Reducing drift in VO by inferring sun direction using a Bayesian CNN

Valentin Peretroukhin, Lee Clement, and Jonathan Kelly

ICRA 2017 | Singapore | Visual-Based Navigation

Institute for Aerospace Studies
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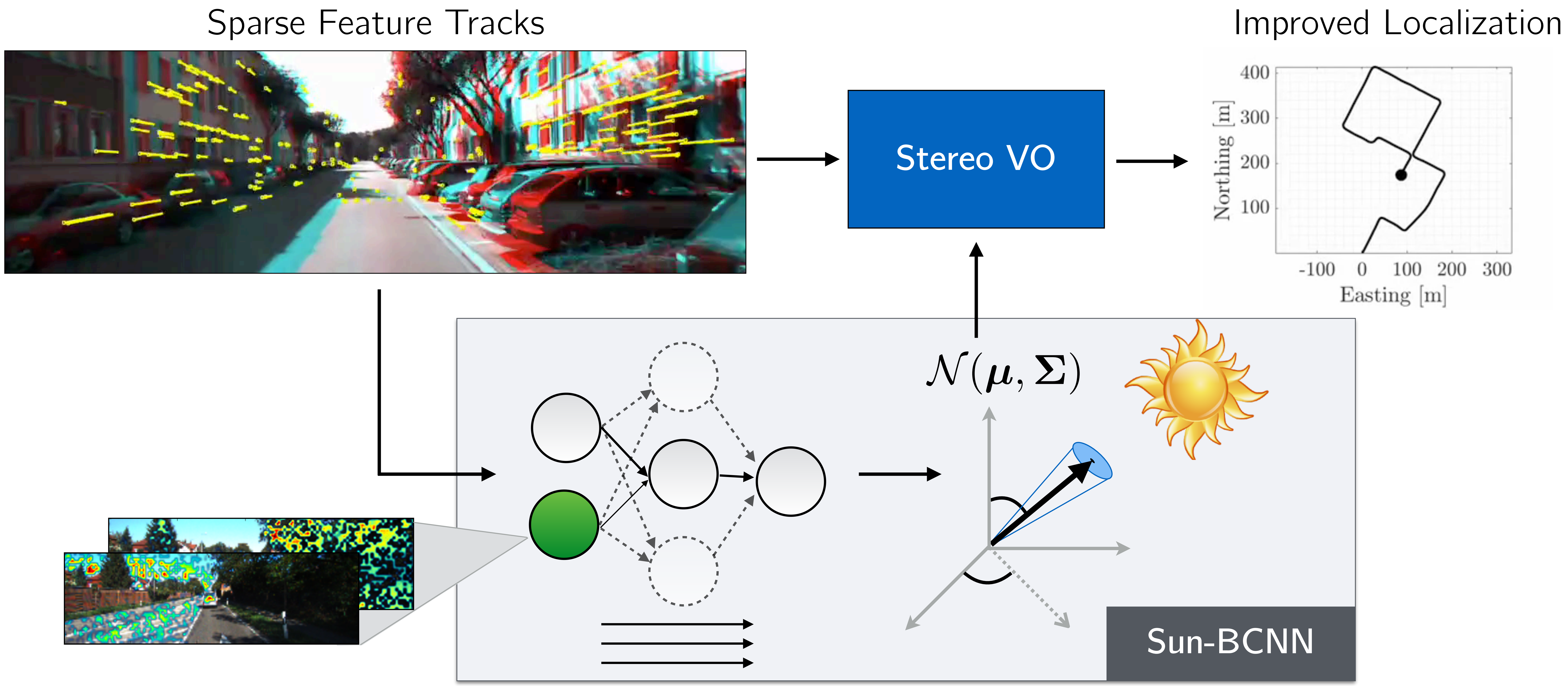

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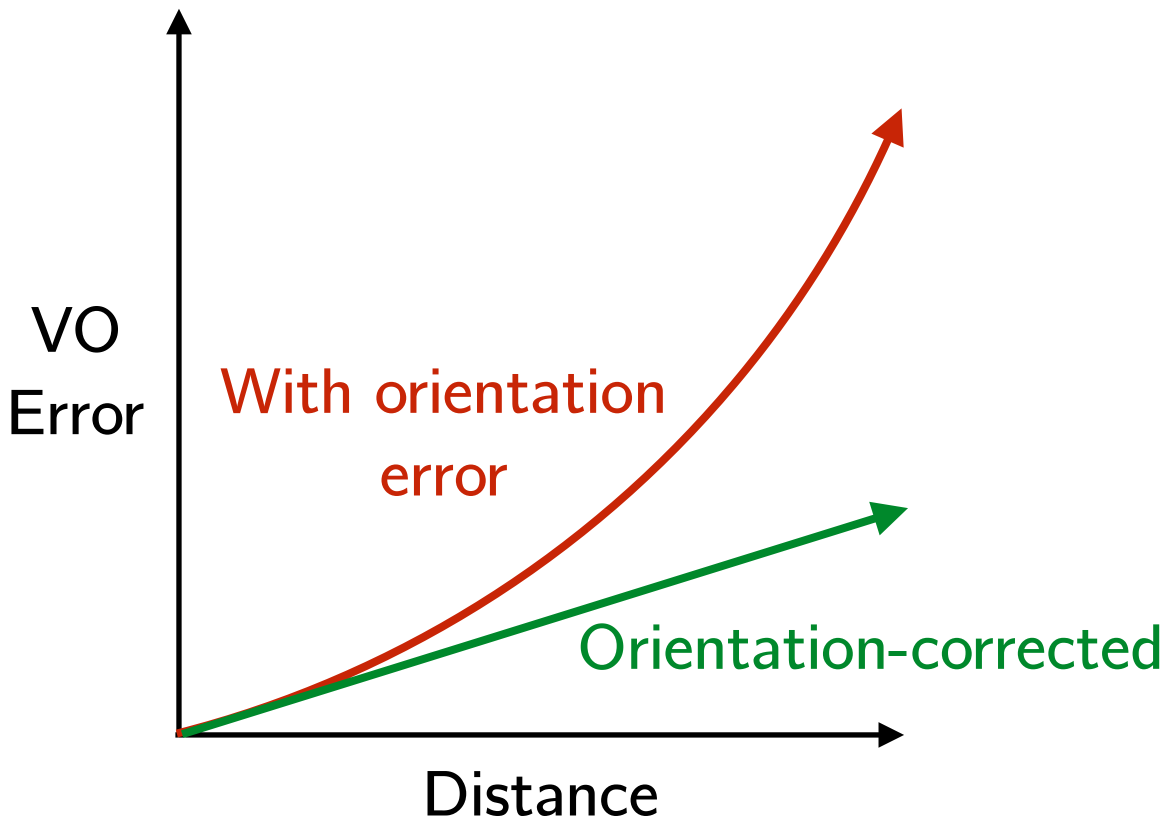
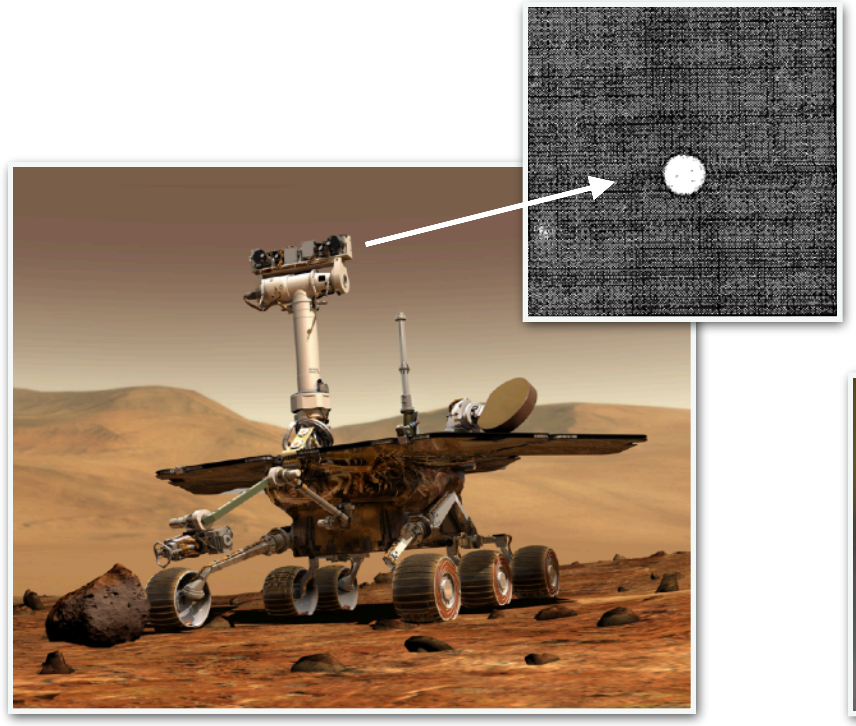
Error growth in visual odometry

