Introduction

Institute for Aerospace Studies
UNIVERSITY OF TORONTO

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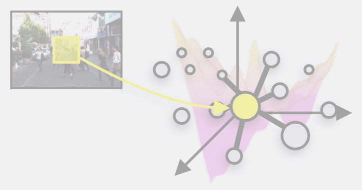
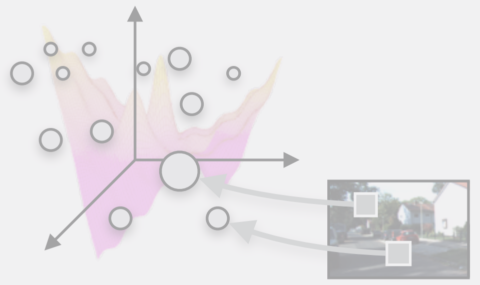
Motivation

Approach



$p\left(\mathbf{R}_i\right) = \mathrm{IW}\left(\mathbf{R}; \mathbf{\Psi}_i, \nu_i\right)$

Training & Testing



Results

Conclusions

PROBE-GK: Predictive Robust Estimation using Generalized Kernels

Valentin Peretroukhin, William Vega-Brown, Nicholas Roy, and Jonathan Kelly

ICRA 2016 | Stockholm, Sweden | Visual-Based Navigation

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Goal

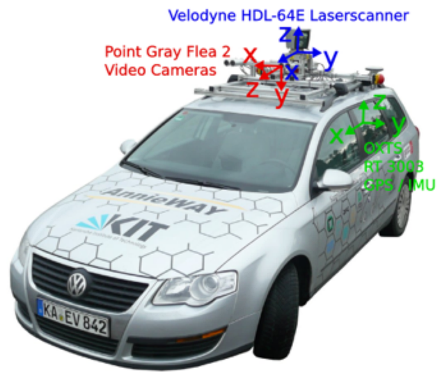
To **improve the state estimates** by modelling the relative amount of information content contained within sensor data.

Approach

We **learn** a **predictive model for observation uncertainty**. We use this model to generate a predictively robust cost that can be minimized using traditional techniques.

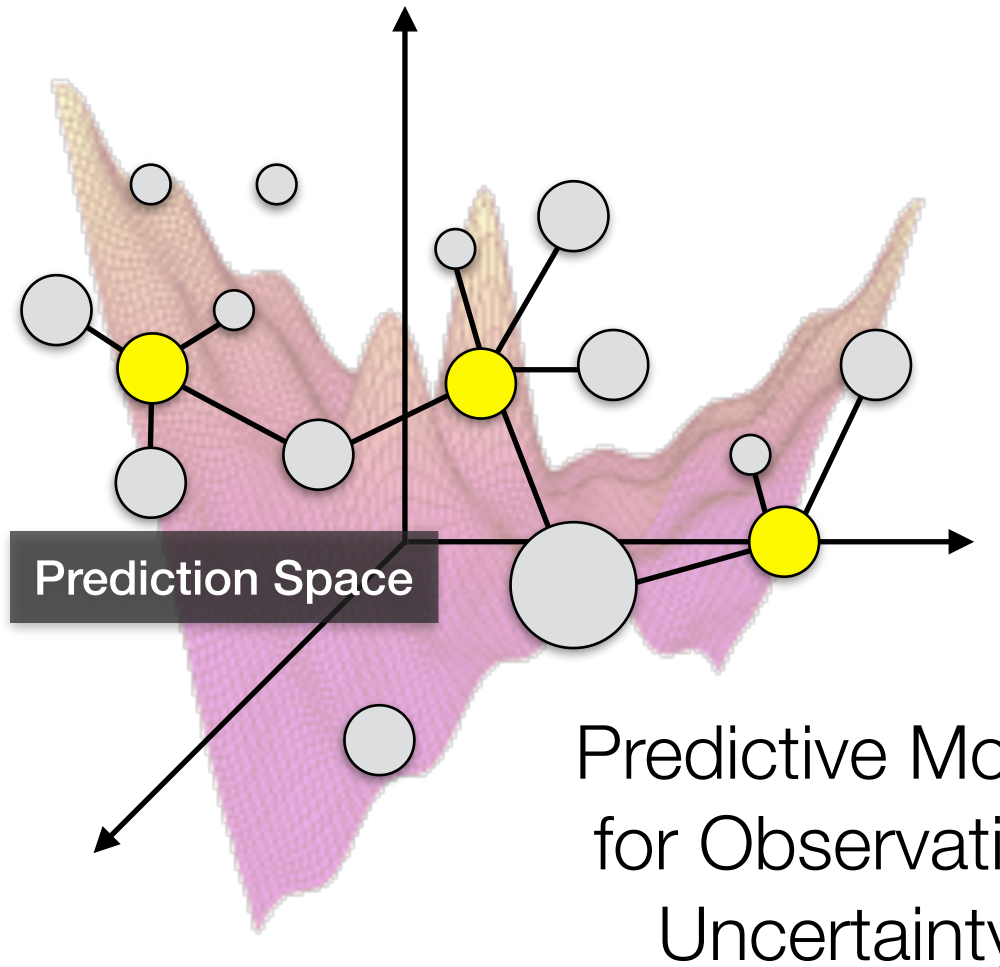
Applications

1. Sparse visual odometry
2. Visual SLAM
3. General sensor fusion



Sensor Data

→

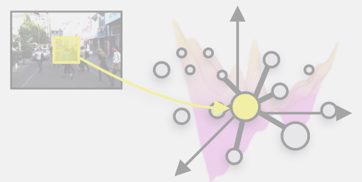


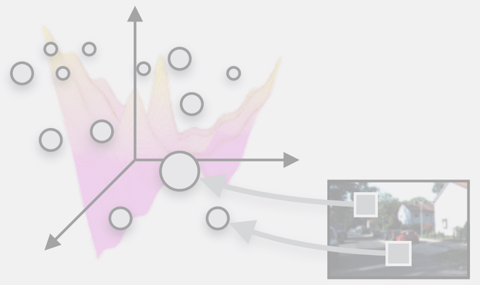
Predictive Model for Observation Uncertainty

→

$$\min \sum_i (\nu_i + 1) \log\left(1 + \boldsymbol{e}_i{}^{\top} \mathbf{\Psi}_i^{-1} \boldsymbol{e}_i\right)$$

