

Active Covariance Scaling for Feature Tracking Through Motion Blur

Valentin Peretroukhin, Lee Clement, and Jonathan Kelly

Workshop on Scaling Up Active Perception

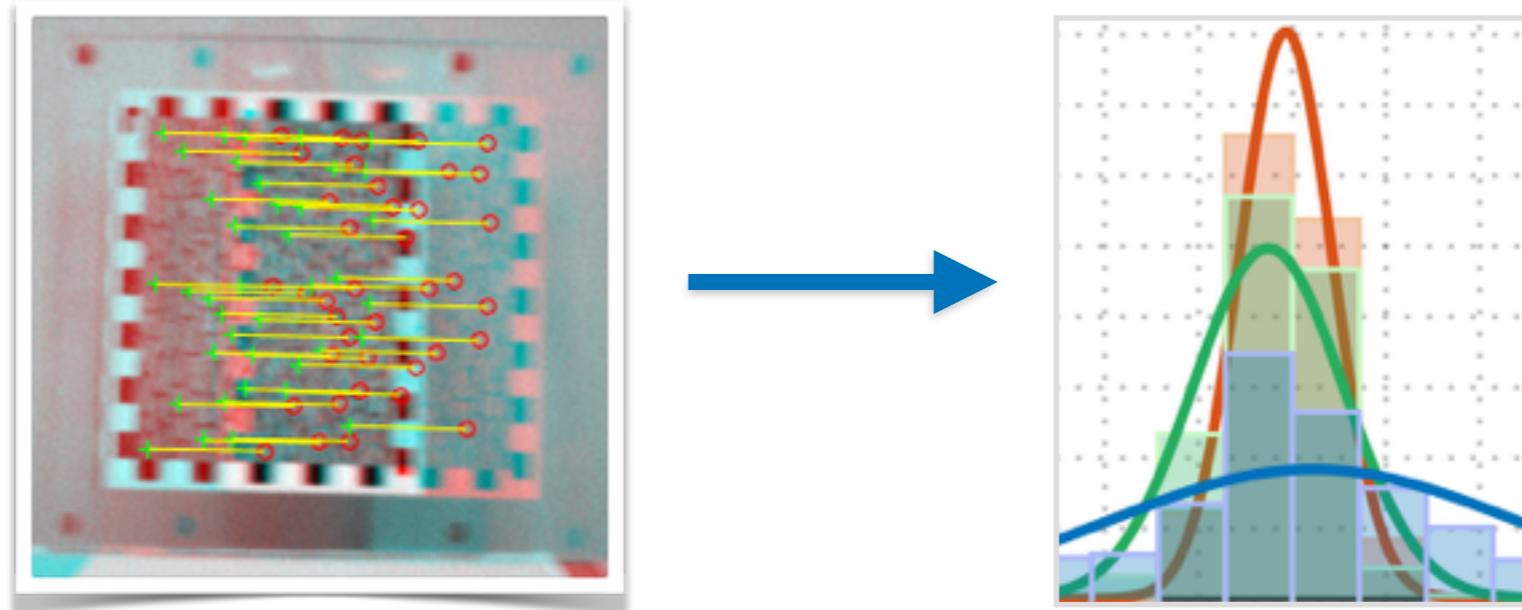
ICRA 2015, Seattle, USA



Institute for Aerospace Studies
UNIVERSITY OF TORONTO

S T A R S
L A B O R A T O R Y

Outline: Motion Blur and Feature Tracking



1. Motivation

A simple way to detect and account for **motion blur** in sparse feature tracking.

2. Methods

KLT tracking of SURF, dataset of Guglitz et al. 2011.

3. Results

Feature tracking error distributions under motion blur.

4. Application

Consistency of stereo visual odometry.



Motivation: Motion Blur Degrades Feature Tracking

In many robotics applications, fast-moving platforms require **accurate** and **consistent** estimates of their egomotion.



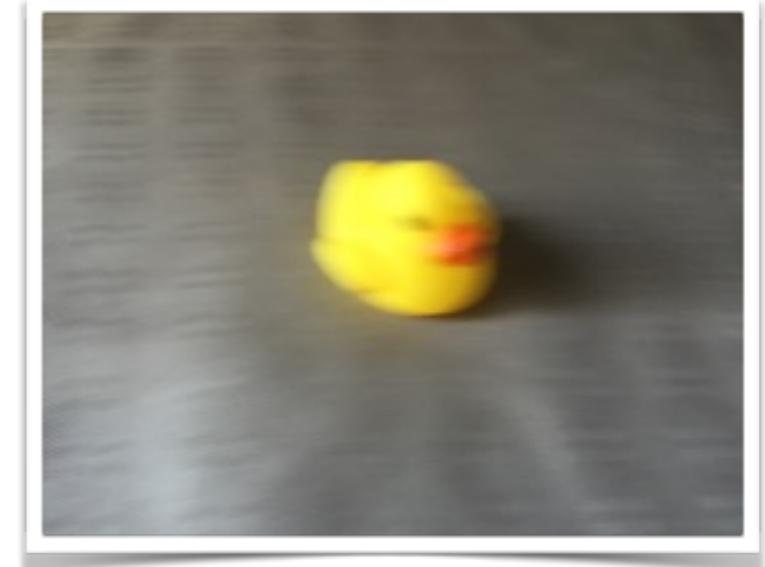
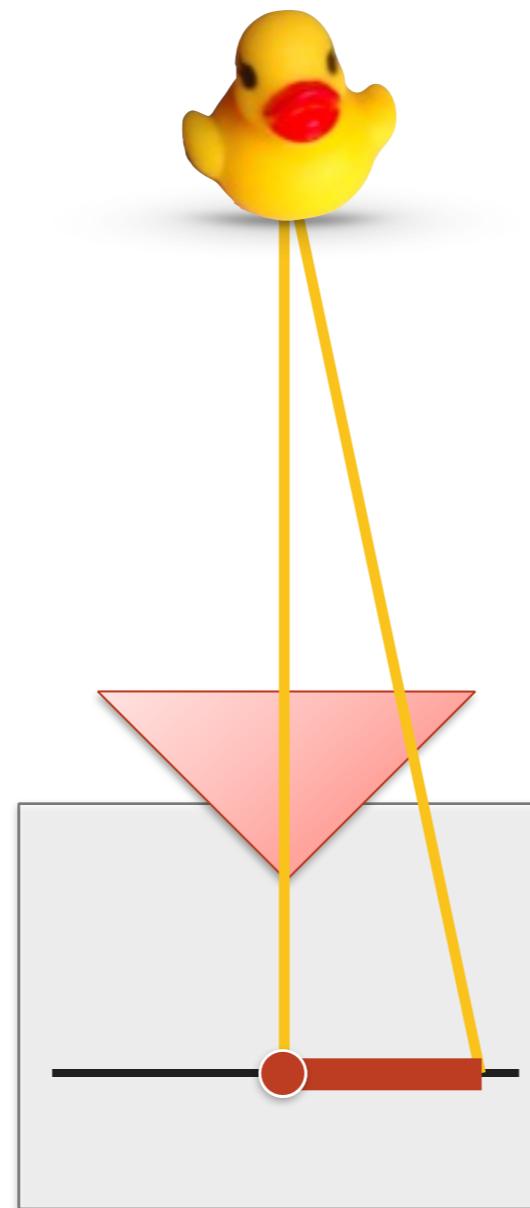
Sparse feature tracking commonly degrades in the presence of **motion blur**.