VO is a dead-reckoning technique and suffers from super-linear error growth, largely due to accumulated orientation error

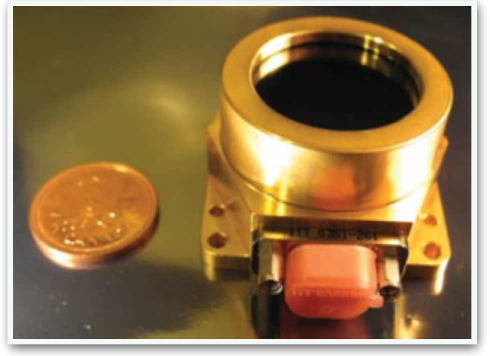


Correcting drift with absolute orientation

Drift can be reduced using orientation information from a sun sensor



Specially oriented camera (e.g., MERs)



Specialized sun sensor

? Can we use our existing image stream to infer the direction of the sun from environmental cues?

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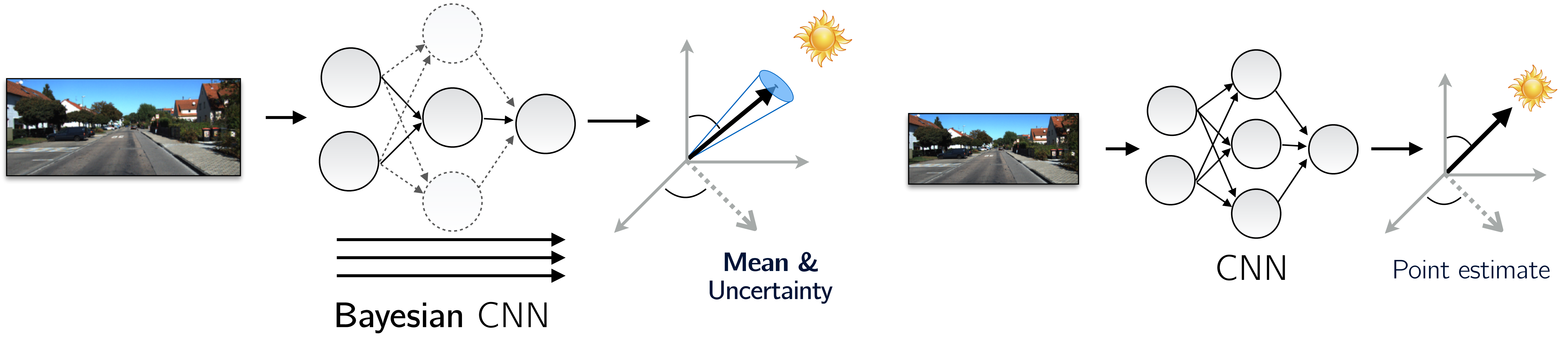
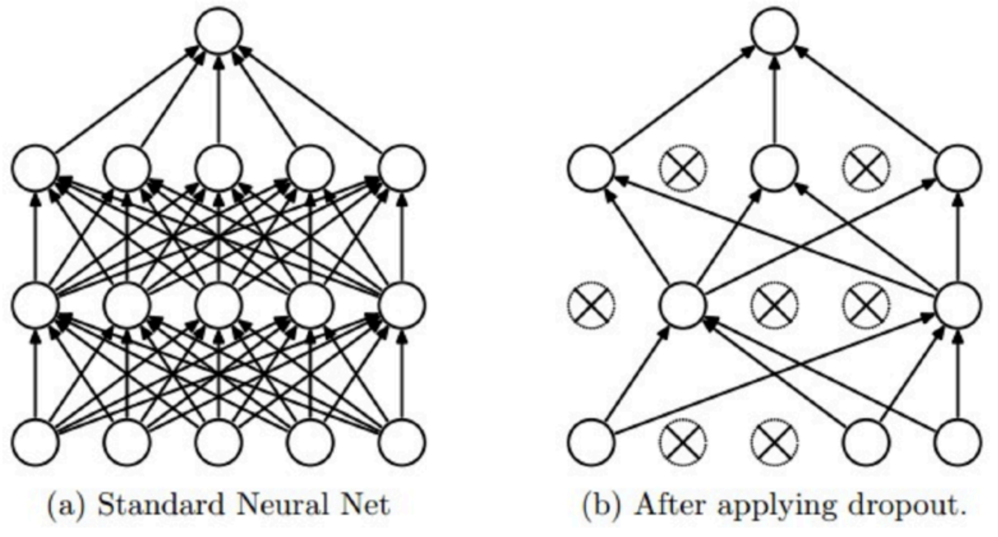
Bayesian Convolutional Neural Networks

Using dropout to compute uncertainty



Dropout

Originally developed to reduce overfitting



Applied *only during training*

Key Insight: Training with dropout ⟶ Variational Inference

1 Given **prior**:

(NN weights)

$$p(\boldsymbol{w}) \longrightarrow p(\boldsymbol{w}|\mathbf{X},\mathbf{S})$$

(training images) (training targets)

2 By defining **variational** distribution:

$$q(\boldsymbol{w}) \sim p(\boldsymbol{w}|\mathbf{X},\mathbf{S})$$

(matrix with K_i weights *for* layer i)

$$q(\boldsymbol{w}_i) = \mathbf{M}_i \ \mathrm{diag}\left\{\{b_j^i\}_{j=1}^{K_i}\right\},$$

$$b_j^i \in \mathrm{Bernoulli}(p_i)$$

(dropout probability)

3 Training with dropout is equivalent to **minimizing the KL divergence** between true posterior and variational distribution:

$$D_{\mathrm{KL}}\left(\ p(\boldsymbol{w}|\mathbf{X},\mathbf{S})\ ||\ q(\boldsymbol{w})\ \right)$$

4 At test time, sample variational distribution stochastically: **(Monte Carlo dropout)**:

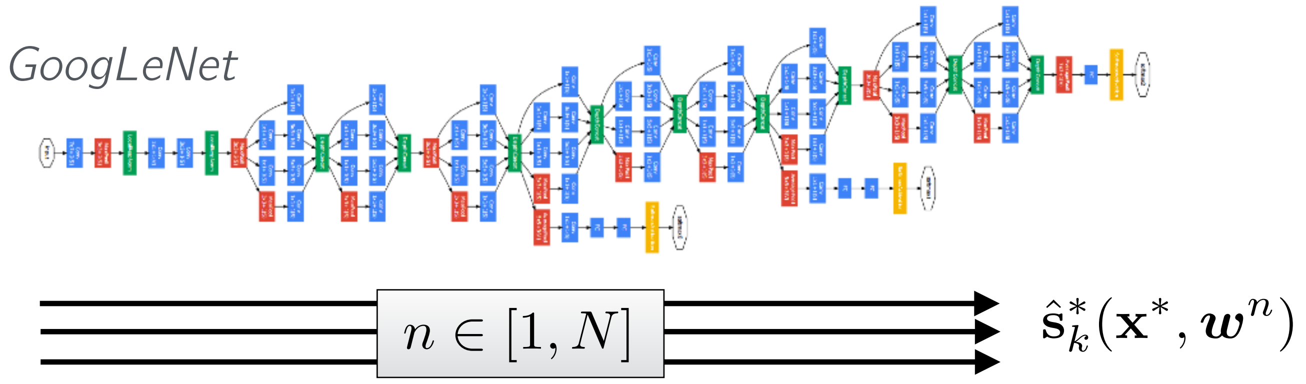
Mean $$\mathbb{E}(\hat{\mathbf{s}}_k^*) = \bar{\hat{\mathbf{s}}}_k^* \approx \frac{1}{N}\sum_{n=1}^{N}\hat{\mathbf{s}}_k^*(\mathbf{x}^*,\boldsymbol{w}^n)$$

model precision

Covariance $$\mathbb{E}(\hat{\mathbf{s}}_k^*\hat{\mathbf{s}}_k^{*T}) \approx \tau^{-1}\mathbf{1} + \frac{1}{N}\sum_{n=1}^{N}\hat{\mathbf{s}}_k^*(\mathbf{x}^*,\boldsymbol{w}^n)\hat{\mathbf{s}}_k^*(\mathbf{x}^*,\boldsymbol{w}^n)^T - \bar{\hat{\mathbf{s}}}_k^*\bar{\hat{\mathbf{s}}}_k^{*T}$$