Predictively Robust
Cost Function





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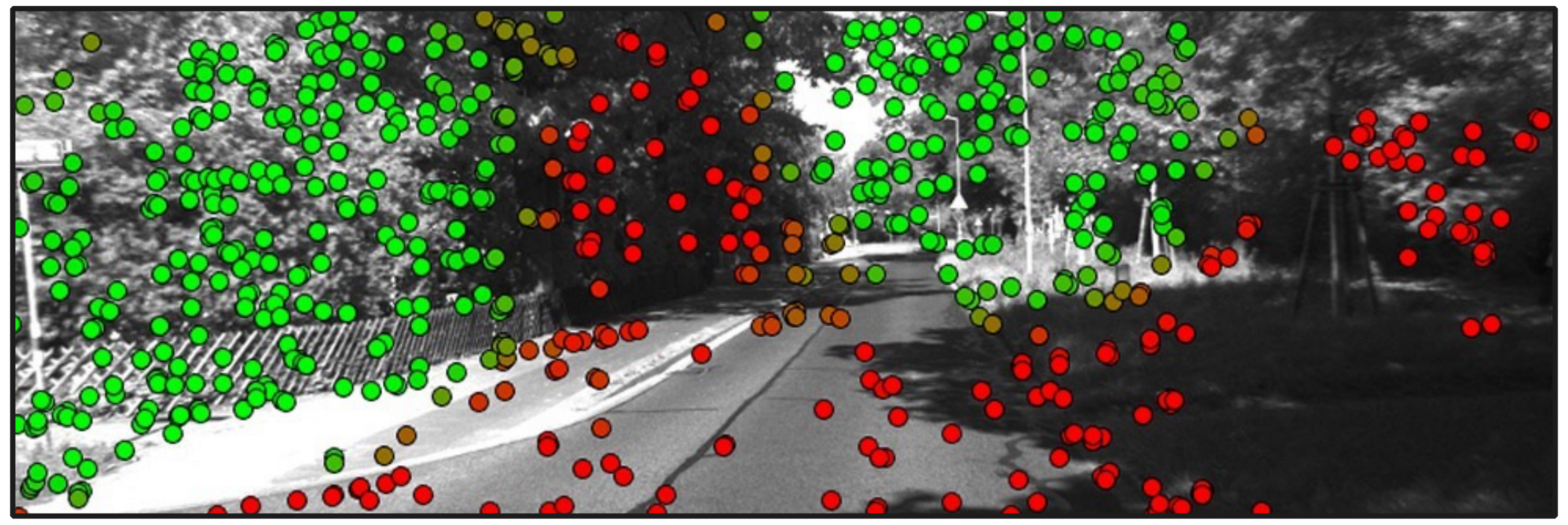
KITTI Urban Driving Dataset. Sequence 2011_09_29_drive_0071

Visual Data

Different regions in image space may contain less **salient information** than others.



Frequency content predictor, originally in PROBE (IROS 2015)

Hig Freq. → Low Freq.

Prediction Space

Effects can be easier to discern within a pre-defined prediction space.

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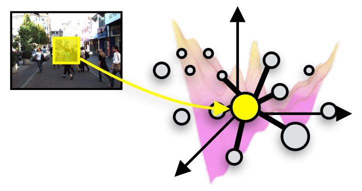

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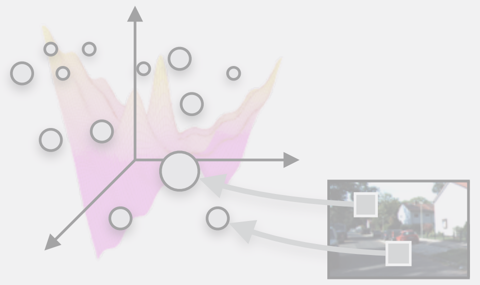

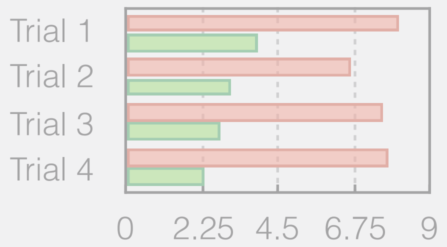

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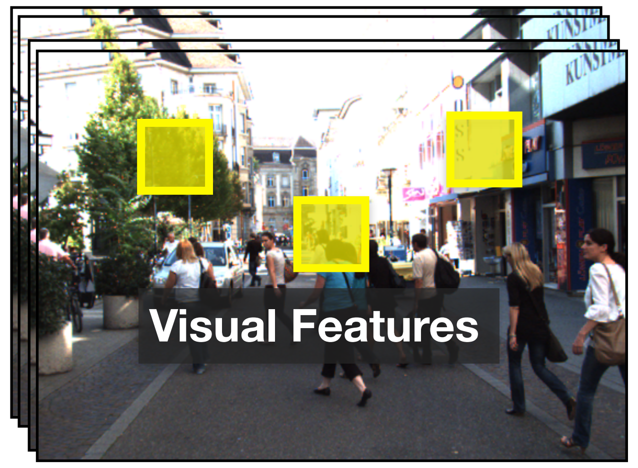
Application: Visual Odometry

We apply **PROBE-GK** to the problem of **stereo visual odometry** with sparse visual landmarks. PROBE-GK learns the information within landmarks.

Traditional Approach



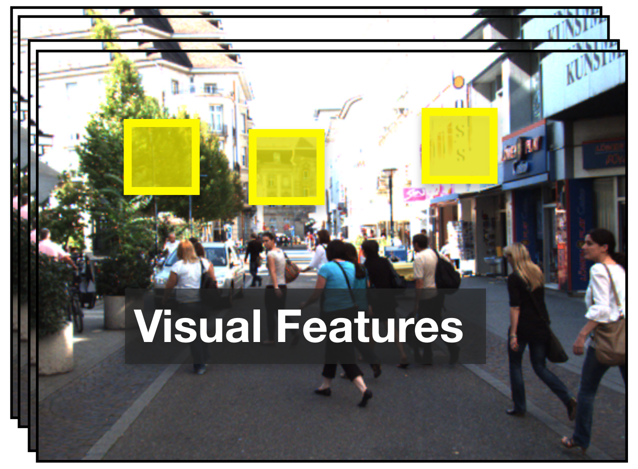
Estimation errors: $\mathbf{e}_i$

Stationary **point** uncertainty: $\mathbf{R}$

MAP Estimator

$$\underset{\mathcal{T}\in\mathrm{SE}(3)}{\arg\min} \sum_{i=1}^{N} \mathbf{e}_i{}^\top \mathbf{R}^{-1} \mathbf{e}_i$$

