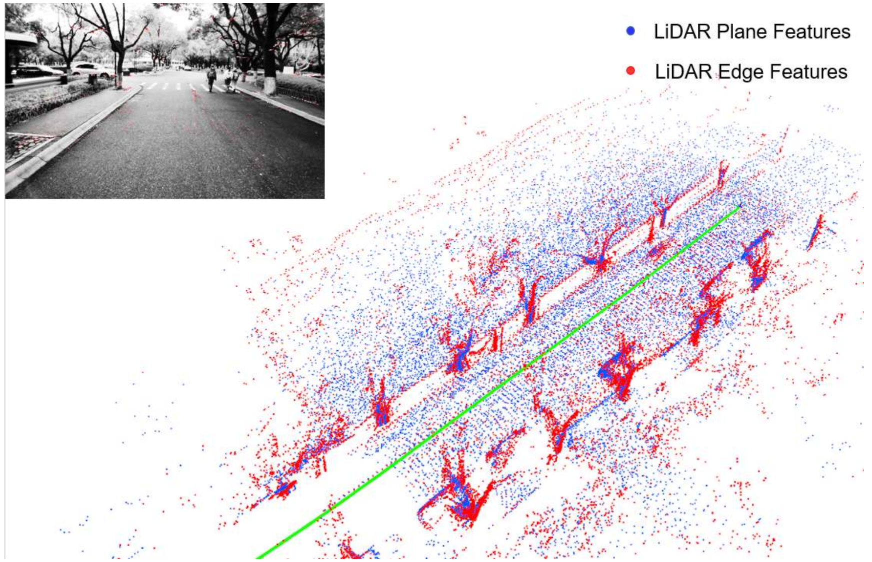


Fig 1. LiDAR and visual features used in the proposed LIC-Fusion.

Contributions

- *Design of a tightly-coupled, light-weight LiDAR-inertial-camera (LIC) odometry*

- *With online spatial and temporal calibrations between different sensor modalities. Correlations between states are explicitly modeled and analytically derived.*

- *IMU measurements, sparse visual features, and two different sparse LiDAR features are used for update in a light-weight EKF framework.*

- *Validate proposed system in both indoor and outdoor environments even under extremely aggressive motion and show superior performance over state-of-the-art.*

System Overview

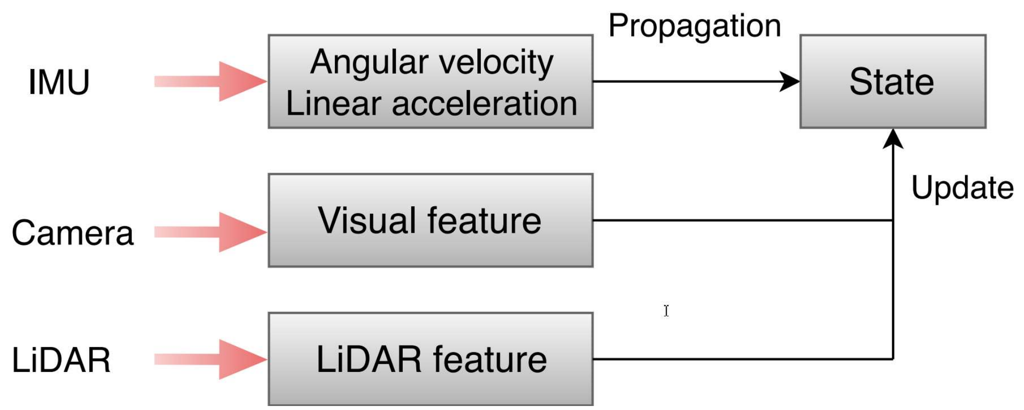


Fig 2. Data flow of LIC-fusion in a EKF based MSCKF framework.