Monte Carlo Dropout

Uncertainty through stochastic sampling using dropout **during testing**



Mean & Covariance

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Sliding window sparse stereo visual odometry

Cost (to minimize)

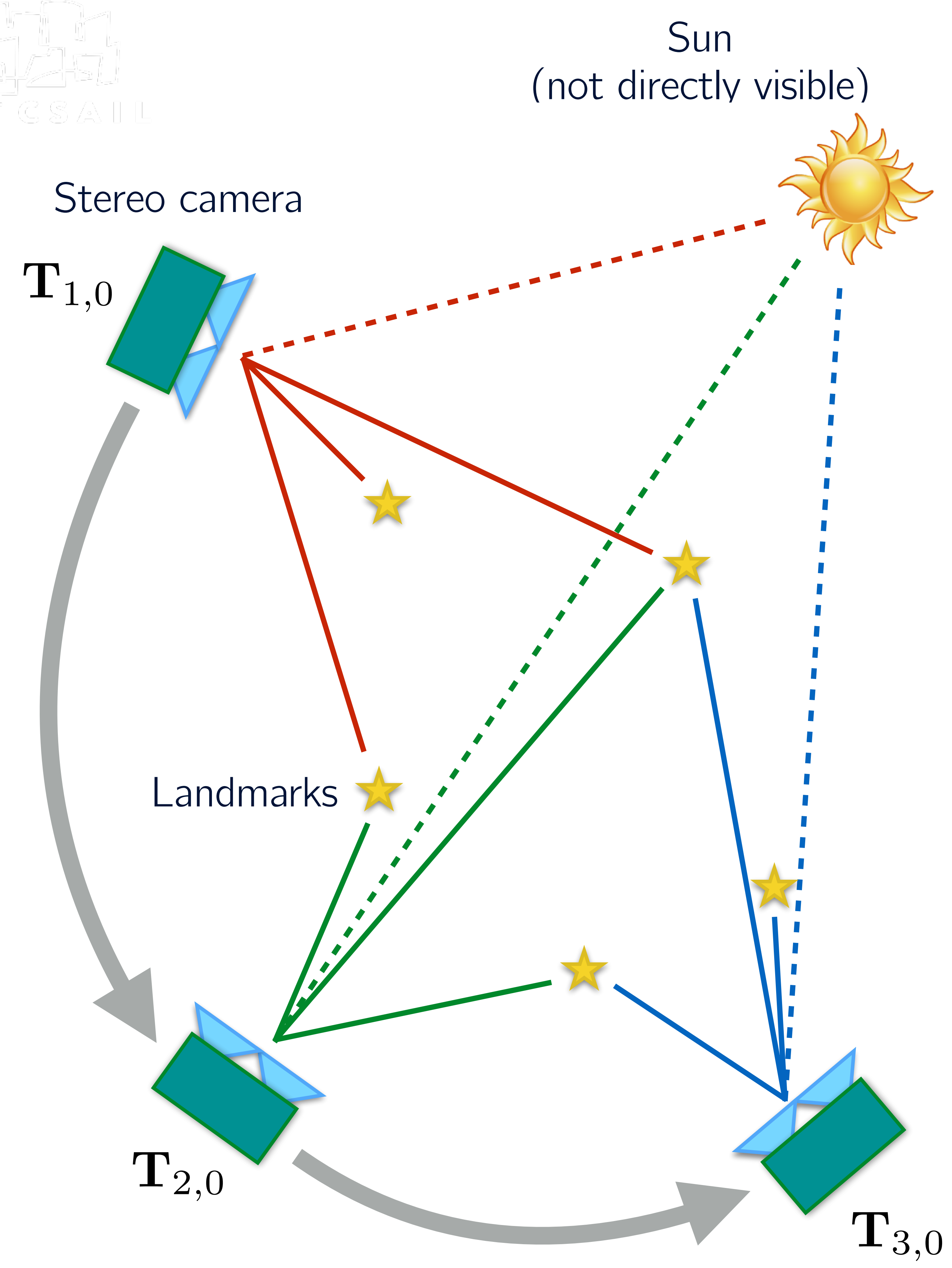
$$\mathcal{J} = \mathcal{J}_{\text{reprojection}} + \mathcal{J}_{\text{prior}}$$

$$\mathcal{J}_{\text{reprojection}} = \sum_{k=k_1}^{k_2} \sum_{j=1}^{J} \mathbf{e}_{\mathbf{y}_{k,j}}^T \mathbf{R}_{\mathbf{y}_{k,j}}^{-1} \mathbf{e}_{\mathbf{y}_{k,j}}$$

$$\mathcal{J}_{\text{prior}} = \mathbf{e}_{\hat{\mathbf{T}}_{k_1,0}}^T \mathbf{R}_{\hat{\mathbf{T}}_{k_1,0}}^{-1} \mathbf{e}_{\hat{\mathbf{T}}_{k_1,0}}$$

Stereo observation model

$$\mathbf{y}_{k,j} = \mathbf{g}\left(\mathbf{p}_k^j\right) = \begin{bmatrix} u \\ v \\ d \end{bmatrix} = \begin{bmatrix} f_u p_{k,x}^j / p_{k,z}^j + c_u \\ f_v p_{k,y}^j / p_{k,z}^j + c_v \\ f_u b / p_{k,z}^j \end{bmatrix}$$



Sun-aided visual odometry

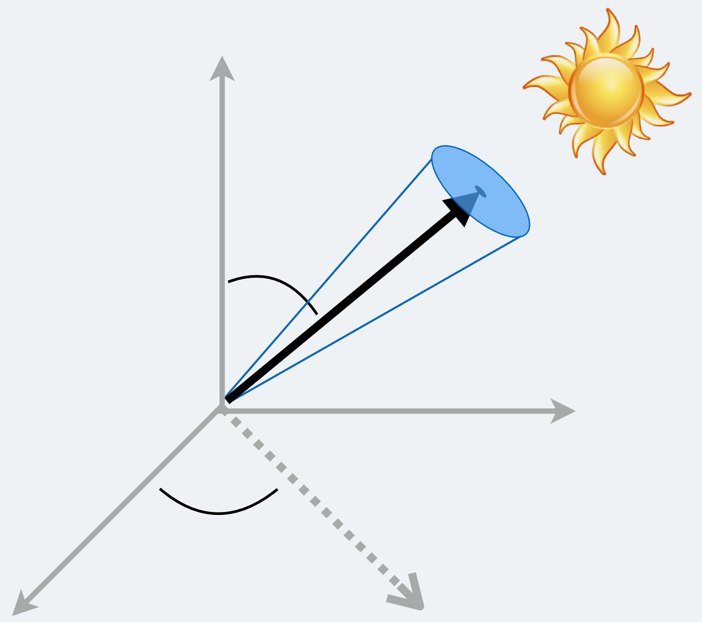
Cost (to minimize)

$$\mathcal{J} = \mathcal{J}_{\text{reprojection}} + \mathcal{J}_{\text{prior}} + \mathcal{J}_{\text{sun}}$$

$$\mathcal{J}_{\text{sun}} = \sum_{k=k_1}^{k_2} \mathbf{e}_{\mathbf{s}_k}^T \mathbf{R}_{\mathbf{s}_k}^{-1} \mathbf{e}_{\mathbf{s}_k},$$

Sun observation model (zenith-azimuth)

$$\begin{bmatrix} \theta \\ \phi \end{bmatrix} = \mathbf{f}\left(\mathbf{s}_k\right) = \begin{bmatrix} \operatorname{acos}\left(-s_{k,y}\right) \\ \operatorname{atan2}\left(s_{k,x}, s_{k,z}\right) \end{bmatrix}$$



