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# StOCaMo: Online Calibration Monitoring for Stereo Cameras



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Sensor calibration

- Sensors are not colocated and have their own internal parameters
  - $\Rightarrow$  We need to know these for proper sensor fusion
- Calibration room or infrastructure-based







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Calibration monitoring

- The calibration is essential for all subsequent parts of autonomous operation
- But it is not stable due to vehicle twisting or thermal dilations
  - $\Rightarrow$  The calibration monitoring could be neccessary







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#### Taxonomy of Calibration

• Off-line calibration

$$(Batch of data B) \longrightarrow (Construct f(\theta|B)) \longrightarrow (argmin_{\theta} f(\theta|B))$$

- time-consuming
- large computational overhead
- high precision
- On-line calibration

Small batch of data 
$$B_0 \longrightarrow \text{Construct } f(\theta|B_0) \longrightarrow \text{argmin}_{\theta} \mathbb{E} [f(\theta|B_0)]$$

- random  $f(\theta|B_0) \rightarrow$  large variance
- $\mathbb{E}[f(\theta|B_0)]$  provides higher precision
- fast response

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- fast response
- On-line calibration monitoring (OCaMo)

 $(Reference calibration \ \theta^{ref}) \longrightarrow (Small batch of data \ B_0) \longrightarrow (Calibration \ \theta^{ref}) \longrightarrow (C$ 

Calibration validity  $P( heta^{ ext{ref}}|B_0)$ 

- needs to run on-line
- small computational overhead

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StOCaMo

• Examining epipolar distance between detected keypoints



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• Examining epipolar distance between detected keypoints



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• Examining epipolar distance between detected keypoints



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- Examining epipolar distance between detected keypoints
  - single frame estimation, without memory
  - small computational overhead
  - robust, without one-to-one matching





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$$\mathcal{KC}(\boldsymbol{\theta}) = -\frac{1}{n} \sum_{i \in \mathcal{I}'} \sum_{j \in \mathsf{kNN}'_i} \exp\left[-\frac{d^2(\mathbf{x}_j^r \mid \mathbf{x}_i^l, \boldsymbol{\theta})}{2\sigma^2}\right] - \frac{1}{n} \sum_{j \in \mathcal{I}'} \sum_{i \in \mathsf{kNN}'_j} \exp\left[-\frac{d^2(\mathbf{x}_i^r \mid \mathbf{x}_j^r, \boldsymbol{\theta})}{2\sigma^2}\right]$$



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$$egin{aligned} \mathcal{F}(oldsymbol{ heta}^{ ext{ref}}) &= rac{1}{| ext{grid}|} \sum_{oldsymbol{ heta} \in ext{grid}} \mathbb{1}\left[\mathcal{KC}(oldsymbol{ heta}) \geq \mathcal{KC}(oldsymbol{ heta}^{ ext{ref}})
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$$V(oldsymbol{ heta}^{ ext{ref}}) = rac{p_c(oldsymbol{ heta}^{ ext{ref}})}{p_c(oldsymbol{ heta}^{ ext{ref}}) + p_d(oldsymbol{ heta}^{ ext{ref}})}$$



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# F-index evaluation & V-index parameters learning

- Synthetic dataset for parameter learning:
  - CARLA [2]: 24° VFOV and 1241×376 px (rectified)
  - 155 sequences with 200 frames each
  - $\blacktriangleright$  Calibration tolerance was set to 0.005  $\rightarrow$  kernel  $\sigma$  and sampling grid size
- Evaluating F-index on seven decalibration magnitudes:

▶  $[-\delta, \delta]$  m or rad,  $\delta \in \{0, 0.0025, 0.005, 0.01, 0.02, 0.05, 0.075\}$ 

• Selecting  $p_c$  and  $p_d$  based on 0.005 and 0.05 magnitudes, respectively



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Synthetic decalibration on real data

- Two real datasets:
  - ▶ KITTI [3]: 29.5° VFOV and 1241×376 px (rectified)
  - ► EuRoC MAV [1]: 55° VFOV and 752×480 px (unrectified)
- Two magnitudes of synthetic decalibration:
  - ► Small: [-0.005, 0.005] m or rad
    - $\rightarrow$  should not report a decalibration (examines TN and FP)
  - ▶ Large:  $[-0.02, -0.01] \cup [0.01, 0.02] \text{ m or rad}$ 
    - $\longrightarrow$  should report a decalibration (examines TP and FN)





	ΤP	FN	ΤN	FP	Prec.	Recall	Acc.
KITTI	11854	156	11666	344	97.2	98.7	97.9
EuRoC	33240	3580	36321	499	98.5	90.3	94.5

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- Tested on KITTI (below) and EuRoC
- Downstream = ORB-SLAM2, failure = RMSE larger than threshold (as in [6])
- 100 decalibrations of 6 decalibration magnitudes
  - ▶  $[-\delta, \delta]$  m or rad,  $\delta \in \{0.0025, 0.005, 0.01, 0.02, 0.05, 0.075\}$
  - each decalibration is tested on ten random frames for more informative statistics



Dec.	TP	FN	ΤN	FP	Acc.
0.0025	0	0	990	10	99.0
0.005	0	0	959	41	95.9
0.01	262	218	376	144	63.8
0.02	699	191	82	28	78.1
0.05	924	66	3	7	92.7
0.075	928	72	0	0	92.8
Avg.					87.1
[6]					62

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Predicting downstream data processing failure

- Tested on KITTI (below) and EuRoC
- Downstream = ORB-SLAM2, failure = RMSE larger than threshold (as in [6])
- 100 decalibrations of 6 decalibration magnitudes
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  - each decalibration is tested on ten random frames for more informative statistics

FP

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41

144

28

7

Acc.

99.0

95.9

63.8

78.1

92.7

92.8

87.1

62

0.44

Regression of the RMSE with validity index of StOCaMo





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### Future Work & Conclusion



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### Future Work & Conclusion



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