Some blurred features may be rejected as outliers, while others may carry useful information!



Background: What Is Motion Blur?



Note: translational motion blur depends on feature depth, but rotational motion blur is depth-independent and usually dominates.



Related Work: Compensating for Motion Blur

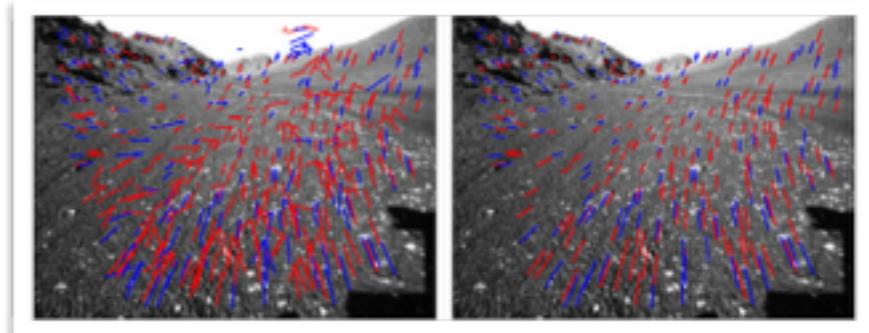
Image stabilization hardware

- ✖ Adds hardware complexity



Reject blurred features as outliers
(e.g., via RANSAC or similar)

- ✖ Discards useful features



Drop video frames with blurred features

Mutlu et al., “A real-time inertial motion blur metric” ICRA 2014.

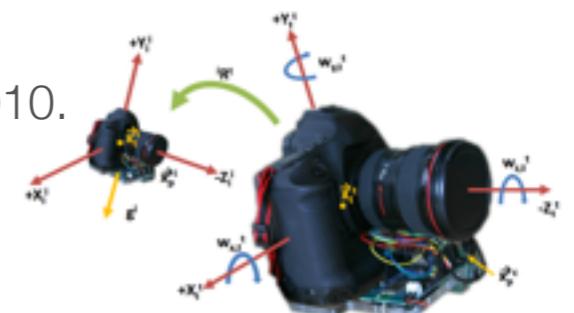
- ✖ Removes entire images



Attempt to compensate using a de-blurring technique

Joshi et al., “Image deblurring using inertial measurement sensors,” ACM Trans. Graph., 2010.

- ✖ Designed for offline use

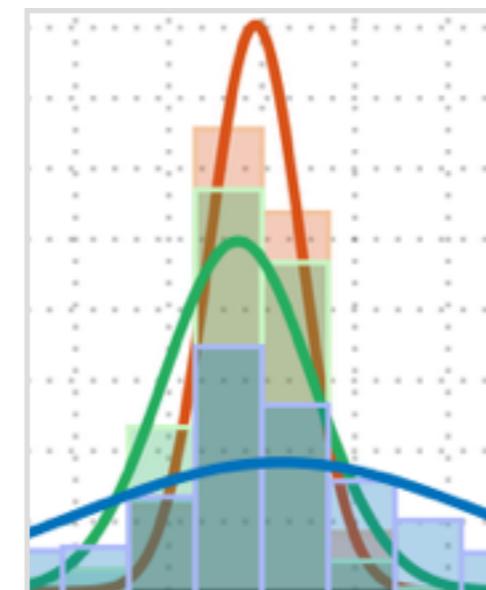
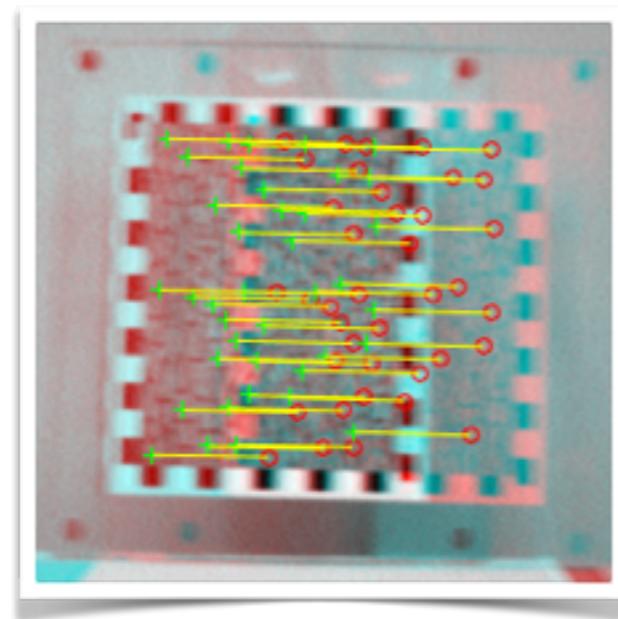


Our Idea: Modelling Tracking Through Motion Blur

Current approaches attempt to compensate for blur by preventing blurred feature tracks from entering the estimator.