Mean and uncertainty

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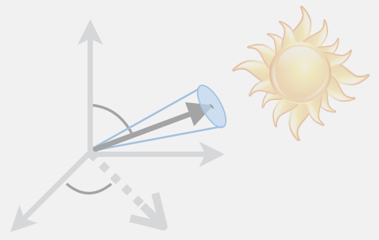
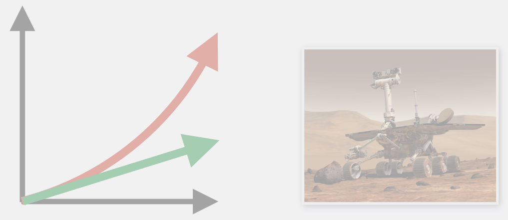
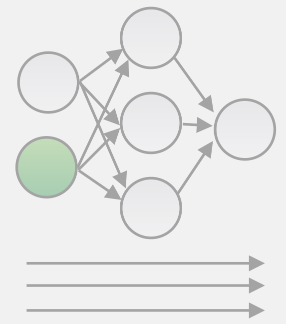
Introduction



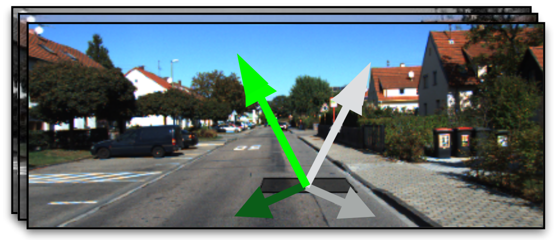
Motivation



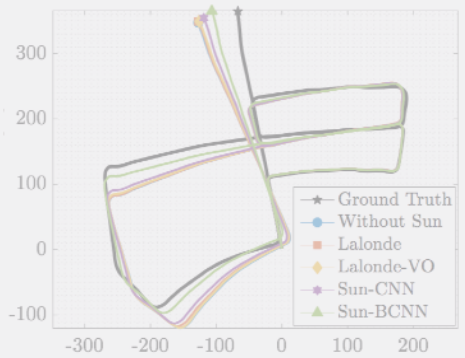
Approach



Training & Testing



Results



Conclusions

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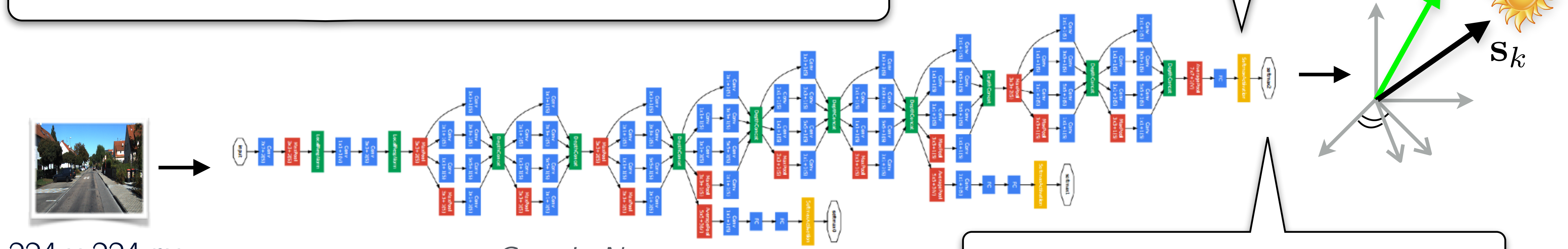
Training & Testing

How to build a Sun-BCNN

Dropout (p=0.5) after all conv. and FC layers.

L_2-Norm Layer
(enforce unit norm)



Full KITTI Image

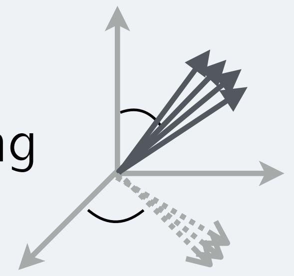
Cost Function
(Euclidian dist. of unit vectors)

$$\mathcal{L}(\hat{\mathbf{s}}_k) = 1 - (\hat{\mathbf{s}}_k \cdot \mathbf{s}_k)$$

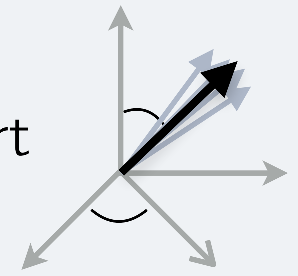
$$\begin{aligned}\frac{1}{2}\|\hat{\mathbf{s}}_k - \mathbf{s}_k\|^2 &= \frac{1}{2}\left(\|\hat{\mathbf{s}}_k\|^2 + \|\mathbf{s}_k\|^2 - 2(\hat{\mathbf{s}}_k \cdot \mathbf{s}_k)\right) \\ &= 1 - (\hat{\mathbf{s}}_k \cdot \mathbf{s}_k) \\ &= \mathcal{L}(\hat{\mathbf{s}}_k).\end{aligned}$$

Testing

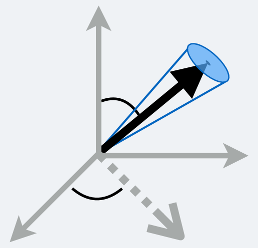
1 Compute **N=25** stochastic samples using Monte-Carlo dropout.



2 **Mean:** Compute mean vector, normalize, convert to azimuth and zenith



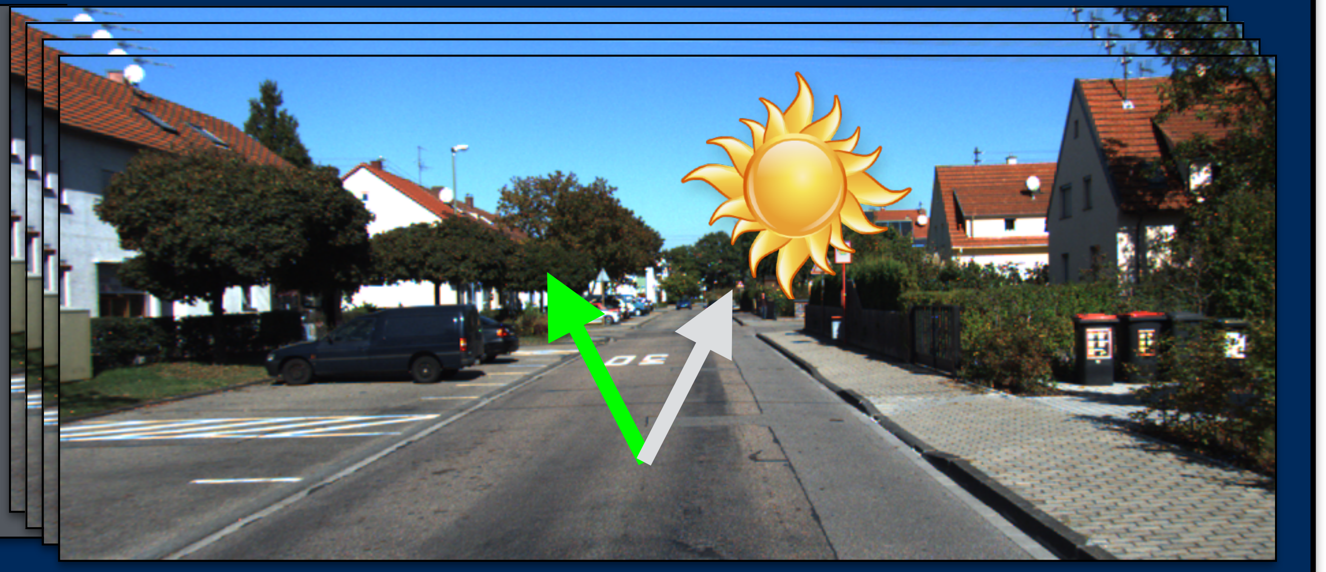
3 **Covariance:** Convert to azimuth, zenith angles. Compute empirical covariance, add inverse model precision.