- *System composed of two main parts: (i) . Propagation by high-frequency IMU, (ii). Update by sparse visual and LiDAR feature*
- *State vector including the extrinsics between sensors, cloned IMU states at the time instant of receiving the image and LiDAR scan:*

$$x = \begin{bmatrix} x_I^{\top} & x_{calib\_C}^{\top} & x_{calib\_L}^{\top} & x_C^{\top} & x_L^{\top} \end{bmatrix}^{\top}$$

- *States are correlated and the covariance matrix is maintained.*

Propagation

- *Propagate up to IMU time $\hat{t}_{I_k}$, which is the current best estimate of the measurement collection time in the IMU clock.*

For example, if a new LiDAR scan is received with timestamp t_{L_k} , we will propagate up to $\hat{t}_{I_k} = t_{L_k} + \hat{t}_{dL}$

- *Augment the state vector by stochastic cloning*

- *The propagation is a function of the temporal and spatial extrinsics, which allow our measurements model to update the poses and extrinsics jointly.*

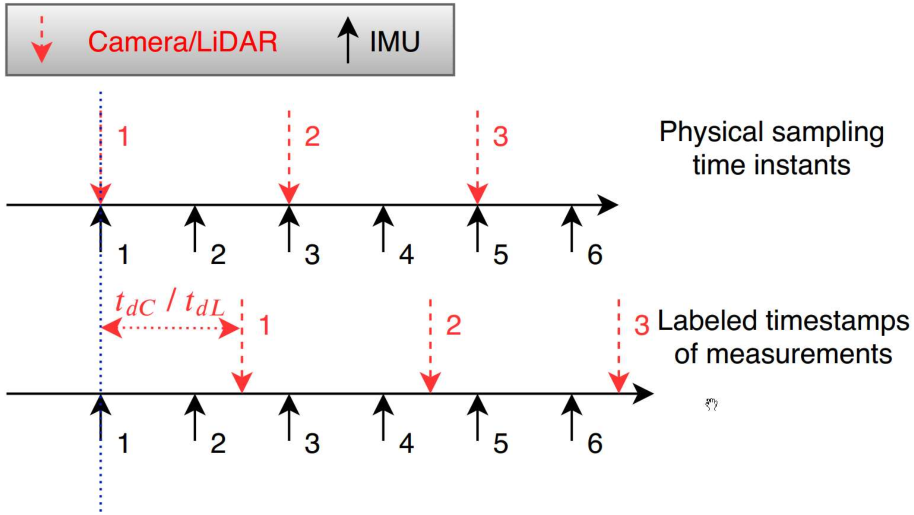


Fig 3. Time offset between IMU and Camera/LiDAR

Update by Measurements

- *LiDAR Features: extract high and low curvature sections of LiDAR scan rings which correspond to edge and planar surf features [Ji Zhang 2014]. Matching those features between scans.*

- *Visual features: initialize in 3D by triangulation Null-space operations are performed for remove the dependency of 3D features.*

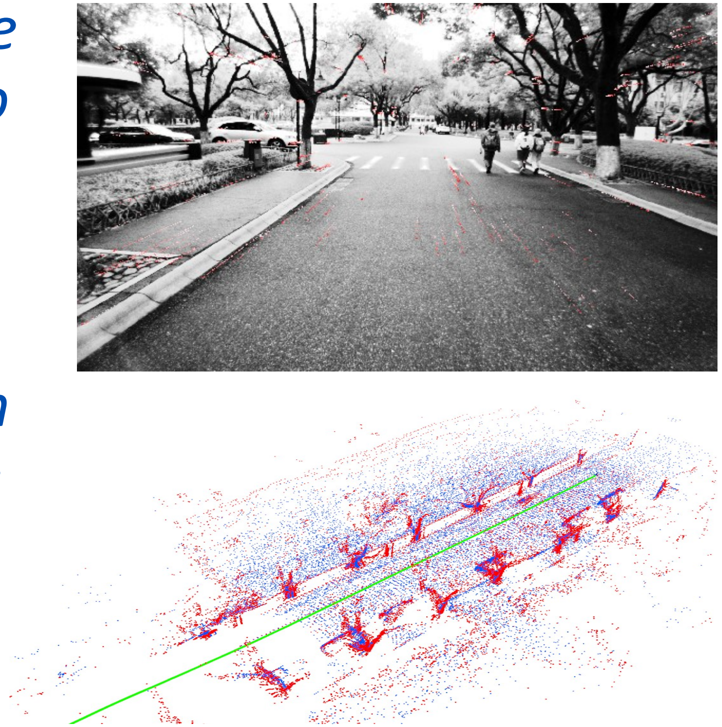
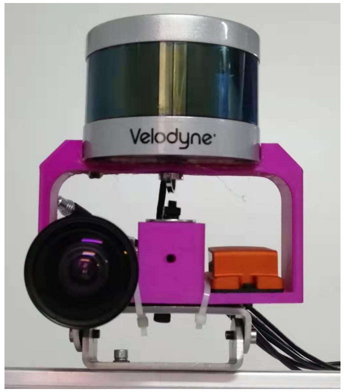
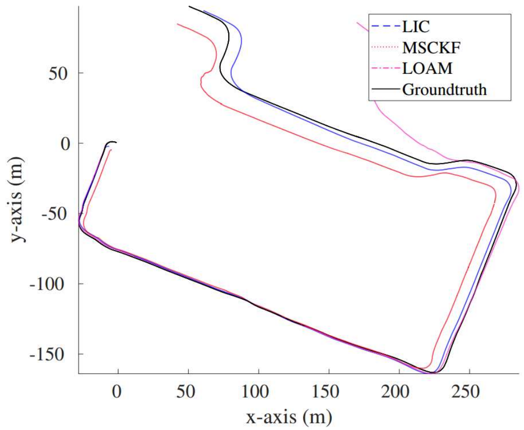