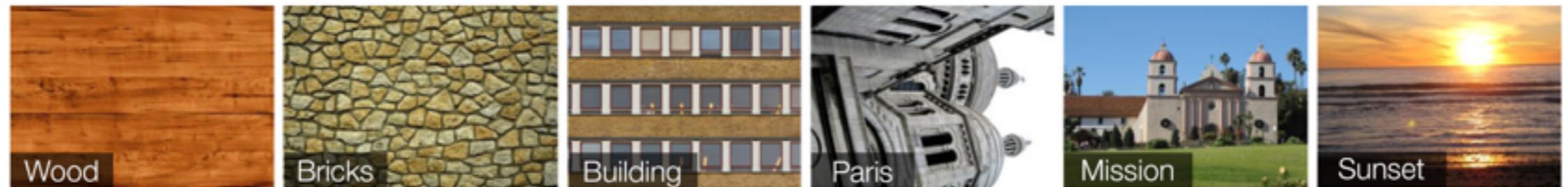
Can we **identify** motion blur and **characterize** its effect on tracking error?



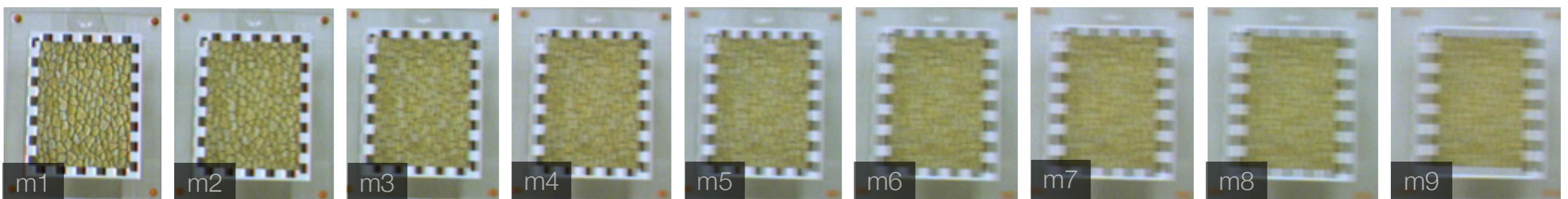
Dataset: Planar Texture, Moving Camera

We use the dataset of Gauglitz et al., in which a global-shutter camera on a pan-tilt head observes a planar texture while undergoing a panning motion.

Six textures

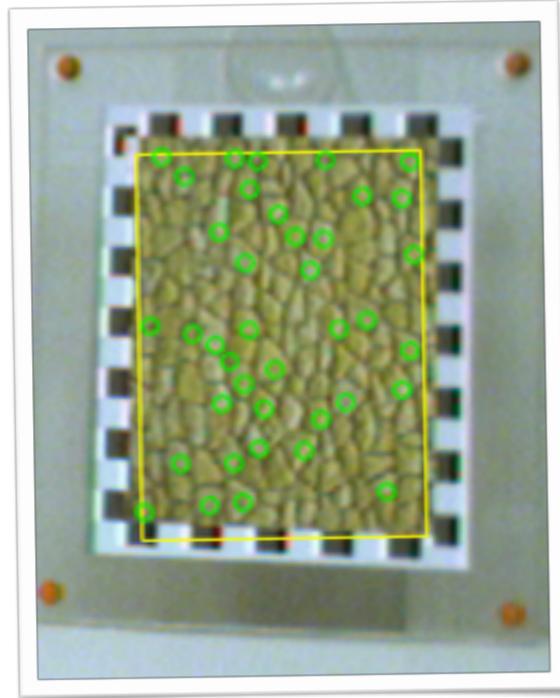


Nine pan speeds



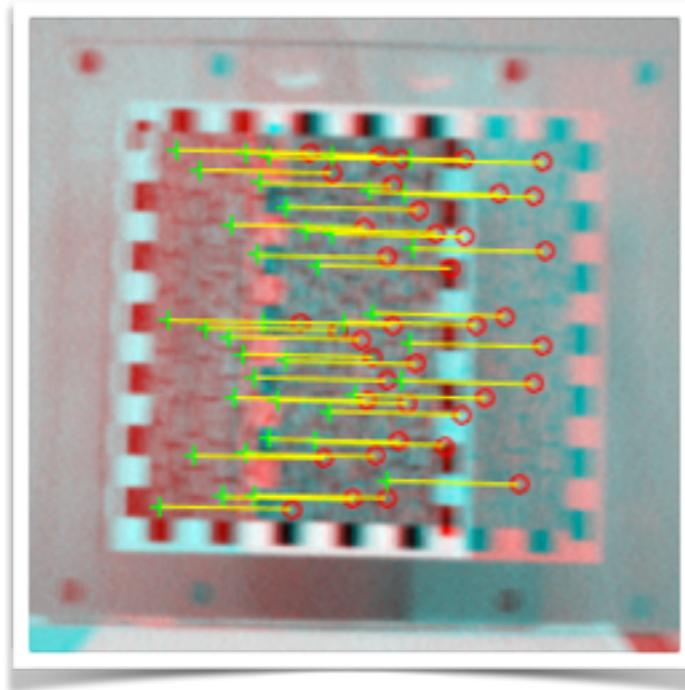
S. Gauglitz et al., “Evaluation of interest point detectors and feature descriptors for visual tracking,” IJCV 2011.