Dataset

KITTI Odometry Benchmark

- 10 sequences
- 9/1 test/train split for each sequence
- 20k images per training set



Implementation Details

- **Caffe** Implementation
  - L2-Norm layers from Caffe SL
- Dropout after all convolutional and FC layers
  - p = 0.5
- **GoogLeNet**
  - Pre-trained on MIT Places
  - 224 x 244 RGB resized images
  - SGD, 1000 epochs, batch size of 64

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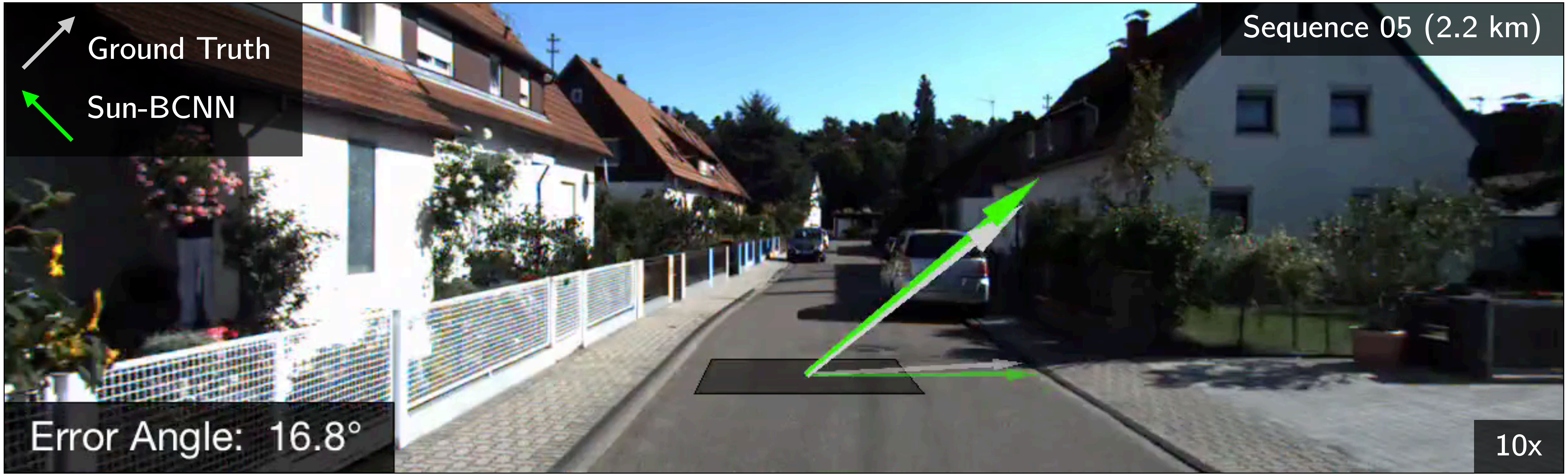
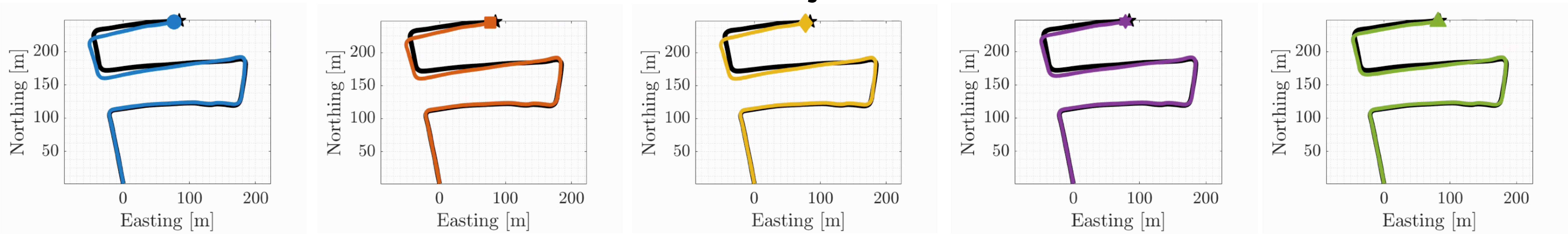


VO Trajectories



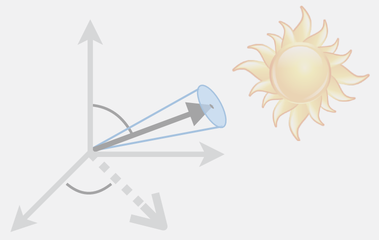
Without sun
Ground Truth

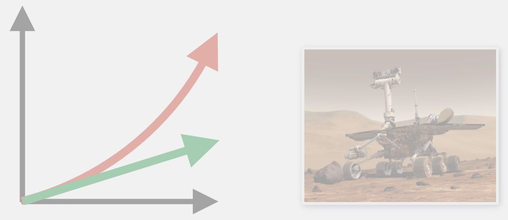
Lalonde
(Lalonde et al. 2011)

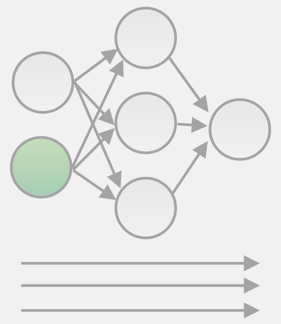
Lalonde-VO
(Clement et al. 2016)

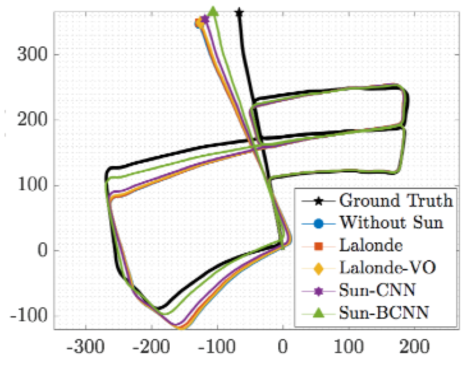
Sun-CNN
(Ma et al. 2017)

Sun-BCNN
(ours)









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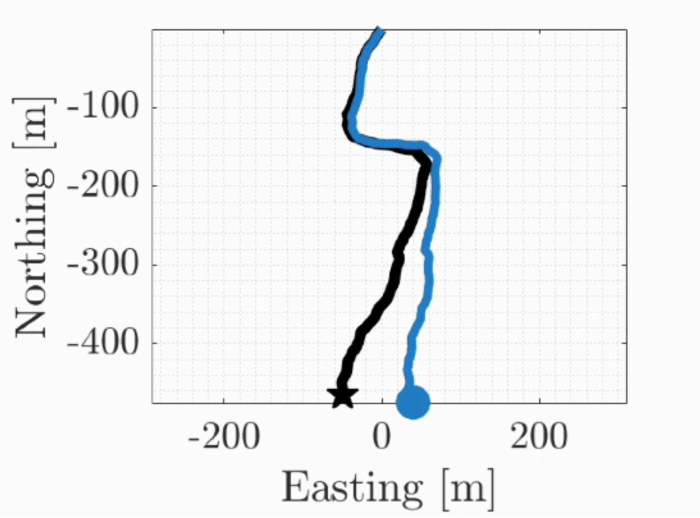
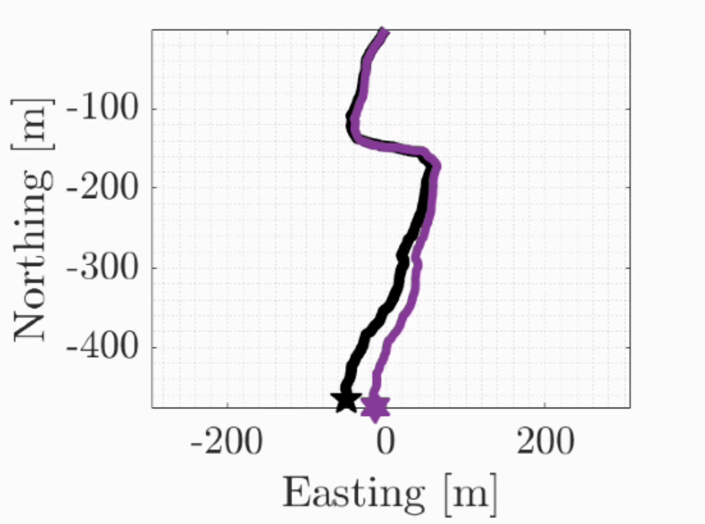
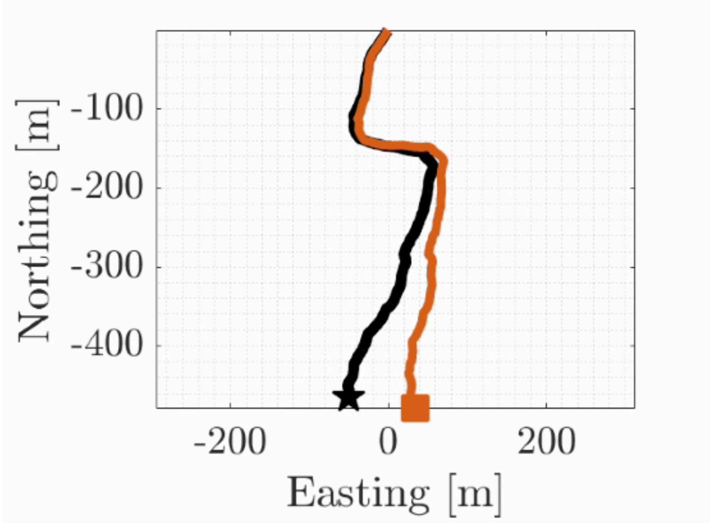
Ground Truth