Fig 5. Measurements from multiple modalities for update.

Experiments Results I : Outdoor





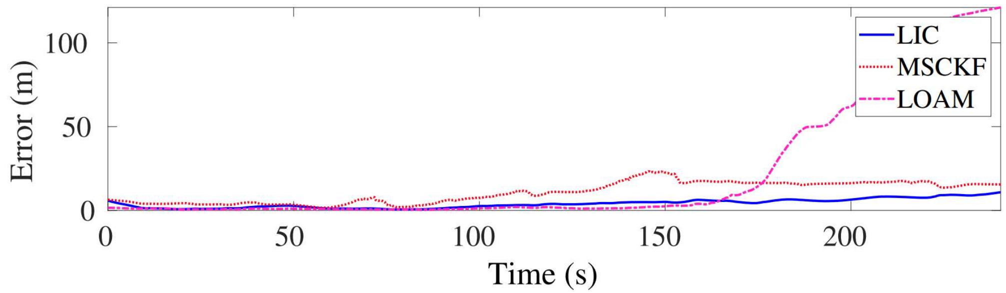


Fig 6. The self-assembled LiDAR-inertial-camera rig .

Fig 7. Estimated trajectories compared with MSCKF, Loam, Ground truth from RTK-GPS. And the Average mean squared errors.

- *• 800 meters in length recorded in a university campus scenario while mounting the sensors rig on a car.*

- *LIC-fusion shows superior performance regarding accuracy.*

Experiments Results I : Outdoor

Table 1: Trajectory RMSE with different levels of prior map noises.

	MSCKF	LIC-Fusion	LOAM
Average ATEs (m)	10.75	4.06	23.08
1 Sigma (m)	3.56	3.42	2.63

- *800 meters in length recorded in a university campus scenario while mounting the sensors rig on a car.*

- *LIC-fusion shows superior performance regarding accuracy.*

Experiments Results II : Indoor

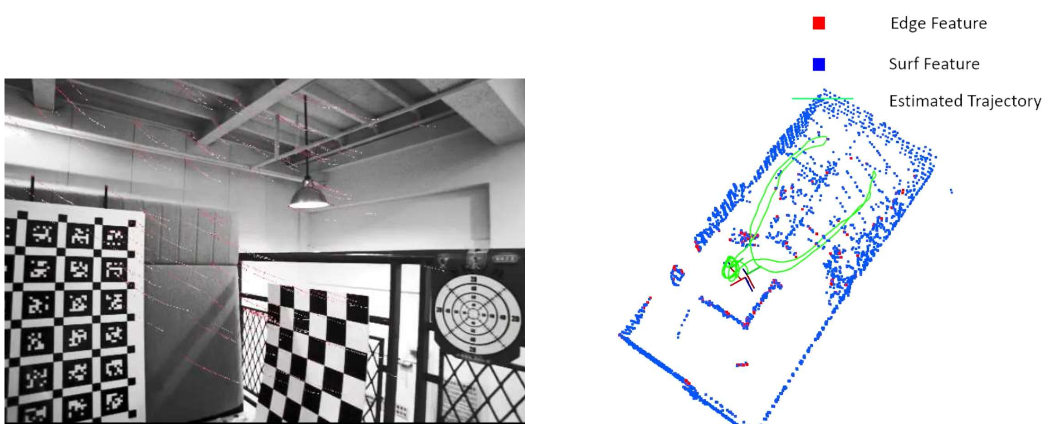


Fig 6. The Indoor-A scenario.

