Map-based Visual-Inertial Localization: A Numerical Study

Patrick Geneva and Guoquan Huang

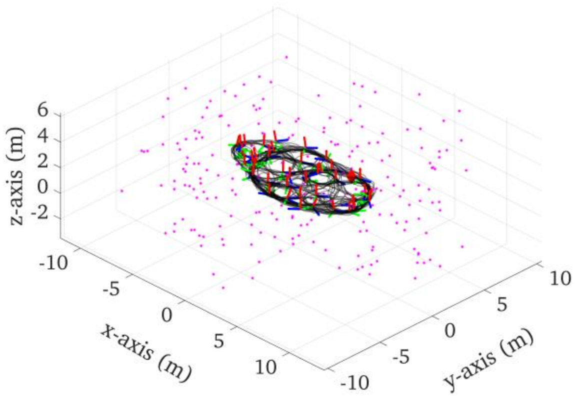
Robot Perception and Navigation Group (RPNG)
University of Delaware (UD), Newark, DE, USA

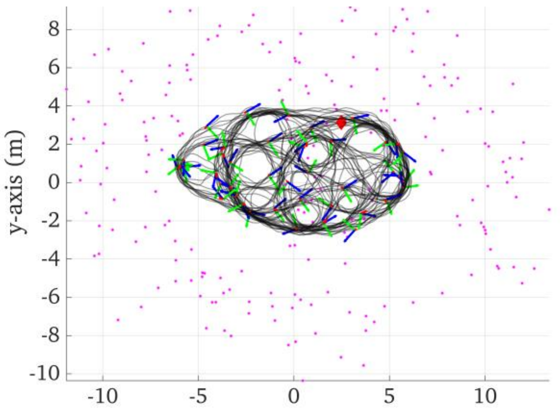
Motivation

- Leverage prior map to improve visual-inertial estimator performance
  - Prior points map with 2D-to-3D meas
  - Prior keyframes map with 2D-to-2D meas

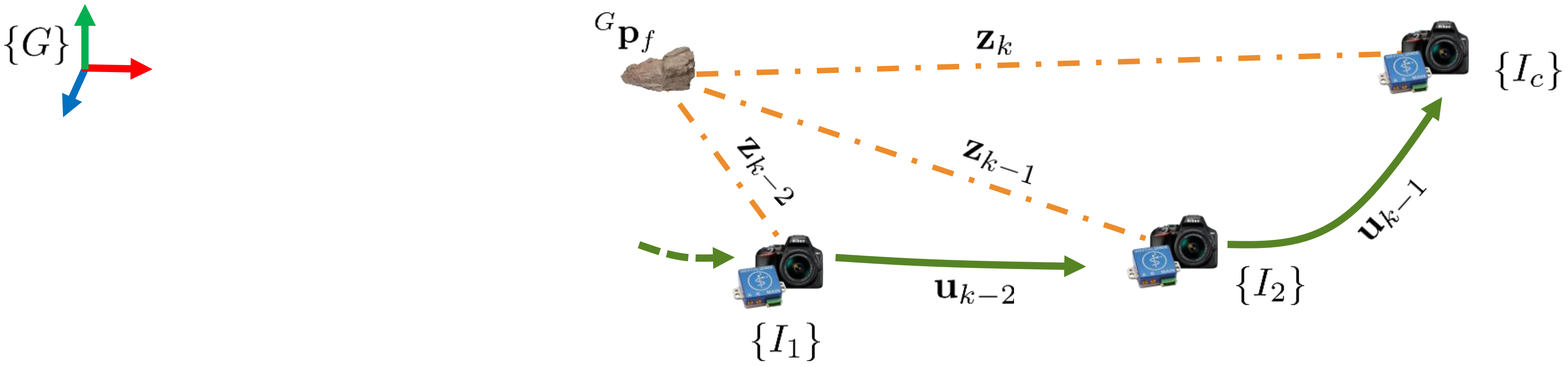
- **<u>Contribution:</u>** Summary of different techniques for incorporating loop-closures
  1. Extended Kalman filters (EKF)
  2. Schmidt-Kalman filters (SKF)
  3. Measurement inflation models (INF)

- **<u>Contribution:</u>** Investigate accuracy, consistency, computational complexity, and memory