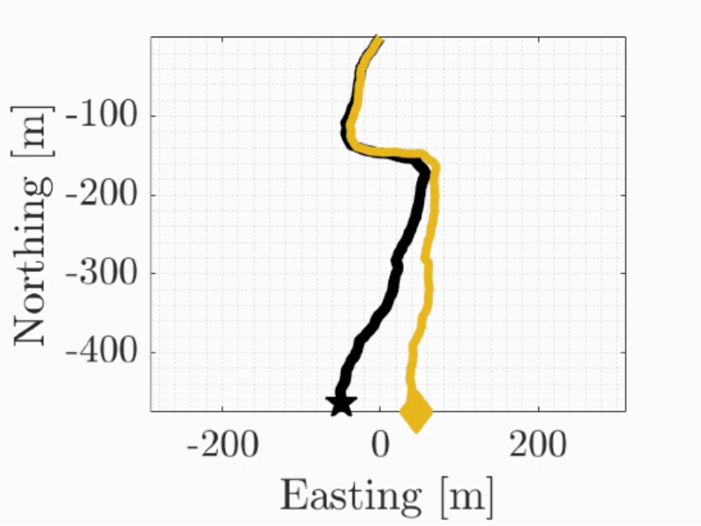
Without sun



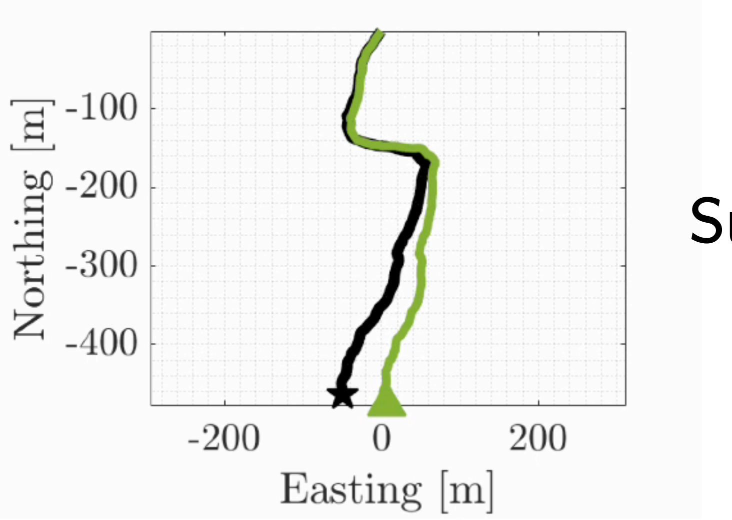
Hardware Sun Sensor



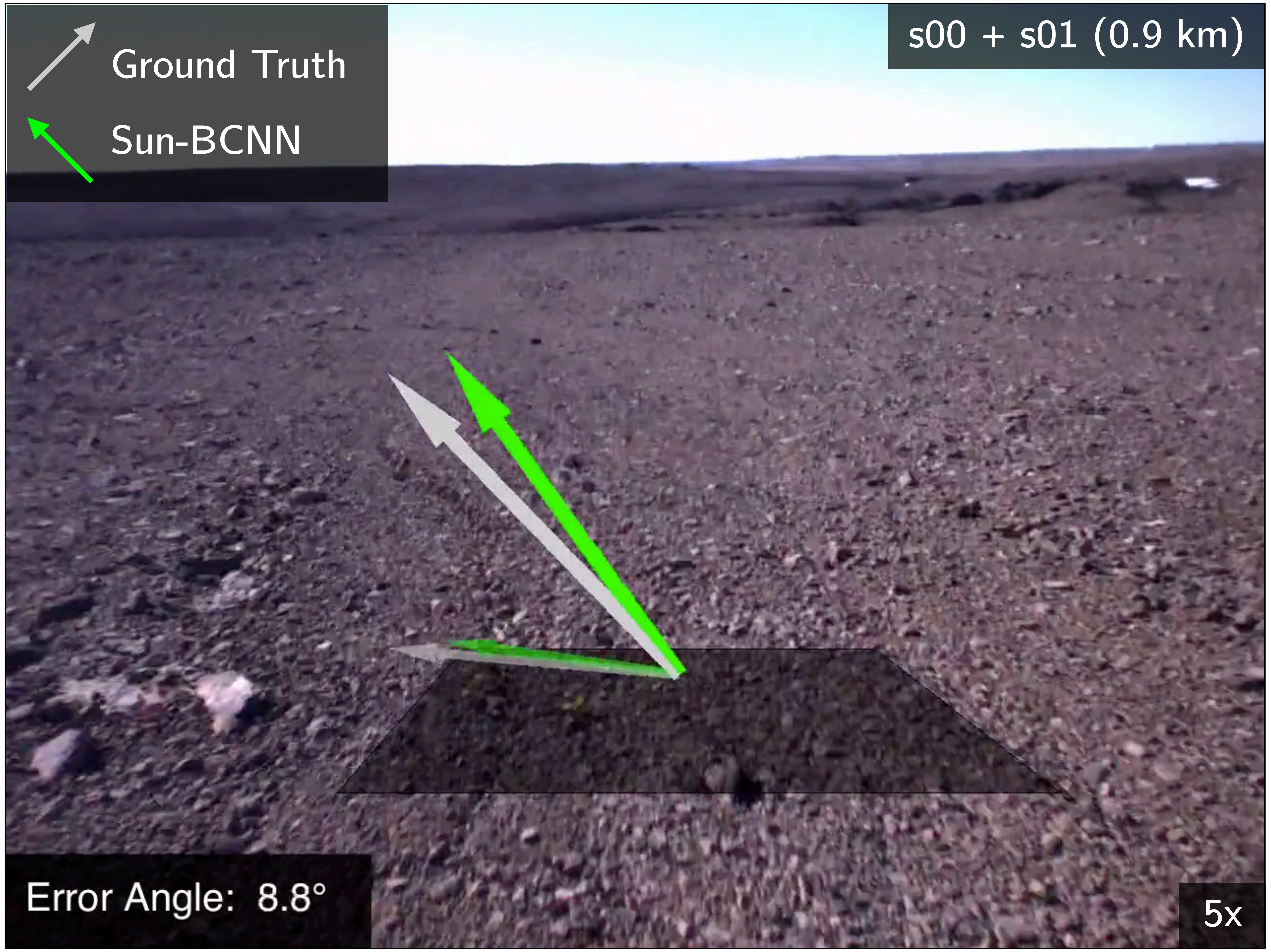
Lalonde
(Lalonde et al. 2011)



Lalonde-VO
(Clement et al. 2016)



Sun-BCNN
(ours)



P. Furgale, P. Carle, J. Enright, and T. D. Barfoot, "The Devon Island rover navigation dataset," IJRR, 2012.

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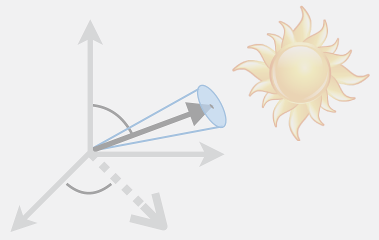

