nFEX: A Neurosymbolic Approach to Adaptive Feature Extraction in SLAM

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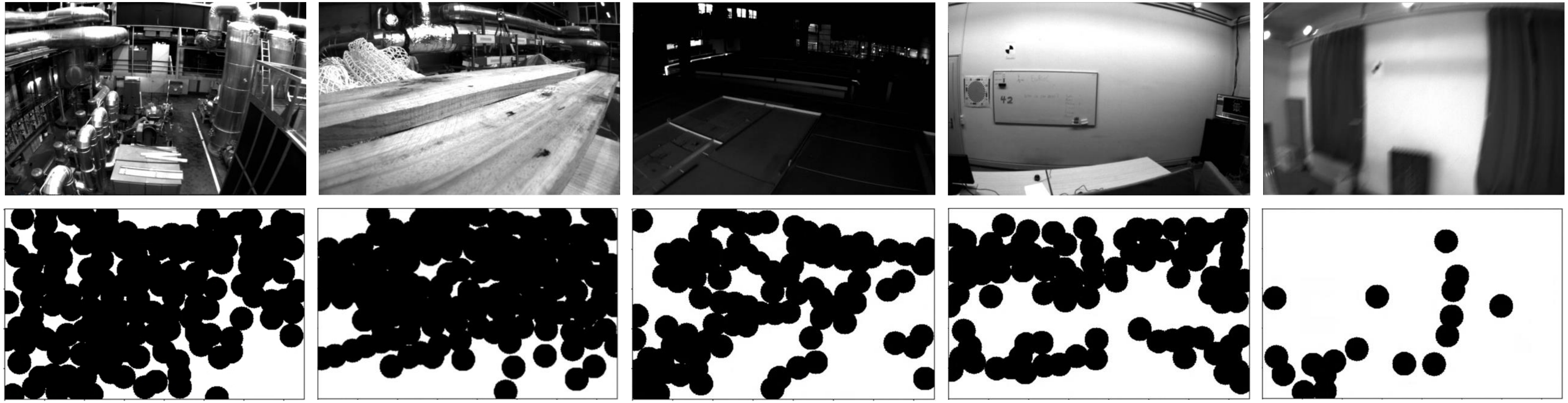
Fundamental Issues in Tracking

- Environment
- Motion
- Algorithm

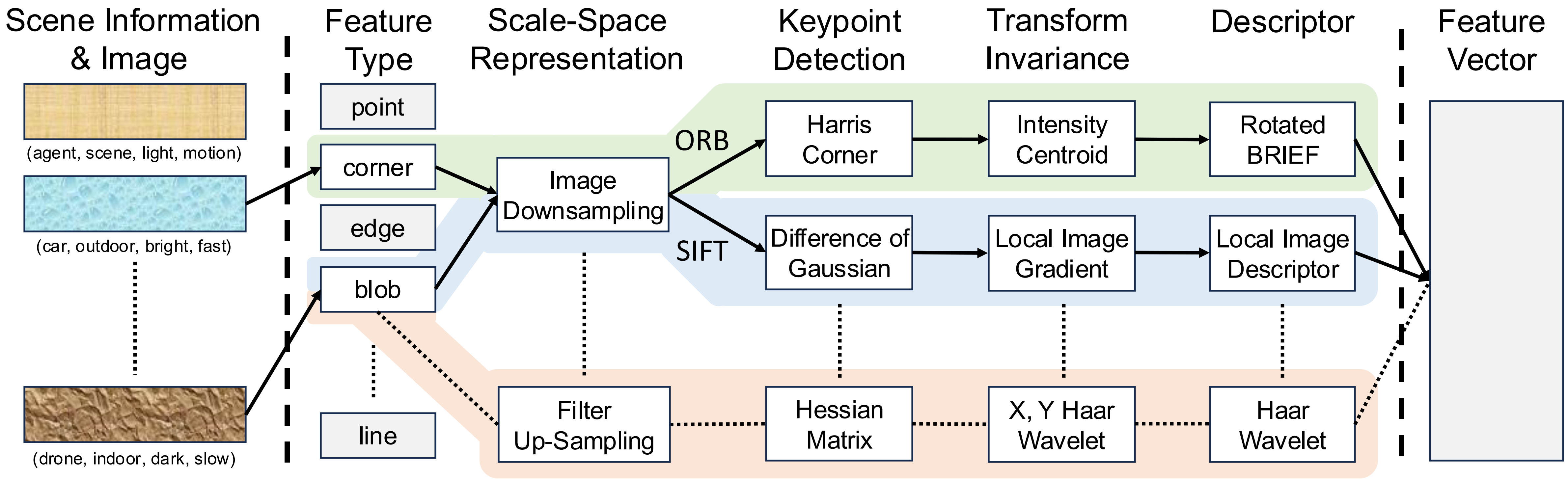
Insights to Improve Tracking?