PROBE-GK



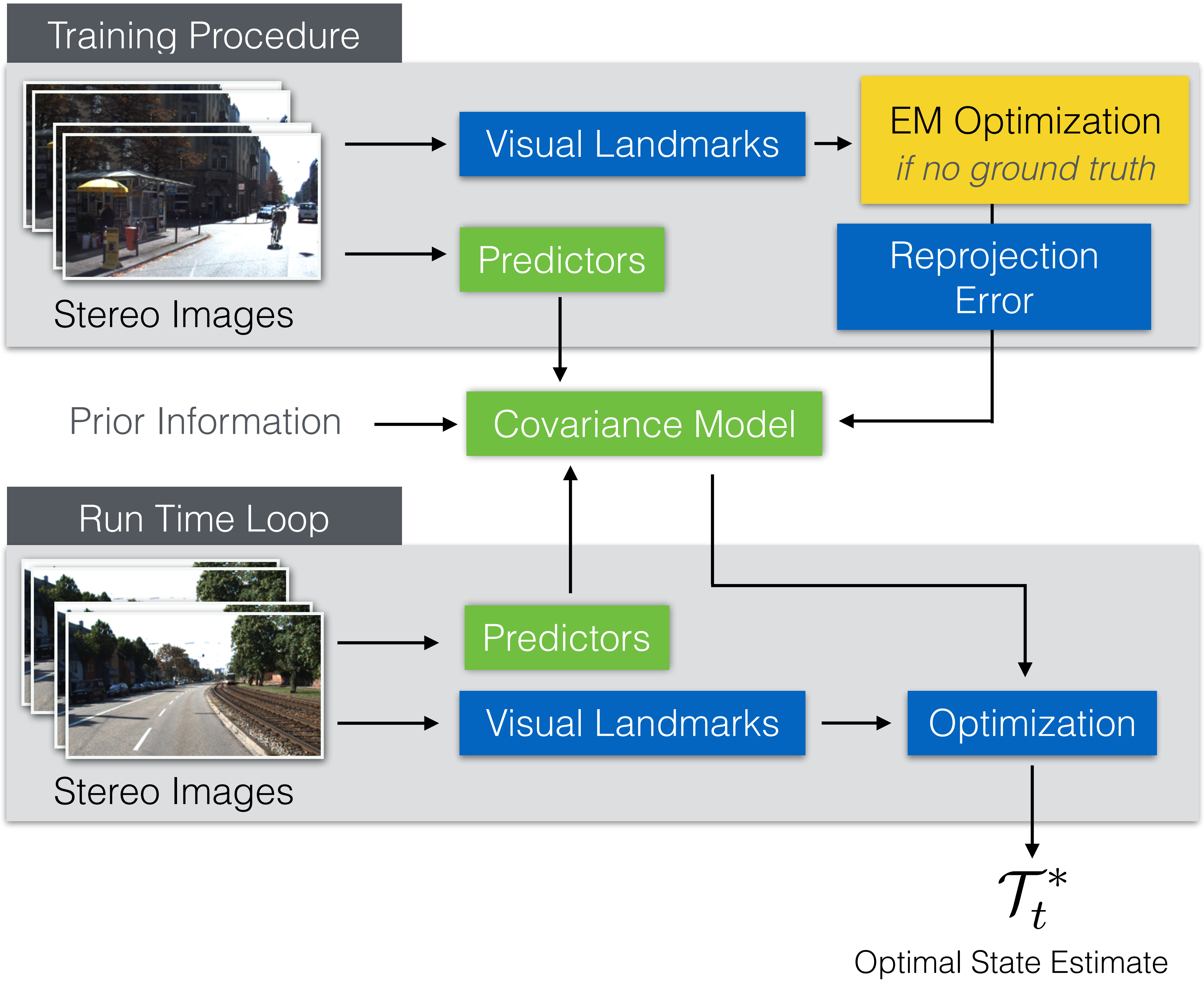
Estimation Errors: $\mathbf{e}_i$

Bayesian, kernel based covariance probability:

$$p\left(\mathbf{R}_i\right) = \mathrm{IW}\left(\mathbf{R}; \mathbf{\Psi}_i, \nu_i\right)$$

Predictively Robust Estimator

$$\underset{\mathcal{T}\in\mathrm{SE}(3)}{\arg\min} \sum_{i=1}^{N} (\nu_i + 1) \log\left(1 + \mathbf{e}_i{}^\top \mathbf{\Psi}_i^{-1} \mathbf{e}_i\right)$$



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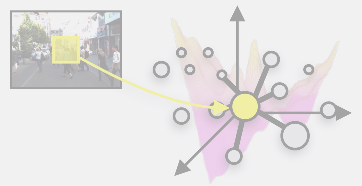
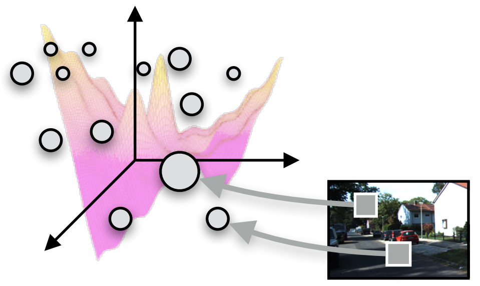
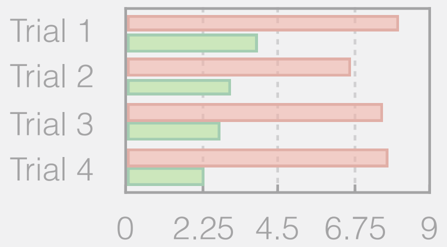


$p\left(\mathbf{R}_i\right) = \mathrm{IW}\left(\mathbf{R}; \mathbf{\Psi}_i, \nu_i\right)$

Training & Testing



Results



Conclusions

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Training

1. **Define** an Inverse-Wishart prior on covariance matrices at all locations within prediction space:

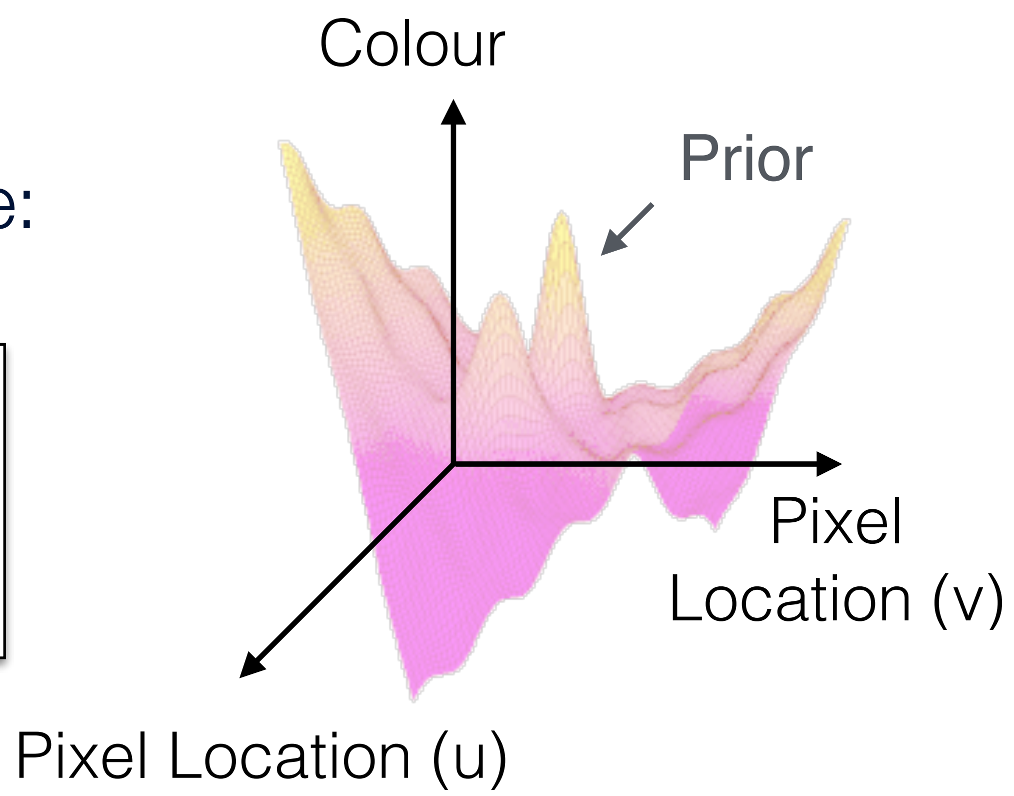
Prediction Space

$$\boldsymbol{\phi} \in \{\dots\}$$

e.g. pixel location, colour, gradient strength, density

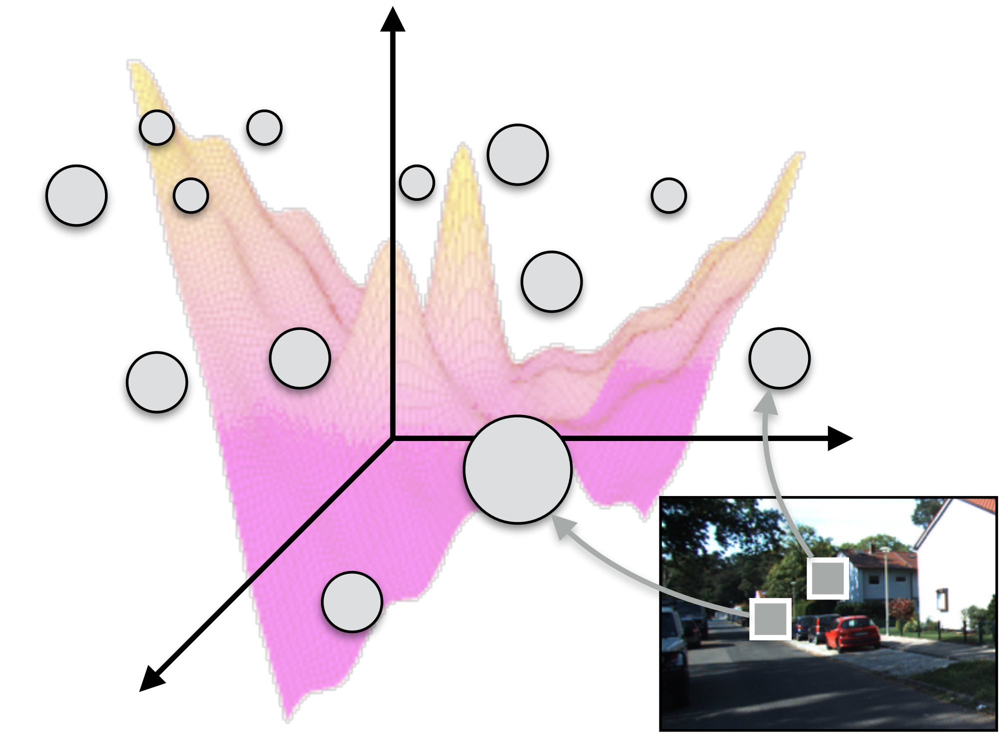
Inverse-Wishart (IW) Distribution

$$p\left(\mathbf{R}\right) = \frac{|\mathbf{\Psi}|^{\nu/2}}{2^{\frac{\nu d}{2}}\Gamma_d(\frac{\nu}{2})}|\mathbf{R}|^{-\frac{\nu+d+1}{2}} \exp\left(-\frac{1}{2}\mathrm{tr}\left(\mathbf{\Psi}\mathbf{R}^{-1}\right)\right) \qquad \mathbf{\Psi} \in \mathbb{R}^{d\times d} \succ 0, \quad \nu \in \mathbb{R} > d-1$$



2. **Collect data** by traversing through characteristic environment. Store (using k-d tree) re-projection errors in a prediction space:

$$\mathbf{e}_{i,t} = \underbrace{\mathbf{y}'_{i,t}}_{\text{stereo pixels}} - \underbrace{f}_{\text{camera model}}(\underbrace{\mathcal{T}_t}_{\text{ground truth}} f^{-1}(\mathbf{y}_{i,t})) \qquad \mathcal{D} = \{\mathbf{e}_{i,t}, \boldsymbol{\phi}_{i,t}\}$$



3. (Optional) Use **Expectation-Maximization** if no ground truth is available:

PROBE-GK EM

E: Build prediction space based on latest estimate of poses

M: Minimize robust non-linear cost.

Likelihood of the data:

$$Q(\mathcal{T}_{1:T}|\mathcal{T}_{1:T}^{(n)}) \cong -\frac{1}{2}\sum_{t=1}^{T}\sum_{i=1}^{N_t}\mathbf{e}_{i,t}^{\top}\left(\frac{1}{\nu_{i,t}^{(n)}}\mathbf{\Psi}_{i,t}^{(n)}\right)^{-1}\mathbf{e}_{i,t}.$$

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Testing

1. **Infer** a posterior distribution on covariance through generalized kernels:

$$
\begin{aligned}
p(\mathbf{R}_*|\mathcal{D}, \boldsymbol{\phi}_*) &\propto \prod_{i,t} \mathcal{N}(\boldsymbol{e}_{i,t}|\mathbf{0}, \mathbf{R}_*)^{k(\boldsymbol{\phi}_*, \boldsymbol{\phi}_{i,t})} \\
&\quad \times \mathrm{IW}(\mathbf{R}; \mathbf{\Psi}(\boldsymbol{\phi}_*), \nu(\boldsymbol{\phi}_*)) \\
&= \mathrm{IW}(\mathbf{R}_*; \mathbf{\Psi}_*, \nu_*)
\end{aligned}
$$

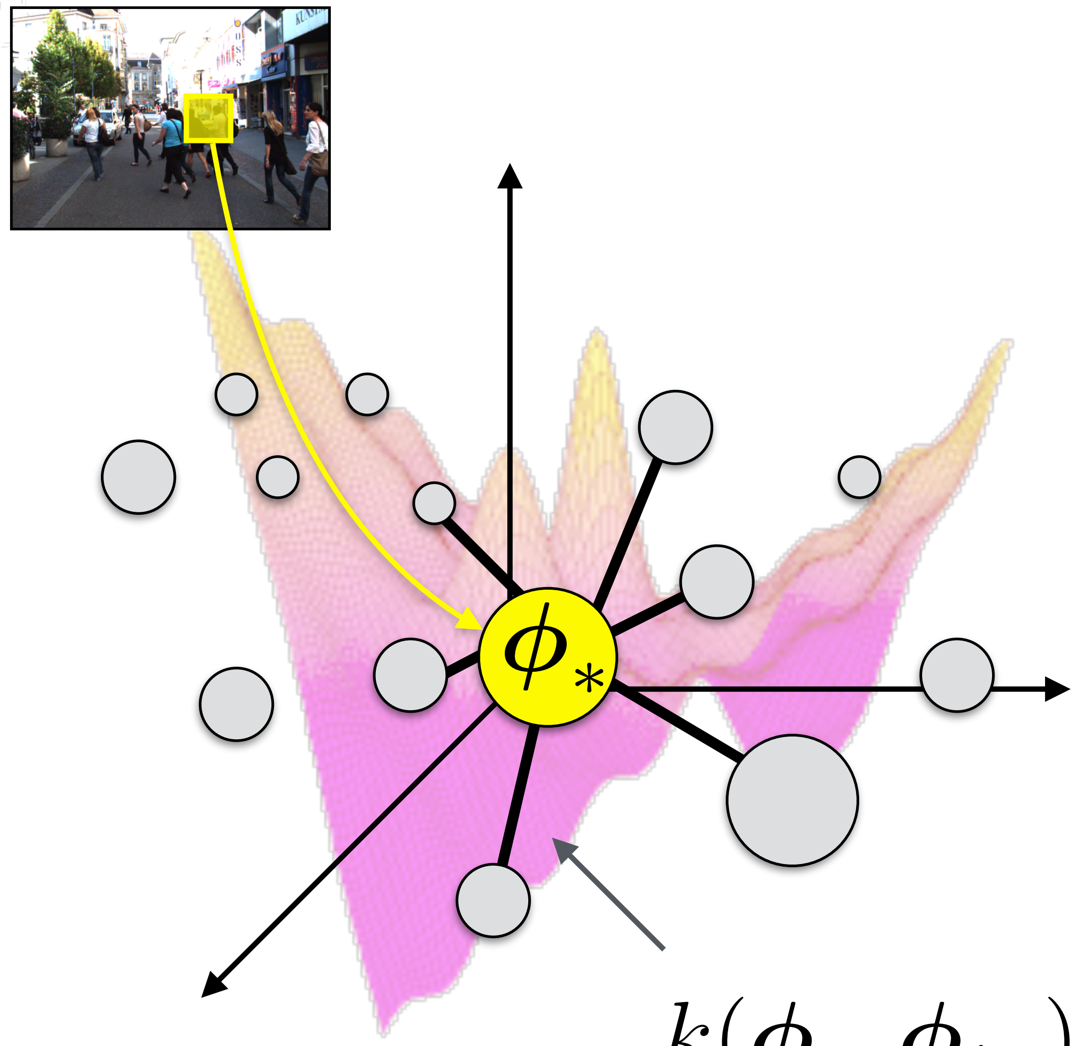
$$
\begin{aligned}
\mathbf{\Psi}_* &= \mathbf{\Psi}(\boldsymbol{\phi}_*) + \sum_{i,t} k(\boldsymbol{\phi}_*, \boldsymbol{\phi}_{i,t}) \boldsymbol{e}_{i,t} \boldsymbol{e}_{i,t}{}^{\top} \\
\nu_* &= \nu(\boldsymbol{\phi}_*) + \sum_{i,t} k(\boldsymbol{\phi}_*, \boldsymbol{\phi}_{i,t})
\end{aligned}
$$