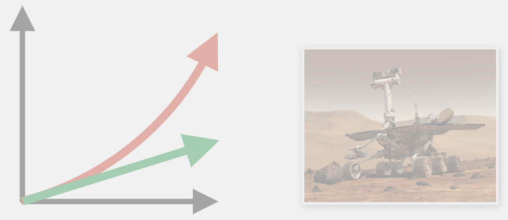

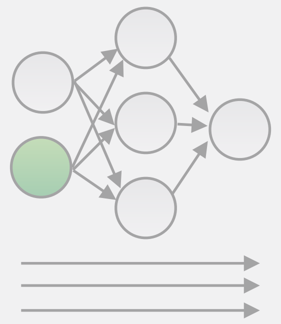

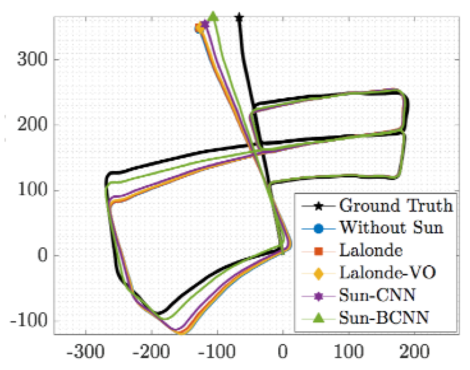

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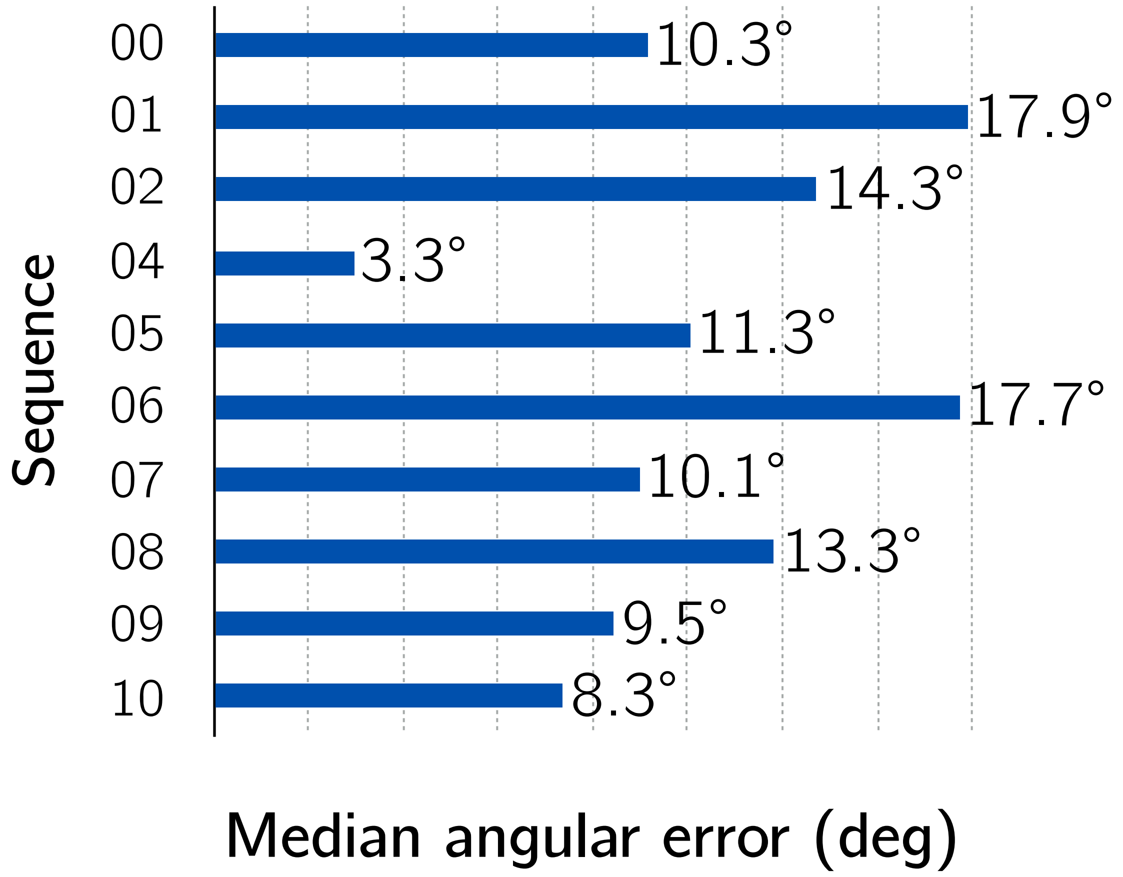
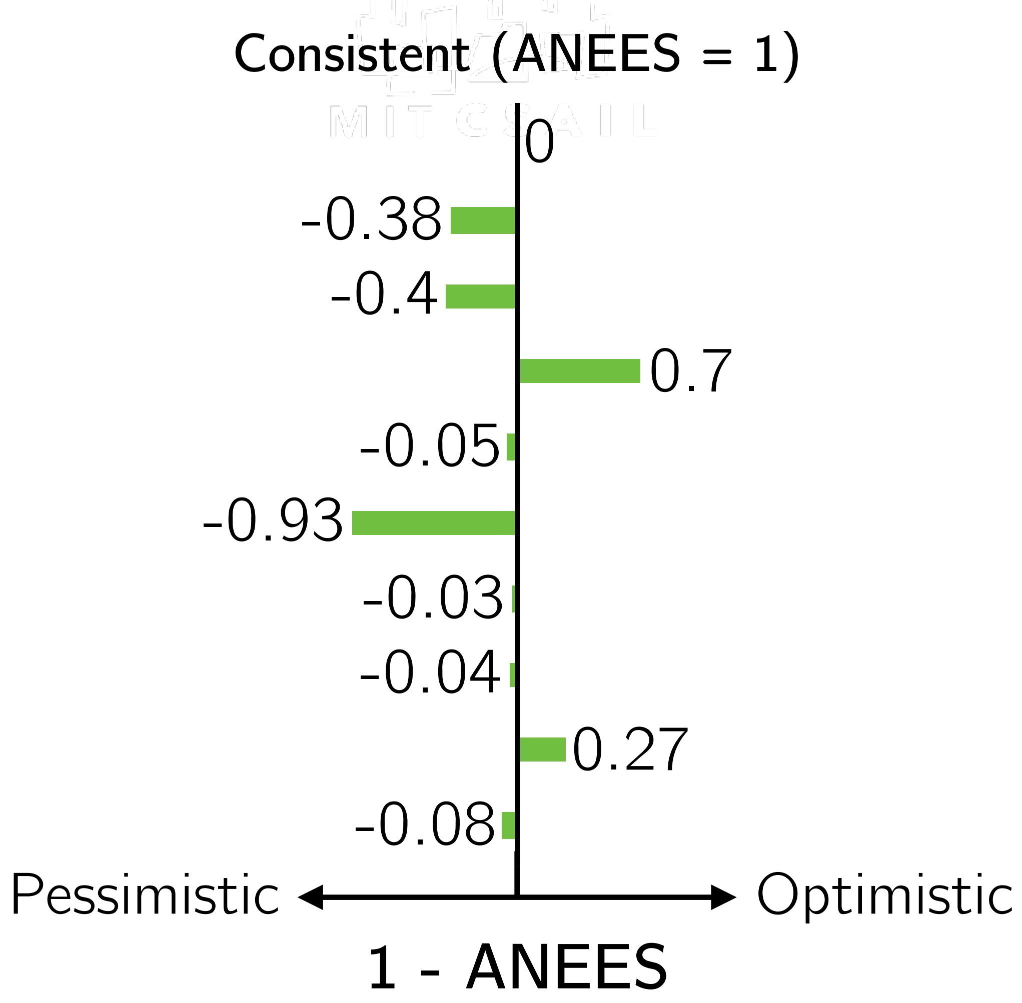
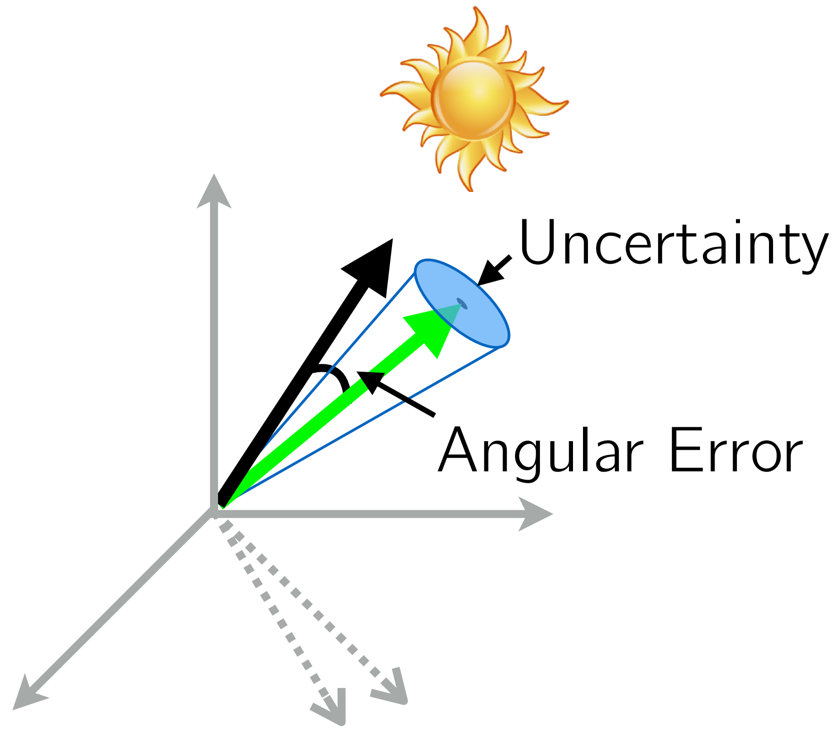
Testing on the KITTI Odometry Benchmark