Quantifying Blur: Feature Tracking Error



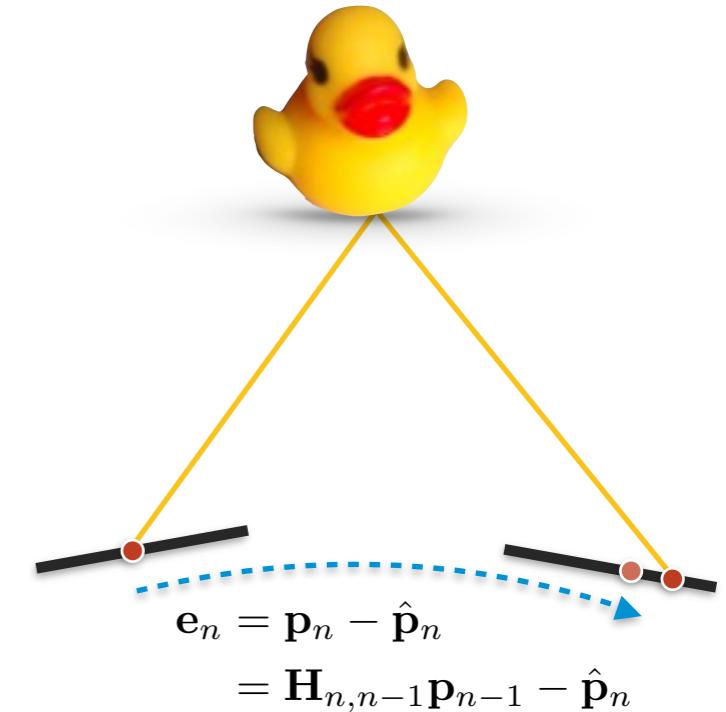
Detect point features
(e.g., using SURF, FAST, Harris).

1



Track features using
Kanade-Lucas-Tomasi (KLT).

2

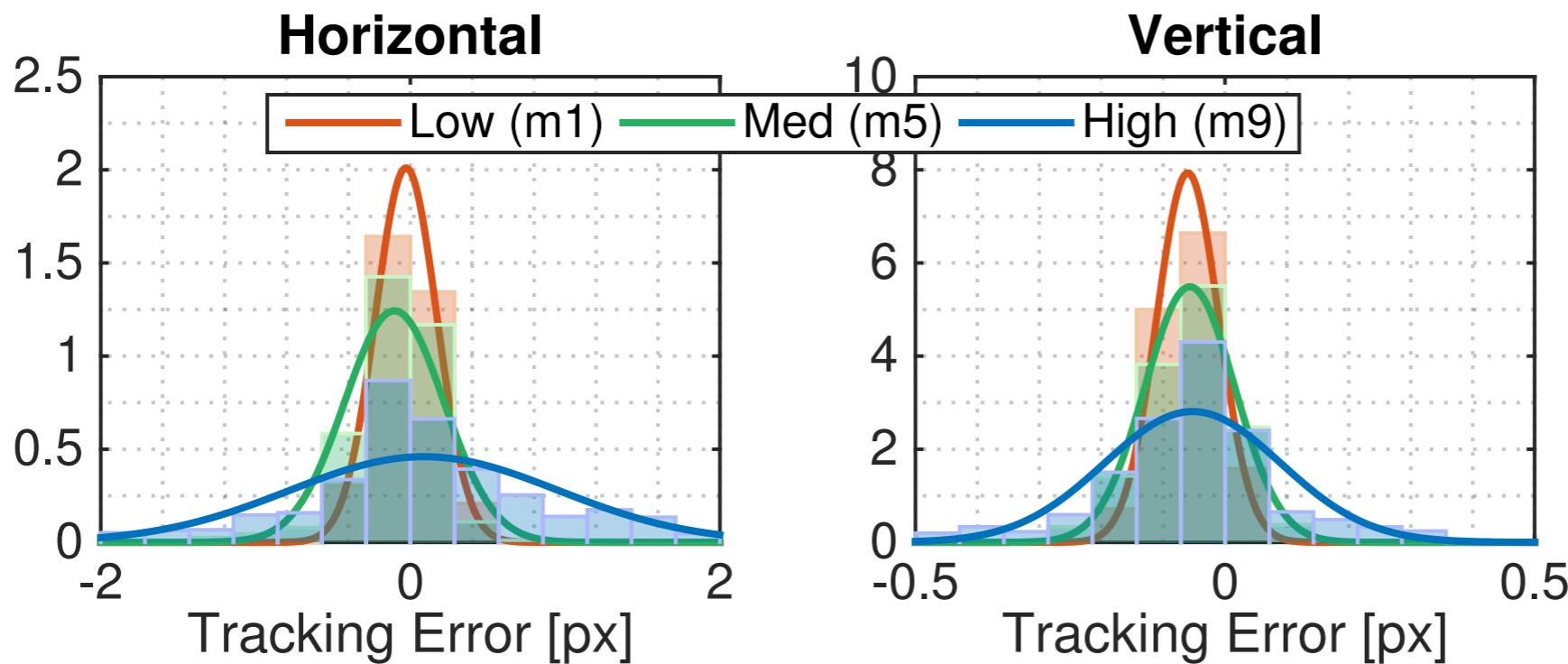


Compute **frame-to-frame**
reprojection error using
ground truth homographies.

3

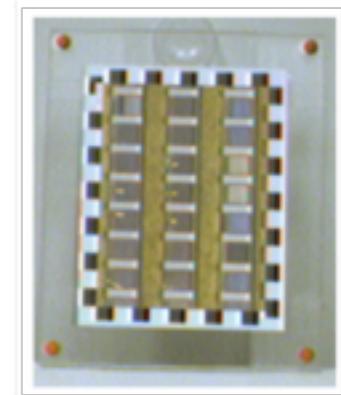


Quantifying Blur: Feature Tracking Error

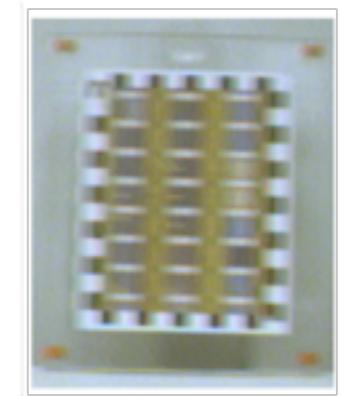


	Mean [px]	Stdev [px]
<i>m1</i>	-0.03	0.20
<i>m5</i>	-0.10	0.32
<i>m9</i>	0.09	0.87