Generalized Kernels

GK extends local kernel estimation to Bayesian inference.

Assumptions:

- Training data is independent given inputs, and target.
- Model varies smoothly over prediction space, with bounds on KL divergence.



Distance Kernel:

$k(\boldsymbol{\phi}, \boldsymbol{\phi}) = 1 \quad k(\boldsymbol{\phi}_i, \boldsymbol{\phi}_j) \in [0, 1]$

2. **Marginalize** over the covariance to arrive at Student's t cost with parameters that vary for every visual landmark.

$$
\int d\mathbf{R}_{i,t} \mathcal{N}\left(\boldsymbol{e}_{i,t}; \mathbf{0}, \mathbf{R}_{i,t}\right) \mathrm{IW}(\mathbf{R}_{i,t}; \mathbf{\Psi}_*, \nu_*) \longrightarrow \boxed{\mathcal{T}_t^* = \underset{\mathcal{T}_t \in \mathrm{SE}(3)}{\arg\min} \sum_{i=1}^{N_t} (\nu_{i,t} + 1) \log\left(1 + \boldsymbol{e}_{i,t}{}^{\top} \mathbf{\Psi}_{i,t}^{-1} \boldsymbol{e}_{i,t}\right)}
$$

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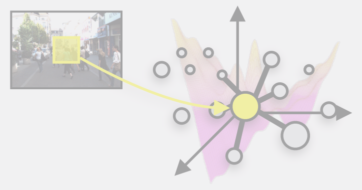

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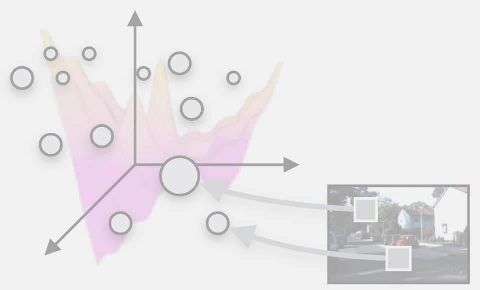
Training & Testing



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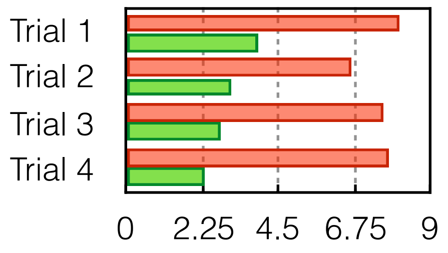

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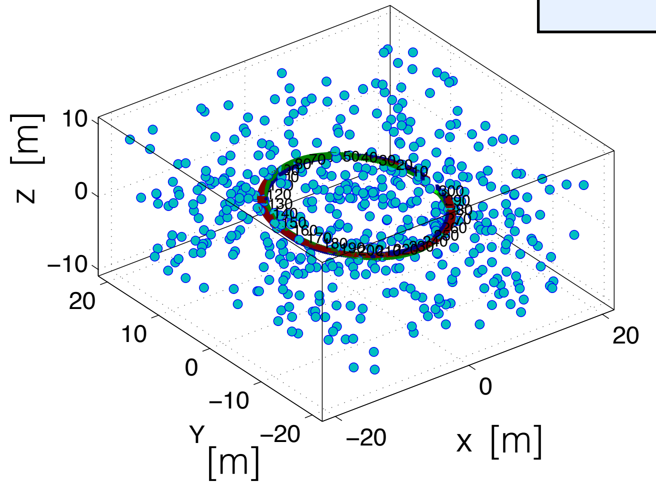
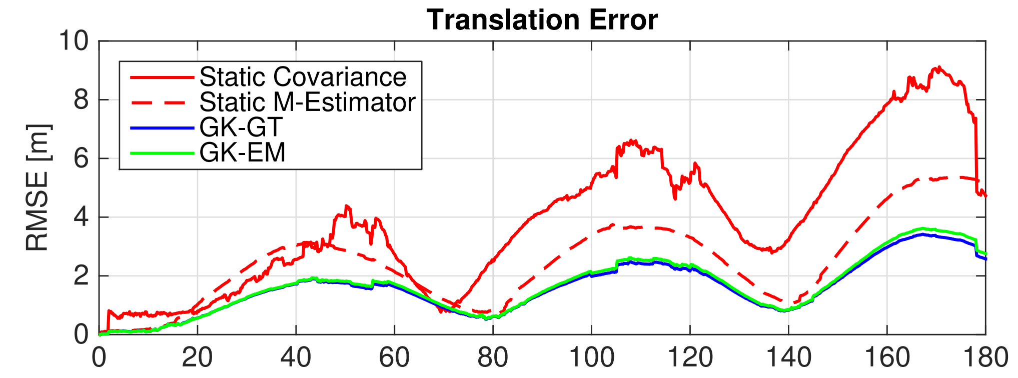
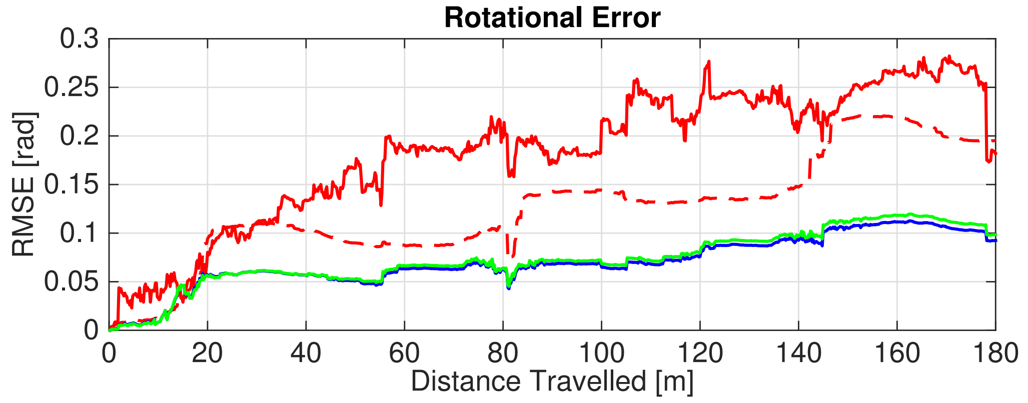
Simulation Data