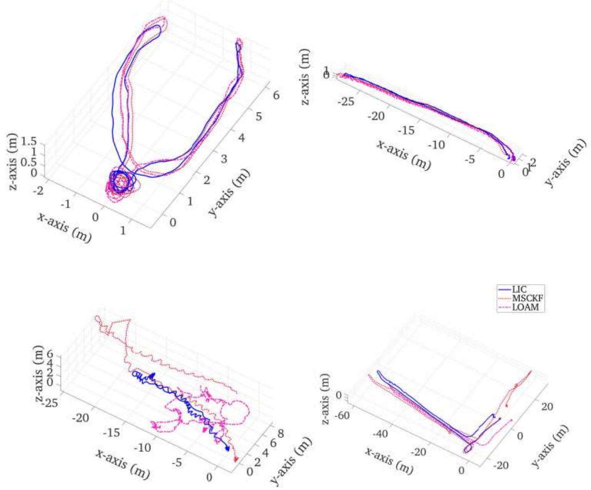


Fig 7. The estimated trajectories in indoor scenarios.

- *Tested in multiple indoor scenarios while holding the sensors rig by hand.*
- *LIC-fusion shows superior performance regarding accuracy.*

Experiments Results III : Aggressive Motion Test

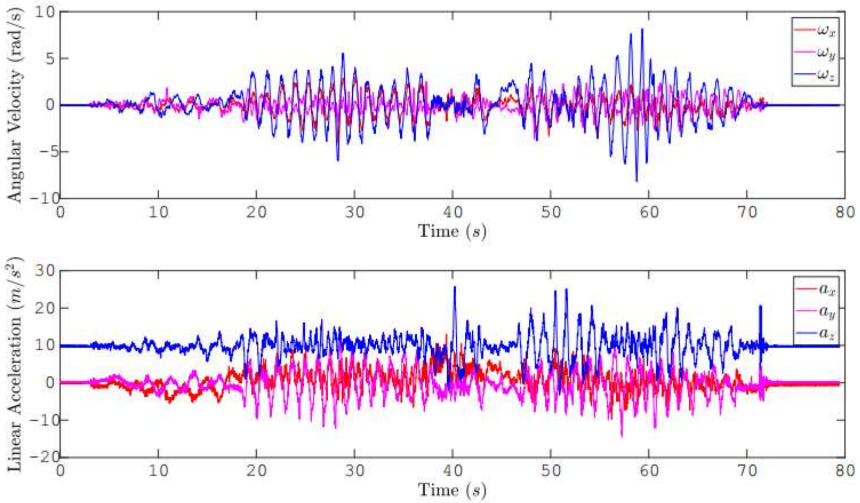


Fig 8. Raw IMU measurements over the high-dynamic Indoor-C sequence.