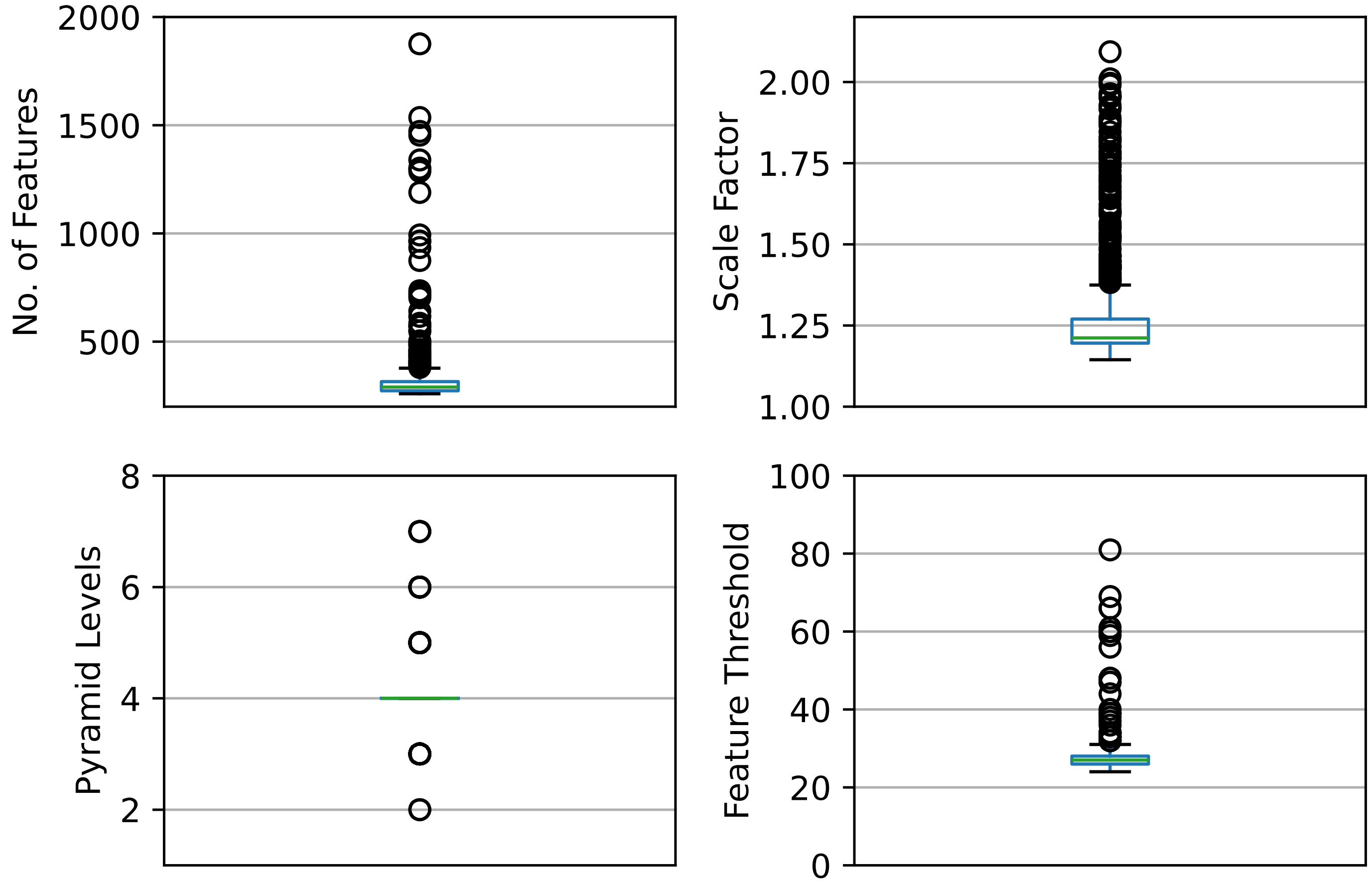
reflections | occlusion | low light | low texture | blurry

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**.