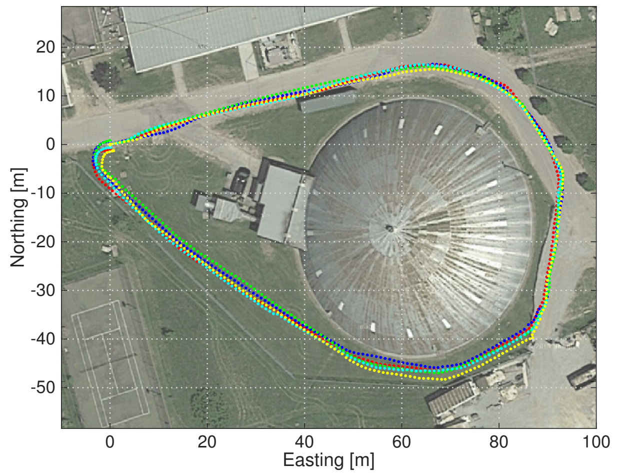




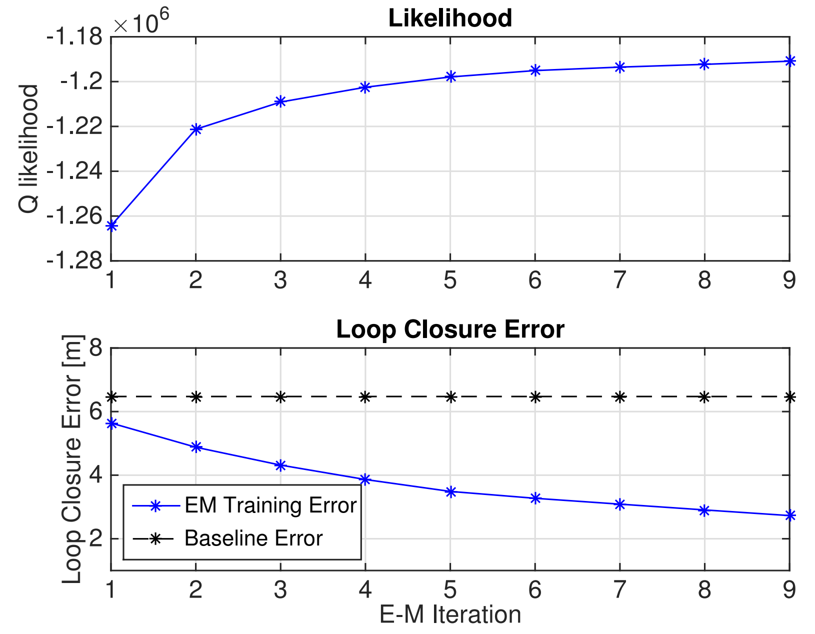
Train/test traversals through **point world of 2000** landmarks

Gaussian noise of different variance & outliers

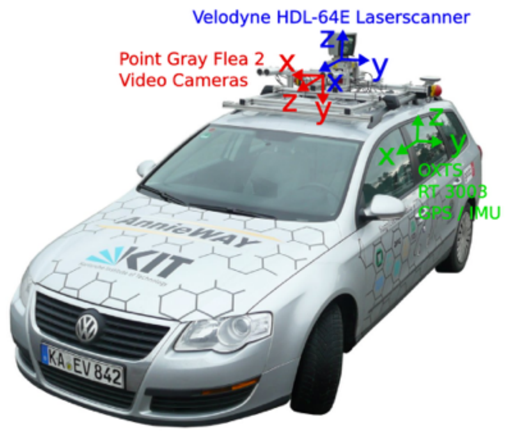
UTIAS Experiments



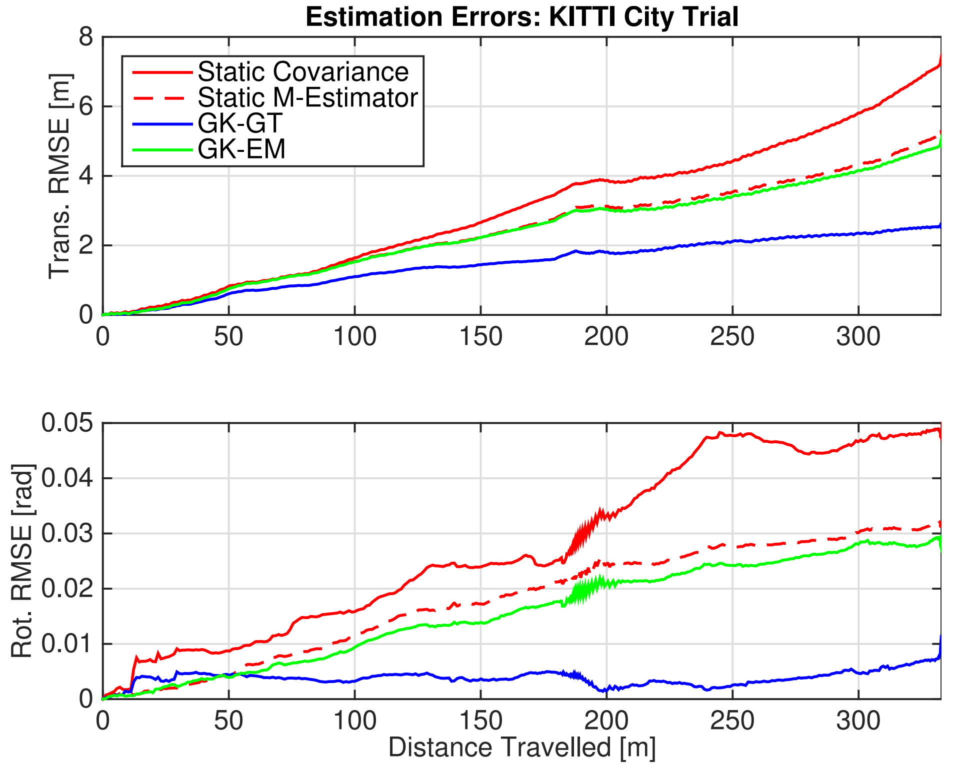
Loop closure error reduced by **up to 70%**.