Prior Maps Methodologies



- Local sliding window of states with observations

[1] Geneva, Patrick, James Maley, and Guoquan Huang. "An efficient schmidt-ekf for 3D visual-inertial SLAM." Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 2019.
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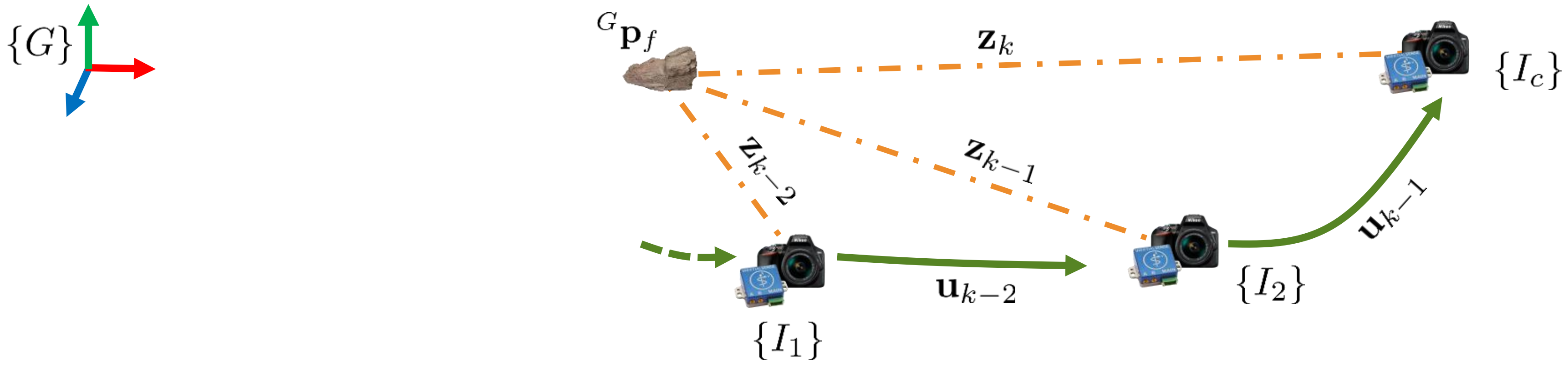

- Local sliding window of states with observations
- Point-based map (2D-to-3D) measurement function of feature

$$\mathbf{r} = \mathbf{H}_I \tilde{\mathbf{x}}_{I_{1..c}} + \mathbf{H}_f {}^G\tilde{\mathbf{p}}_f$$

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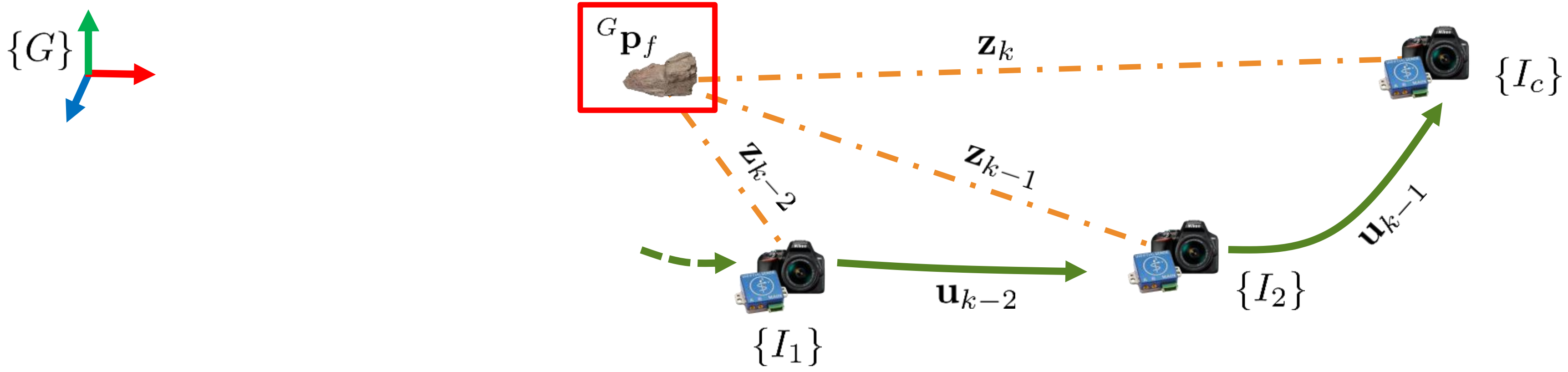

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3D feature in prior map

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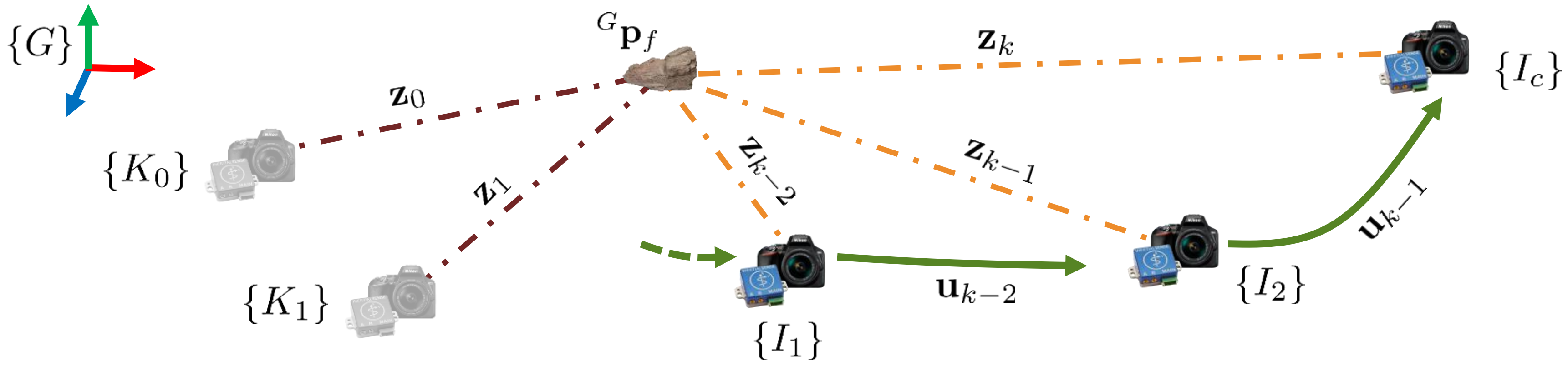