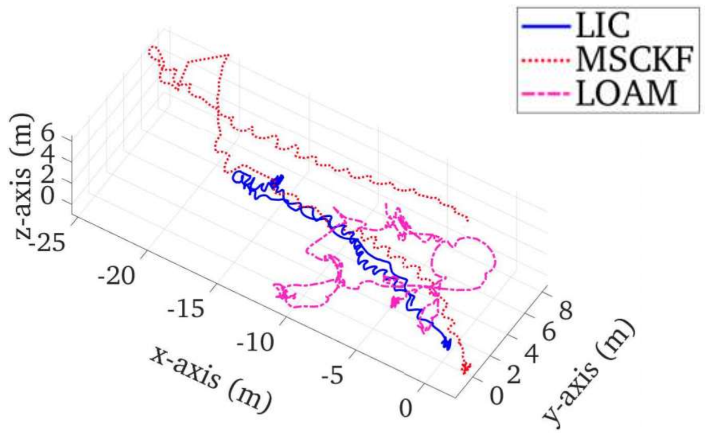
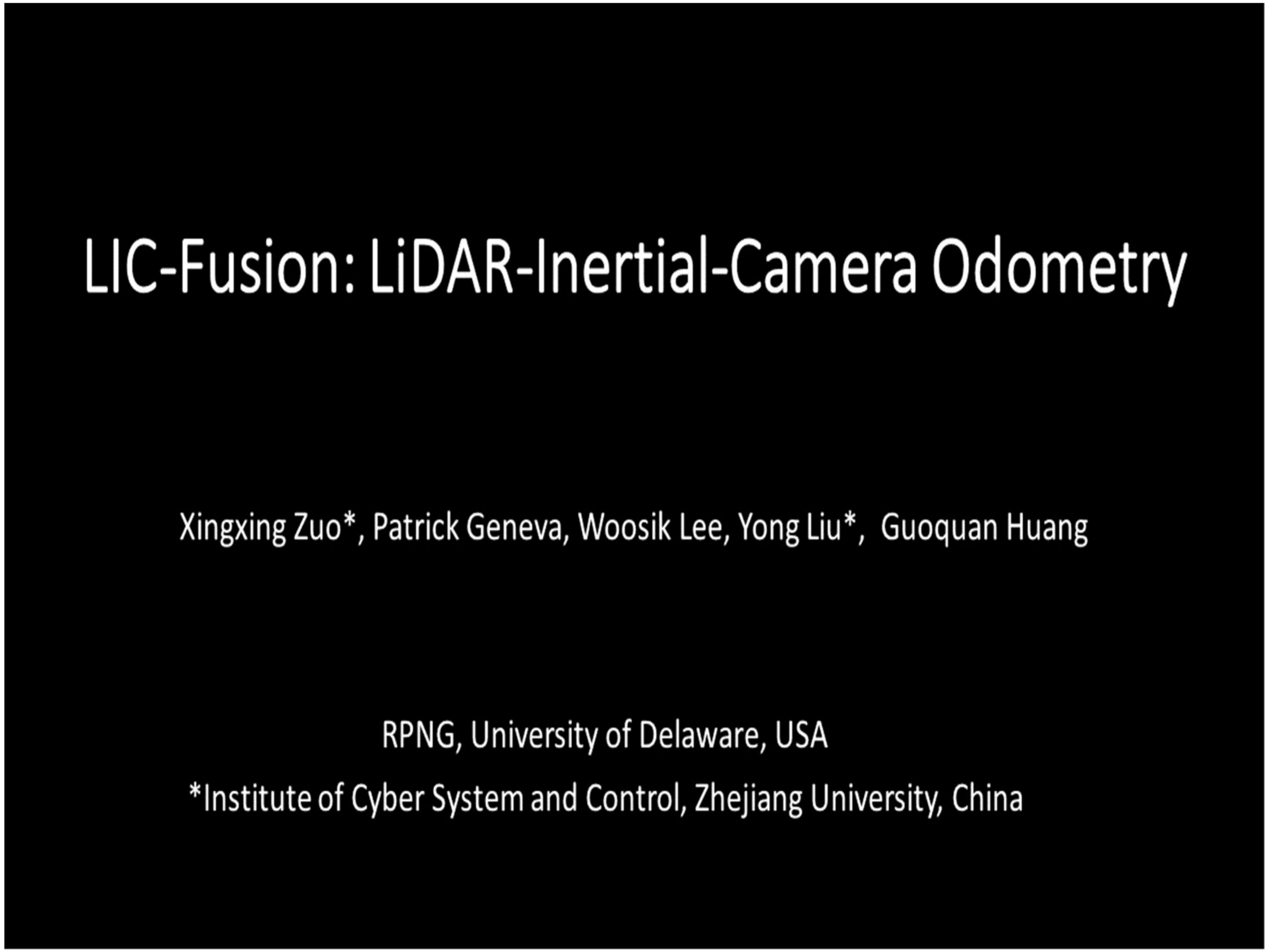


Fig 9. The estimated trajectories over the high-dynamic Indoor-C sequence.

- *Shake the sensors rig as strongly as possible by hand. Violent rotation and acceleration: raw IMU measurements over 8 rad/s and 25 m/s^2 at some instants.*

- *LIC-fusion shows superior performance regarding robustness to high dynamics.*

System Demonstration



Conclusion

- *Proposed tightly-coupled, light-weight LiDAR-inertial-camera (LIC) odometry.*

- *With online spatial and temporal calibrations between different sensor modalities.*

- *System shows robustness to high dynamics.*

- *Outperforms state-of-the-art due to fully utilizing multiple types of measurements in a tightly-coupled way.*

Thanks for listening!

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References

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