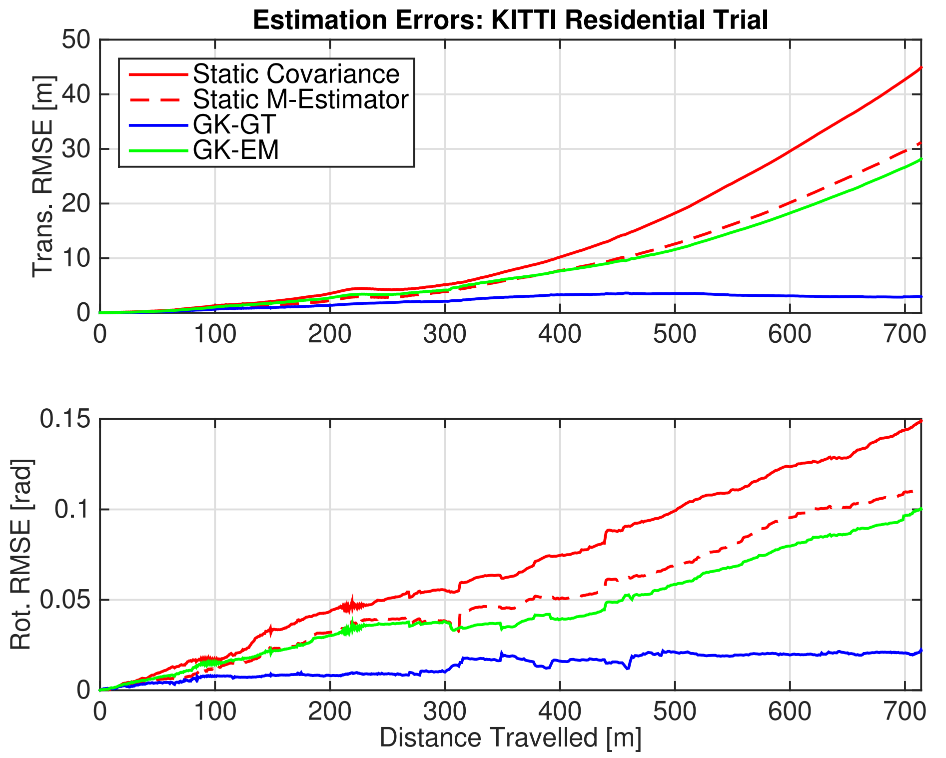


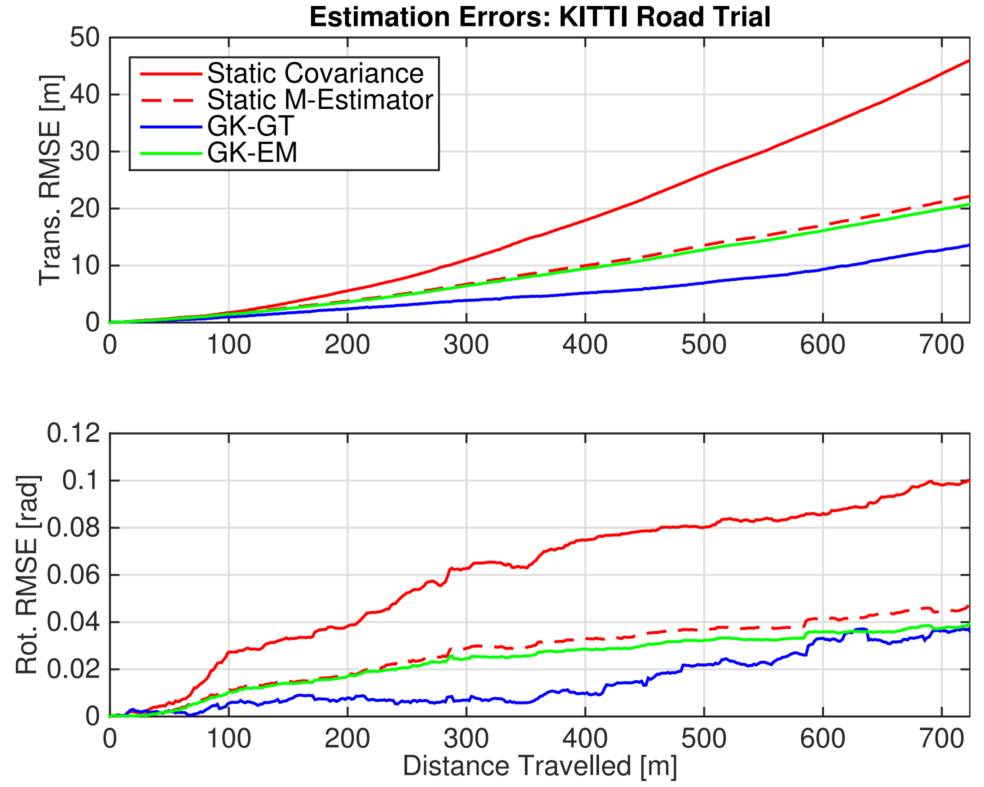
KITTI Data



Separate train/test traversals through **three KITTI environments**







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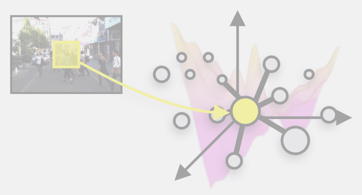

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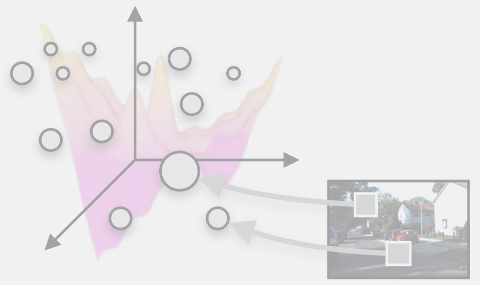

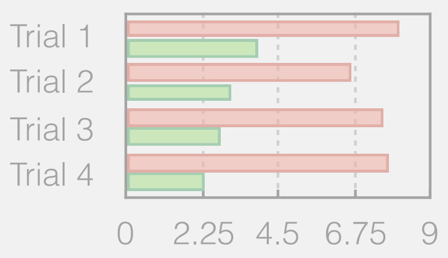

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Conclusions

Modelling observation uncertainty improves the accuracy of stereo visual odometry in a variety of settings.

Using Bayesian inference, an uncertainty model can lead to a predictive robust estimator.

The model can be trained with or without ground truth.

Future Work

Online Learning

Learn the PROBE-GK model online 'as-you-go' obviating training data.