Sun-BCNN:

- consistently achieves **< 18° median angular error**
- performs best with **strong directional illumination cues**
- struggles in **ambiguous lighting conditions**







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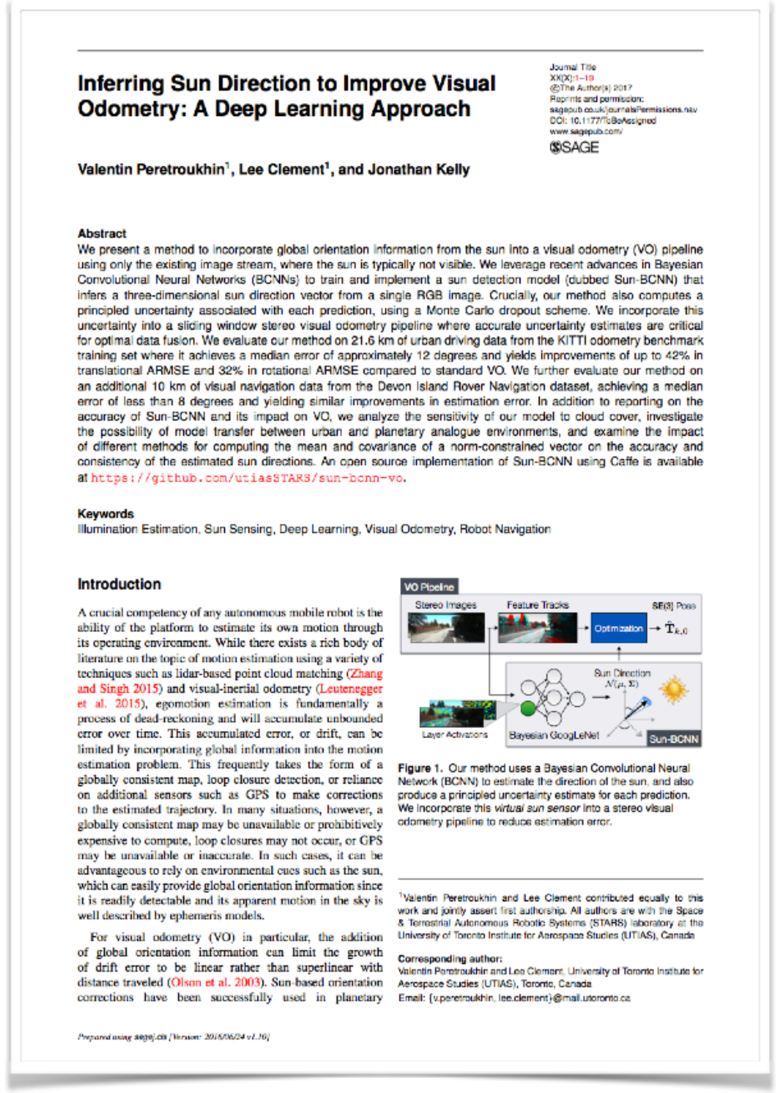
Future Work

- Incorporate temporal consistency (e.g. using RNN)
- Account for different cameras (e.g. by changing variables to remove effect of intrinsic calibration)

Journal Extension



Inferring Sun Direction to Improve Visual Odometry: A Deep Learning Approach

Valentin Peretroukhin[1], Lee Clement[1], and Jonathan Kelly

Abstract

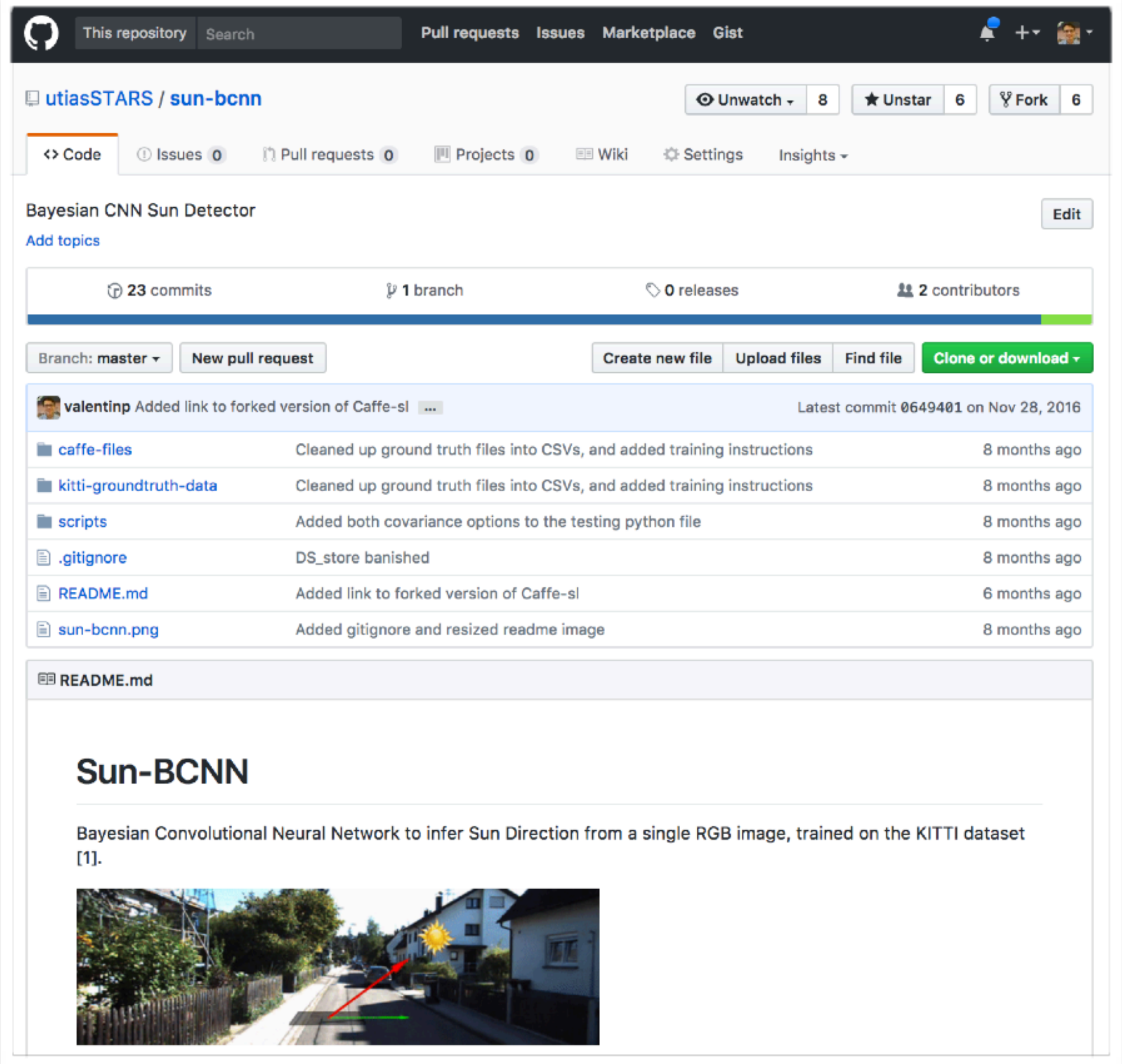
Keywords

Introduction

IJRR Special Issue on ISER

Invited, under review

GitHub



Caffe implementation of Sun-BCNN

github.com/utiasSTARS/sun-bcnn

Acknowledgements

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