	Mean [px]	Stdev [px]
<i>m1</i>	-0.06	0.05
<i>m5</i>	-0.06	0.07
<i>m9</i>	-0.05	0.14



m1: 0.0278 deg/s



m5: 0.1385 deg/s

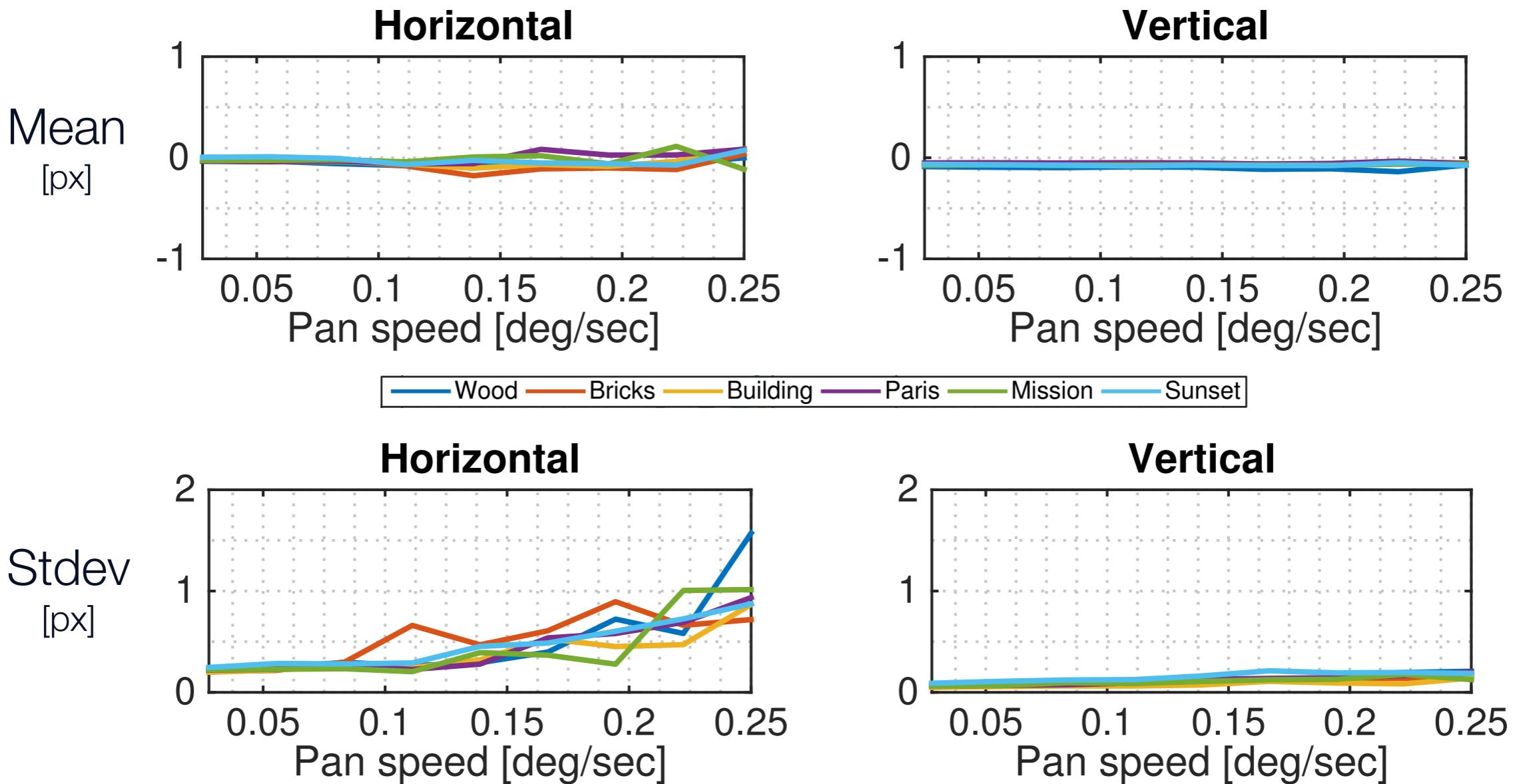


m9: 0.2493 deg/s

Motion blur **inflates variance** of KLT tracking error while keeping it **zero-mean**.