Insight 1: Leverage Expert Knowledge on Tracking



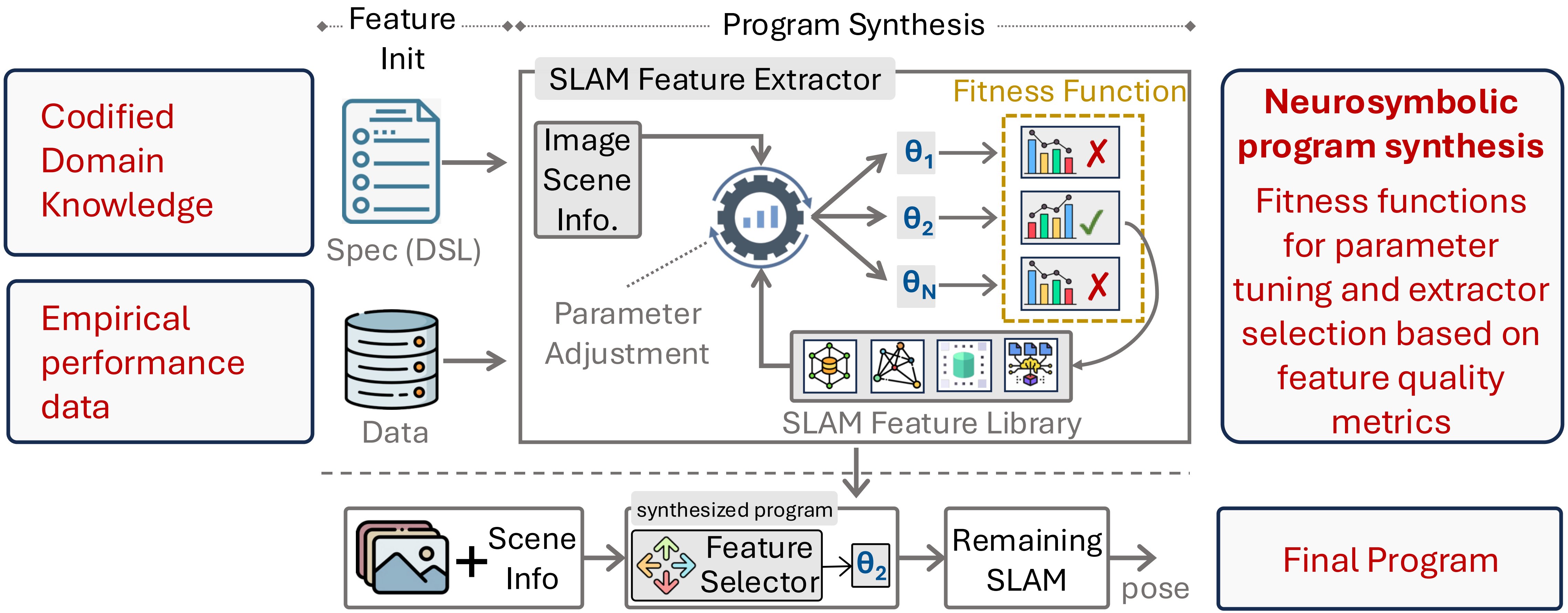
Insight 2: Easy to Obtain Empirical Data



Feature extractor is ORB, sequence is KITTI-1, each point shows the best parameter for a frame that gave lowest ATE.

Easy-to-obtain empirical data on the best-performing parameters for a given feature extractor on all frames of a sequence in a dataset.

A High-Level Overview of Our System



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

Tracking accuracy performance

- Feature extractor variants
  - **Default** SIFT and ORB
  - **Dynamic:** SIFT and ORB with online parameter adjustment
  - **nFEX:** Our end-to-end approach selects one feature extractor and configures its parameters online.

		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**

nFEX matches our outperforms default extractors and our variants with dynamic parameter adjustment.