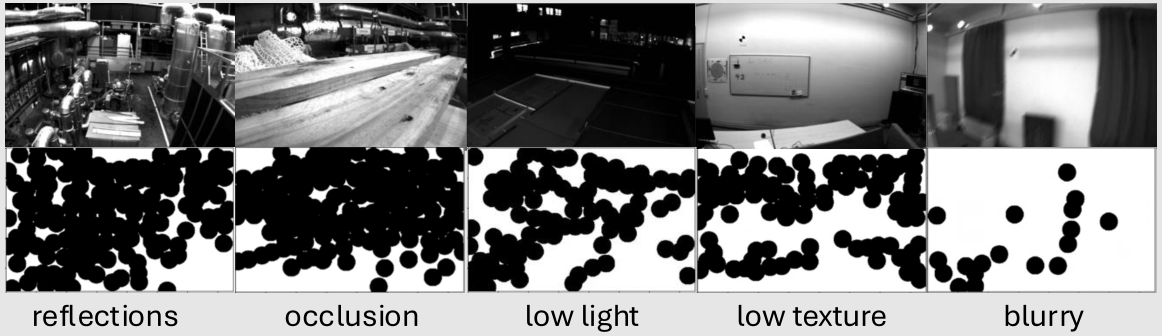
A Neurosymbolic Approach To Adaptive Feature Extraction In SLAM

Yasra Chandio

Experiment Setup

- **Dataset:** EuRoC
- **Feature Extractor:** VINS-Fusion (KTL Sparse Optical Flow)
- **Top Graph:** Images/Samples
- **Bottom Graph:** Feature Mask

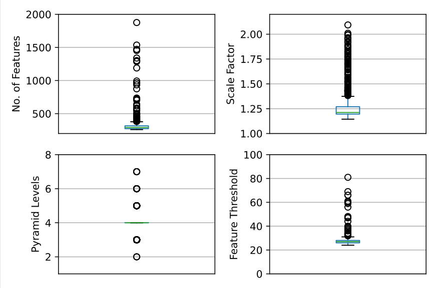


Key Insights

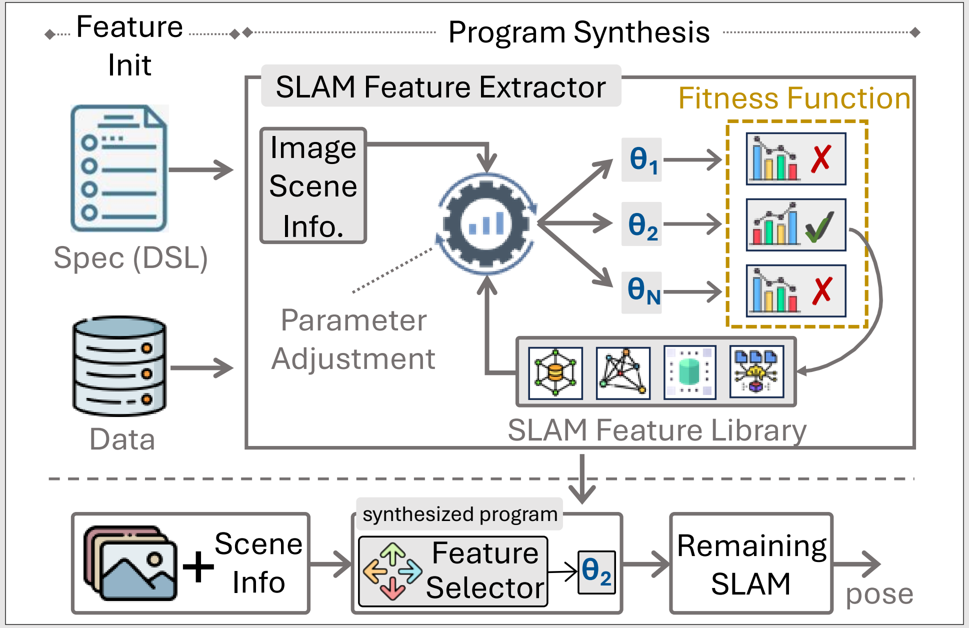
- The **number of features** tracked **impacts tracking** performance.
- The number of features tracked **depends on the scene characteristics**.
- The **type of feature extractor** and its **parameters** can be **adjusted to improve tracking**.

Solution: Leverage neurosymbolic learning to do manual expert-based fine-tuning in an automatic manner.

Codified Domain Knowledge



Empirical Performance Data



Neurosymbolic program synthesis

Fitness functions for parameter tuning and extractor selection based on feature quality metrics

		EuRoC		KITTI		HoloSet	
		MH01	MH05	KITTI-1	KITTI-6	Campus-Center-1	Suburb-Jog-2
ORB	Default	0.855	0.952	2.955	1.173	11.789	11.604
	Dynamic	0.792	0.815	**0.565**	0.126	5.903	5.845
SIFT	Default	0.860	1.038	*fail*	*fail*	13.789	12.825
	Dynamic	0.859	0.882	6.426	5.875	7.049	6.984
nFEX		**0.704**	**0.761**	**0.565**	**0.115**	**4.729**	**5.800**

Performance comparison of different feature extractors using Mean ATE in meters (averaged over ten runs).

University of Massachusetts Amherst, Email: ychandio@umass.edu, Webpage: https://yasrachandio.github.io/