Quantifying Blur: Error Variance Increases with Pan Speed

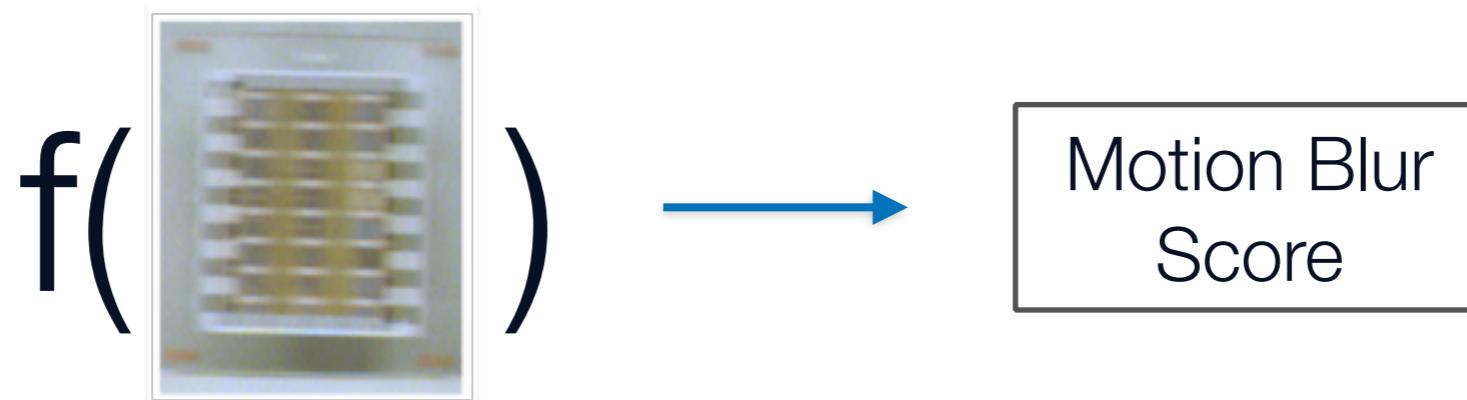
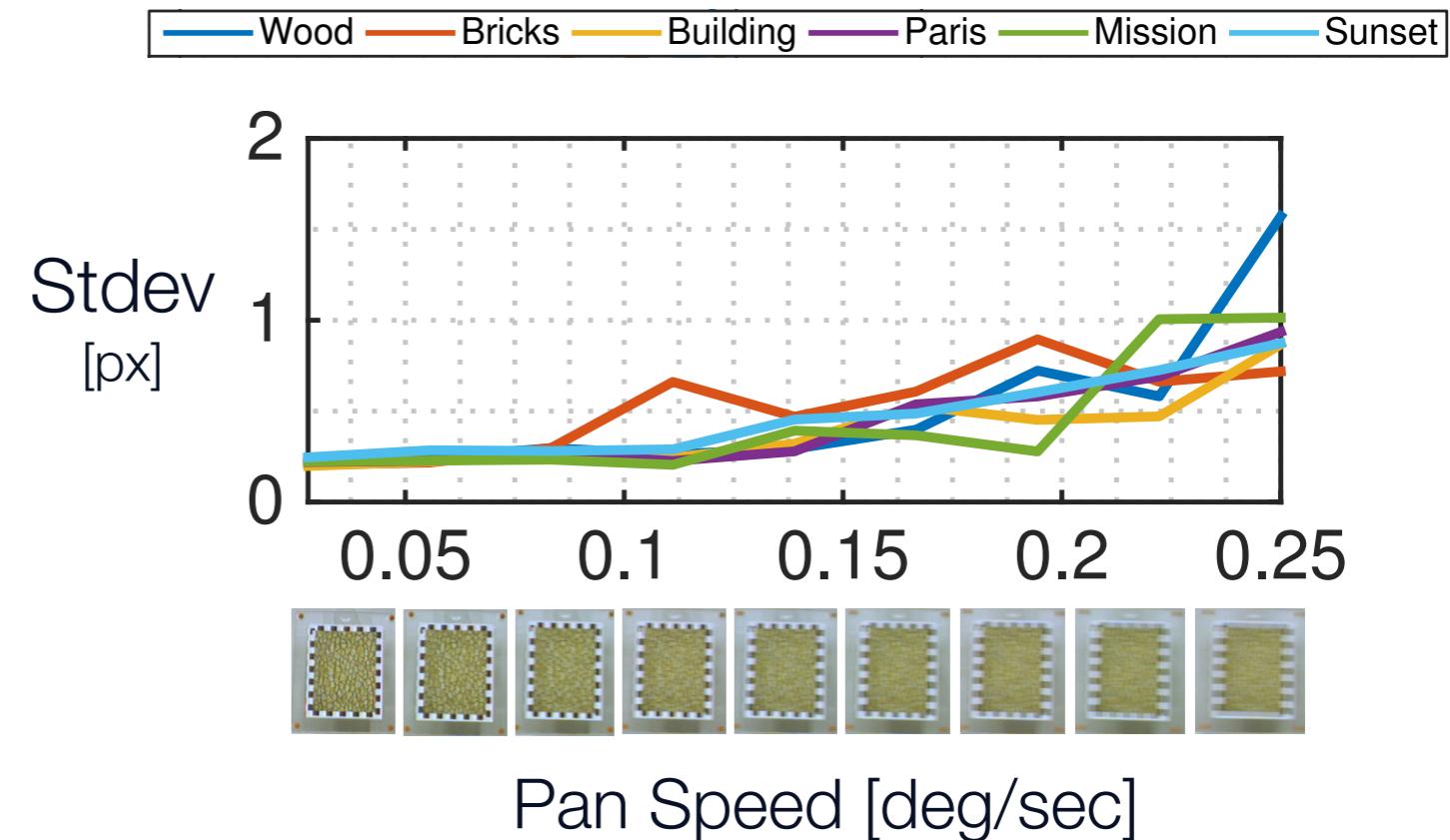


Note: Horizontal blur dominates because the motion is mainly horizontal.