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$$\mathbf{r} = \mathbf{H}_I \tilde{\mathbf{x}}_{I_{1..c}} + \mathbf{H}_f {}^G\tilde{\mathbf{p}}_f$$

- Point-based map (2D-to-3D) measurement function of feature
- Keyframe-based map (2D-to-2D) use map observations and keyframe 6dof poses

$$\mathbf{r} = \mathbf{H}_I \tilde{\mathbf{x}}_{I_{1..c}} + \mathbf{H}_K \tilde{\mathbf{x}}_{K_{0,1}} + \mathbf{H}_f {}^G\tilde{\mathbf{p}}_f$$

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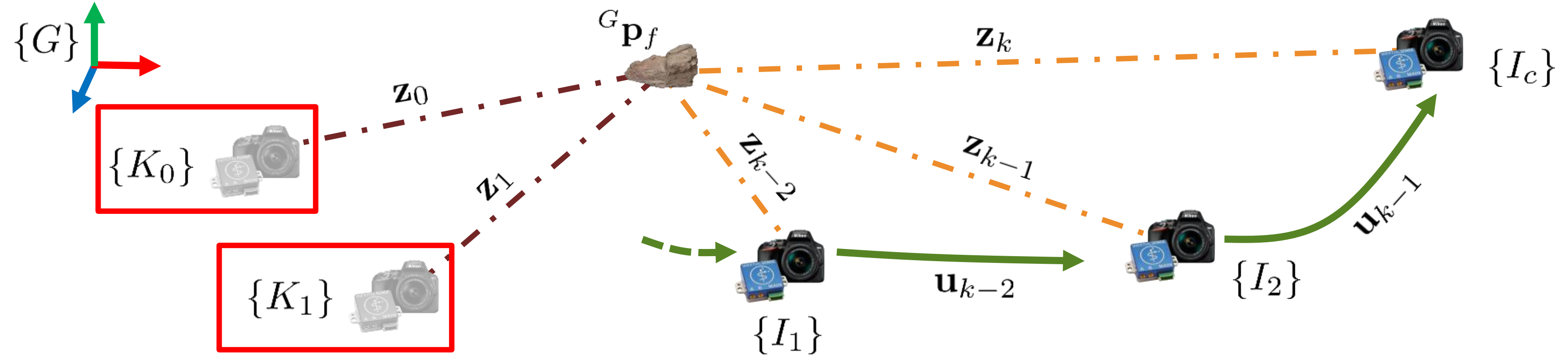

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Remove feature via MSCKF projection

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Keyframe poses in prior map

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Result Summary and Discussion

- Prior maps can be leveraged at even **high noise** levels to improve accuracy

	Prior	Algo.	ATE (deg / m)	NEES (3)
VIO	-	-	2.603 / 0.271	3.524 / 1.591
2D-to-2D	0.5°, 3cm	EKF	0.324 / 0.090	2.933 / 3.327
		SKF	0.374 / 0.099	2.758 / 3.248
	1.0°, 6cm	EKF	0.442 / 0.105	3.236 / 3.698
		SKF	0.518 / 0.130	2.806 / 3.466
	3.0°, 12cm	EKF	0.629 / 0.127	4.353 / 5.335
		SKF	0.941 / 0.167	3.009 / 3.585
2D-to-3D	3cm	EKF	0.051 / 0.010	5.975 / 6.586
		SKF	0.064 / 0.021	2.898 / 3.188
	6cm	EKF	0.068 / 0.014	8.224 / 9.292
		SKF	0.087 / 0.036	2.863 / 3.210
	12cm	EKF	0.079 / 0.015	9.321 / 9.472
		SKF	0.122 / 0.065	2.761 / 3.175

Can still gain accuracy improvement over VIO with 12cm map error!

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- Inflation methods are relatively invariant to their chosen parameters and can handle **large maps**

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Conclusion

- Recommendations:
  - SKF-based estimators should be used for **small workspaces** to ensure accurate, **consistent**, and efficient estimation
  - Keyframe-based maps can be leveraged to **reduce** the **computational cost** while still reducing drift
  - Large environments and map sizes should use **inflation methods** can be leveraged with conservative inflation values
- Future work:
  - Evaluate on large-scale realworld datasets
  - Evaluate on resource constrained platforms

VIDEO GOES HERE

Patrick Geneva

https://pgeneva.com/

https://github.com/rpng/open_vins