

Multi-body Self-Calibration

Andrea Porfiri Dal Cin, Giacomo Boracchi, Luca Magri



Self-calibrating a camera in dynamic environments?

Self-calibration is the problem of estimating camera intrinsic parameters from multiple uncalibrated images.

Self-calibration methods operate under the *static-scene* assumption:

- Moving objects are treated as outliers
- > But each motion (fundamental matrix) constrains the intrinsic parameters

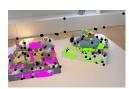
Main contributions:

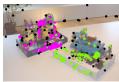
- A new self-calibration approach that capitalizes on rigid motions in a dynamic scene to better constrain self-calibration
- Sparse motion segmentation is revisited for self-calibration to compute initial bounds for the camera focal length

Motion segmentation with initial calibration

Motion segmentation revisited for self-calibration

- 6-point algorithm is used to estimate both fundamental matrices and tentative focal lengths
- \succ Upper and lower limits f_{low} and f_{high} on focal length are derived using robust statistics



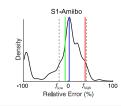


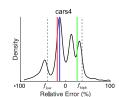
Robust focal length initialization

Self-calibration is casted as a non-linear optimization problem > A good initialization is required

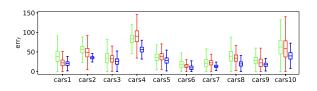
Novel hypothesize-and-verify framework searches in the space of focal lengths defined by f_{low} and f_{high}

Kernel Density Estimator identifies the optimal initial focal length





Probability density functions estimated from KDE by searching the focal length space. Vanilla, Vanilla w/ Kernel Voting and Ours.



Box plot of relative error w.r.t. ground-truth focal length estimated with the probability density functions. Vanilla, Vanilla w/ Kernel Voting and Ours.

Multi-start non-linear optimization of parameters

Internal camera parameters are refined using a *multi-start* non-linear optimization scheme

> At each iteration, the initial point for the optimization is sampled from the focal length distribution to minimize chances of local minima

Dataset	m	$ \mathcal{I} $	Single-body on dynamic datasets						Multi-body on dynamic datasets					
			Ours		BnB [25]		M&C [23]		Ours		BnB [25]		M&C [23]	
			errf	erruv	err_f	erruv	errf	erruv	errf	erruv	errf	erruv	errf	erruv
cars1	2	4	17.41	1.28	16.85	1.21	67.81	74.31	12.45	1.21	16.48	1.21	69.01	73.92
cars2	2	6	33.48	3.03	34.28	2.97	81.47	79.31	15.18	3.14	19.02	2.91	88.13	77.16
cars3	3	4	21.76	6.21	21.01	6.49	156.87	74.01	7.82	2.54	9.10	2.86	184.09	102.42
cars4	2	11	40.62	6.81	38.29	7.02	62.01	48.99	18.36	6.41	20.48	7.14	75.88	38.26
cars5	3	7	23.49	4.21	22.01	4.01	76.01	58.12	11.78	4.01	15.71	4.01	72.45	61.34
cars6	2	6	7.38	1.83	7.38	2.01	41.91	38.74	5.30	1.89	5.30	1.91	67.30	59.34
cars7	2	6	8.79	1.92	8.67	1.85	38.54	41.27	6.51	1.85	8.46	1.98	45.87	31.28
cars8	2	6	19.28	2.87	21.01	2.65	102.48	87.01	9.01	2.81	12.49	2.98	98.06	79.61
cars9	3	12	15.99	2.68	14.87	2.41	27.61	19.47	8.12	2.42	9.34	2.67	38.91	65.81
cars10	3	6	31.62	12.84	31.91	12.62	91.45	78.34	15.82	7.42	16.53	8.01	89.45	62.01
truck1	2	6	14.78	6.84	13.98	7.28	68.12	72.13	4.87	1.87	6.92	2.32	72.58	45.61
truck2	2	4	13.32	7.21	13.38	6.58	68.58	71.20	4.24	2.31	7.18	3.01	74.69	89.30
M1-Amiibo	2	10	3.29	4.28	3.21	4.22	43.29	51.32	1.27	3.86	2.84	4.04	62.88	50.14
M2-Amiibo	3	4	39.28	36.71	39.85	37.21	89.41	92.01	4.97	3.71	7.21	4.28	93.12	92.86
M3-Amiibo	2	4	3.20	5.89	3.28	5.71	41.28	39.62	1.37	3.96	2.19	4.27	53.76	46.12

Self-calibration results on real multi-body datasets. Metrics err_f and err_{uv} represent relative errors in percentage of the focal length and principal point estimation respectively.

Conclusions

- Self-calibration benefits from the additional constraints derived from the multiple rigid motions in a dynamic scene
- Constraints from rigid motions can be detrimental to the accuracy of self-calibration if noise and outliers are not accounted for
- > The proposed self-calibration exploits the constraints from the multiple motions and achieves state-of-the-art accuracy