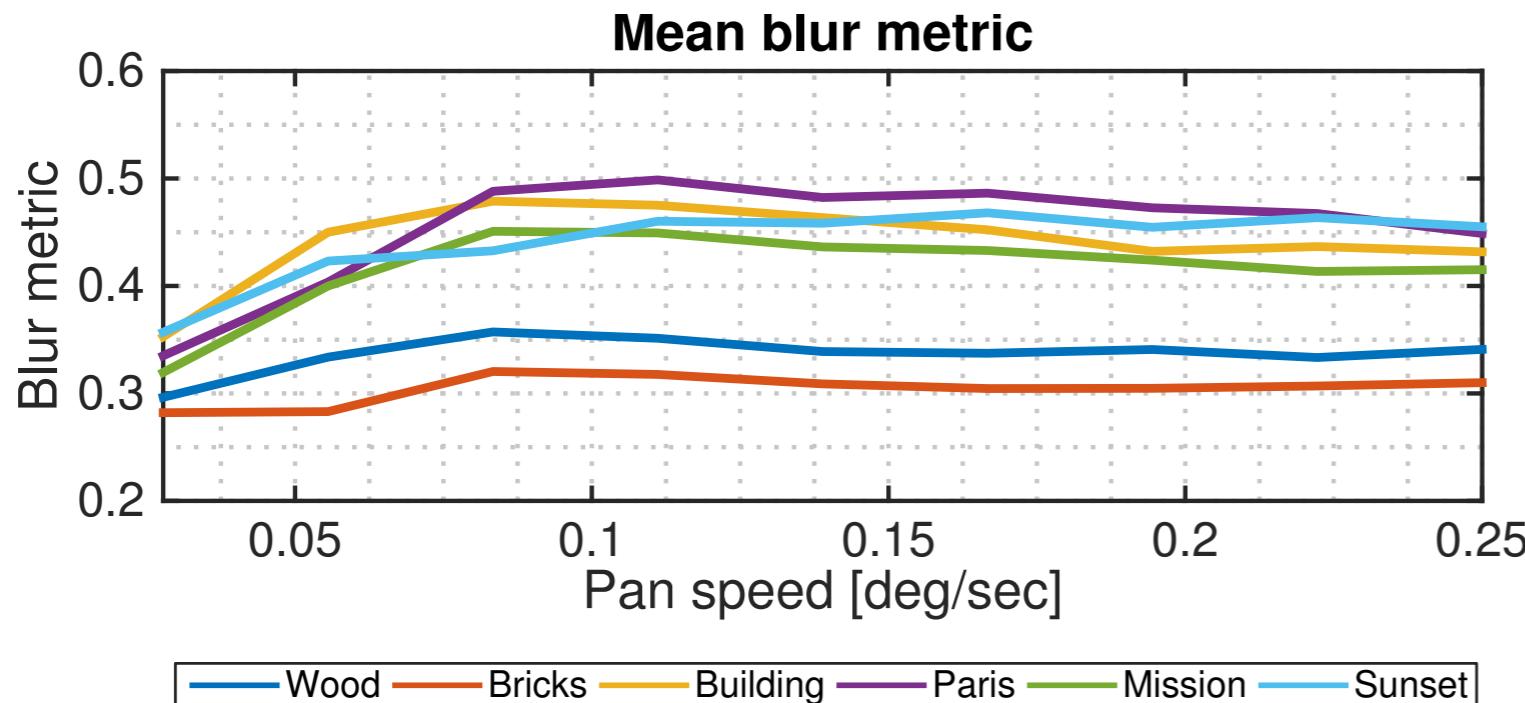
Identifying Blur: Visual vs. Inertial Cues

A **gyroscope** that reports angular rates could be used to predict motion blur.

However, a **vision-based blur metric** would allow motion blur detection without additional sensors.



Identifying Blur: Vision-based Blur Metric



The popular metric of Crete et al. **does not correlate well** with pan speed and varies with image texture.

F. Crete et al., “The blur effect: Perception and estimation with a new no-reference perceptual blur metric,” in Proc. SPIE Electron. Imaging Symp. Conf. Human Vision and Electron. Imaging, Feb. 2007



Motion Blur...

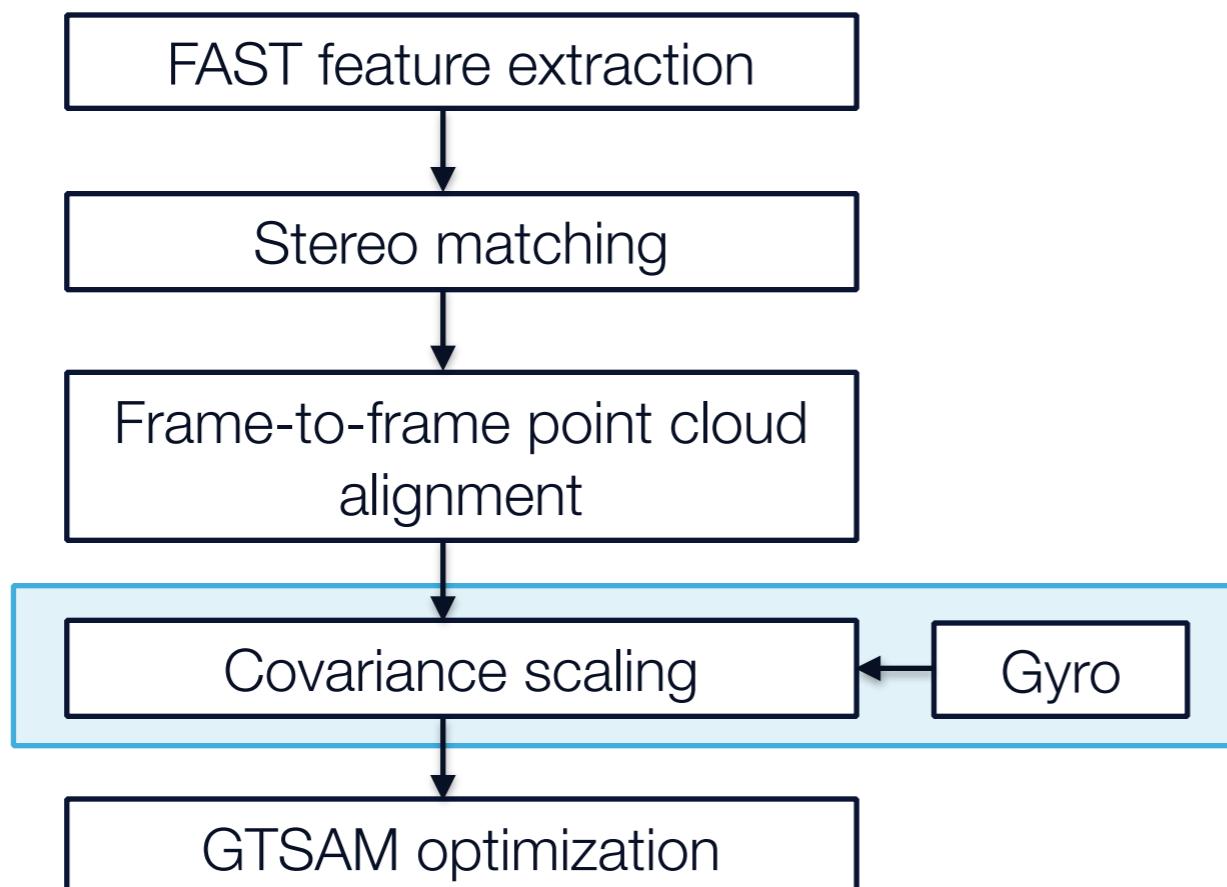
1. correlates well with rotational speed of the camera but is difficult to quantify through visual cues alone.
2. increases the variance of KLT tracking error, while preserving an approximately zero-mean Gaussian distribution.