CNN-Based Features

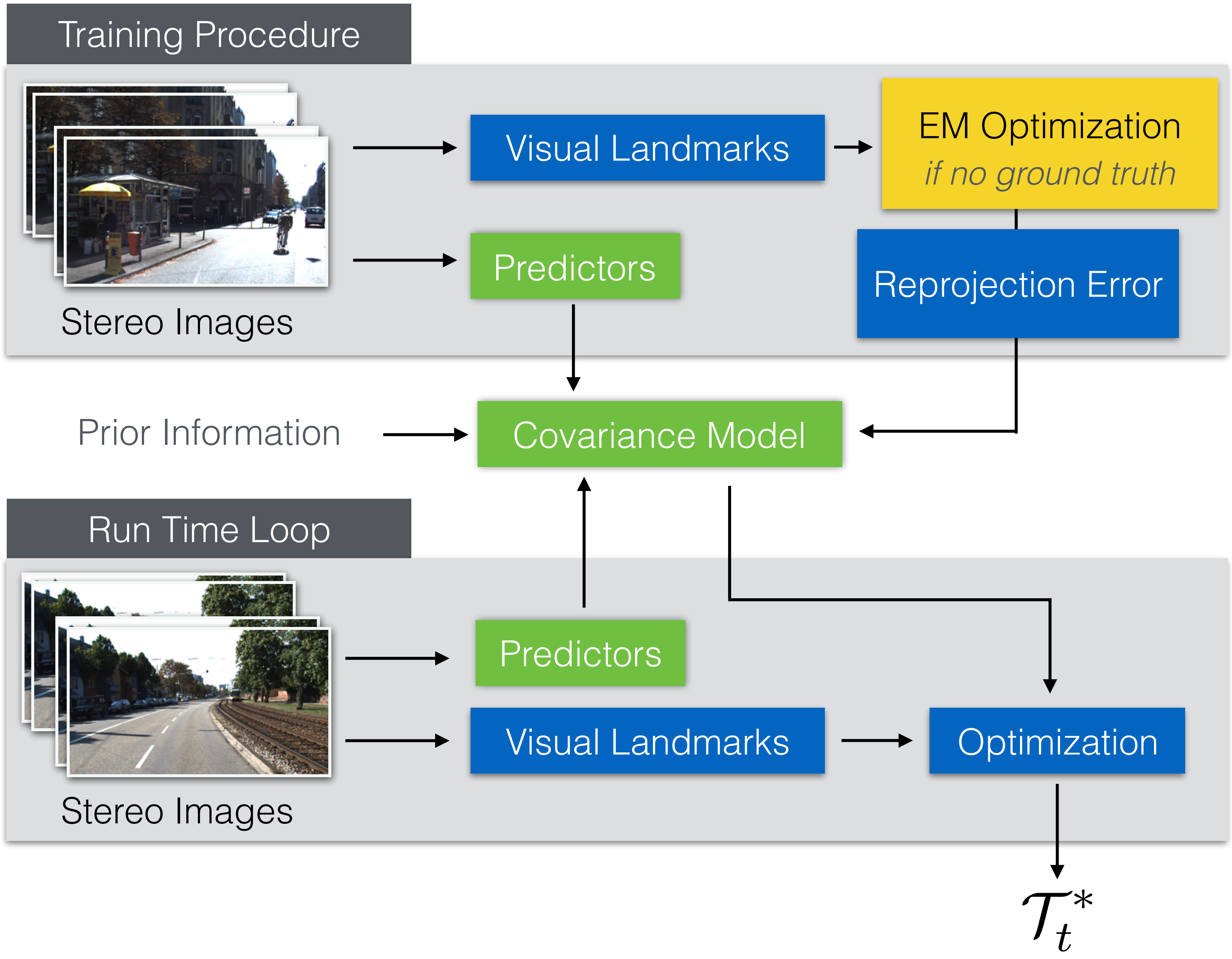
Leverage CNN-based features to remove hand-crafted prediction space.

Acknowledgements

NCFRN NSERC Canadian Field Robotics Network

RCCRT Réseau canadien CRSNG pour la robotique de terrain

NSERC CRSNG



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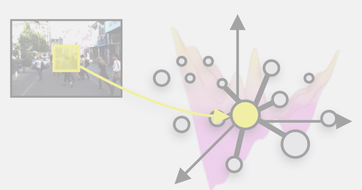

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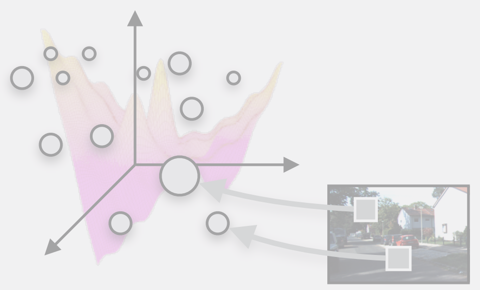

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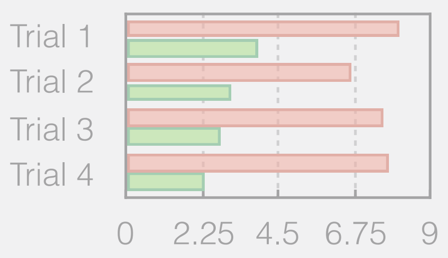

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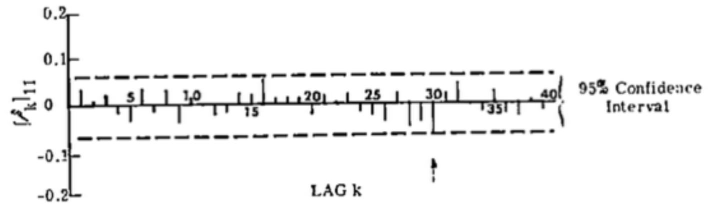
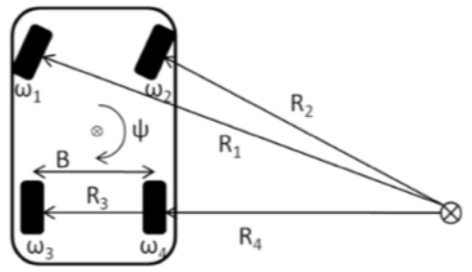
Adaptive Filtering

R. Mehra, "**On the identification of variances and adaptive Kalman filtering**," IEEE Transactions on Automatic Control, Apr. 1970.

E. Özkan et al., "**Marginalized adaptive particle filtering for nonlinear models with unknown time-varying noise parameters**," Automatica, Jun. 2013.

Dingjie Xu et al., "**A Robust Particle Filtering Algorithm With Non-Gaussian Measurement Noise Using Student-t Distribution**," in IEEE Signal Processing Letters, Jan. 2014.





Past Work

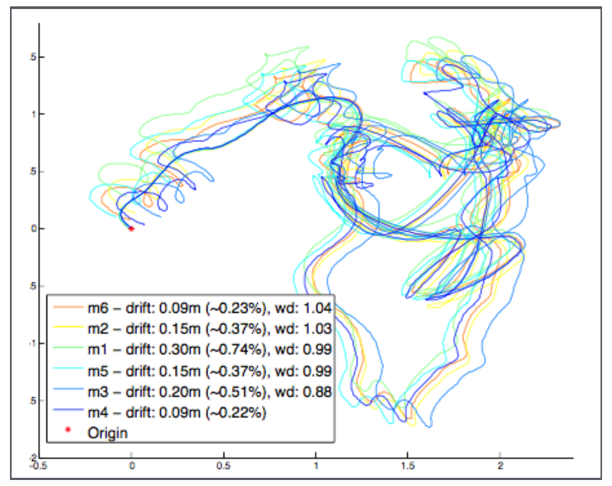
W. R. Vega-Brown, M. Doniec, and N. G. Roy, "**Nonparametric Bayesian inference on multivariate exponential families**," in Advances in Neural Information Processing Systems 27, 2014.

Peretroukhin, Valentin, et al. "**PROBE: Predictive robust estimation for visual-inertial navigation.**" Intelligent Robots and Systems (IROS), 2015 IEEE/RSJ International Conference on, 2015.

Landmark Pruning

I. Cvisic and I. Petrovic, "**Stereo odometry based on careful feature selection and tracking**," 2015 European Conference on Mobile Robots (ECMR)

K. Tsotsos, A. Chiuso and S. Soatto, "**Robust inference for visual-inertial sensor fusion**," 2015 IEEE International Conference on Robotics and Automation (ICRA)



Comparison to PROBE

	PROBE	
Learning Output	Scalar Uncertainty Factor	Distribution over Covariance Matrices
Formulation	Empirical	Bayesian, Inverse-Wishart
Ground Truth Required?	Yes	No
Stored Error	Pose Error	Reprojection Error

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