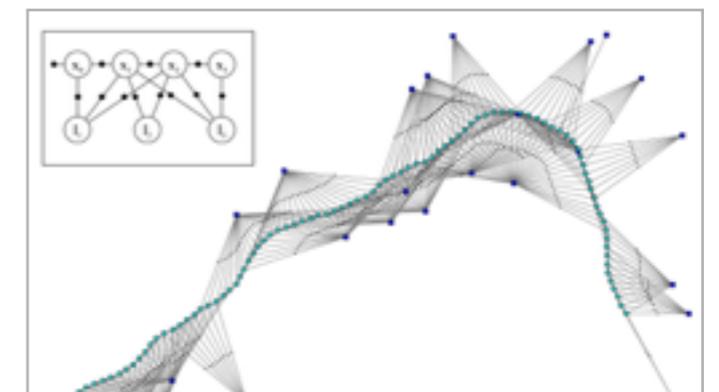
How can we use this information to **improve** our egomotion estimate?

Accounting For Blur: Stereo Visual Odometry

Idea: Use covariance scaling to improve stereo visual odometry.

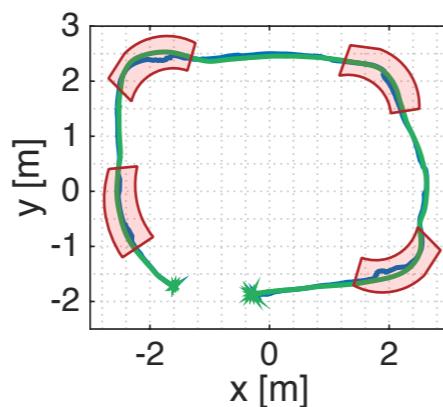


Skybotix VI-Sensor



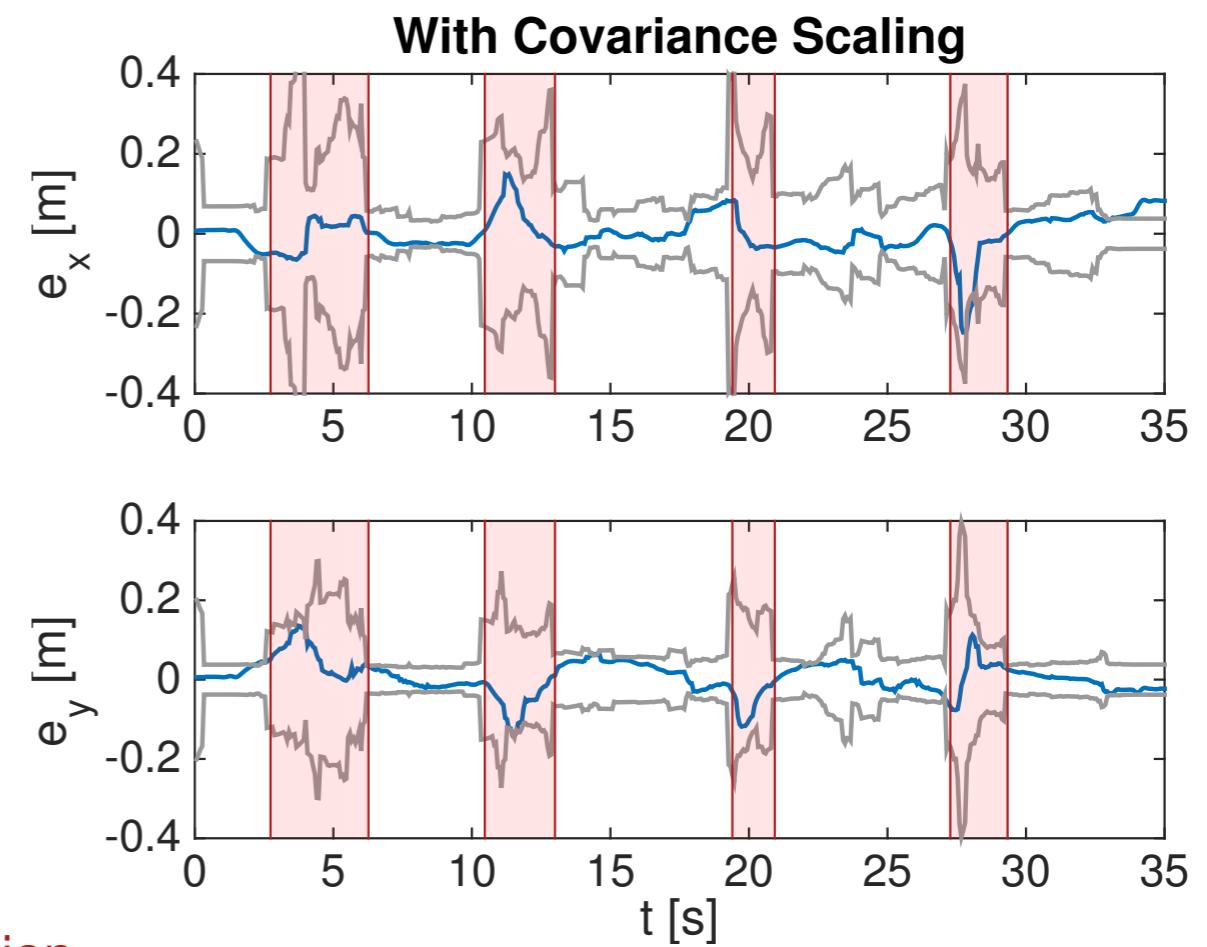
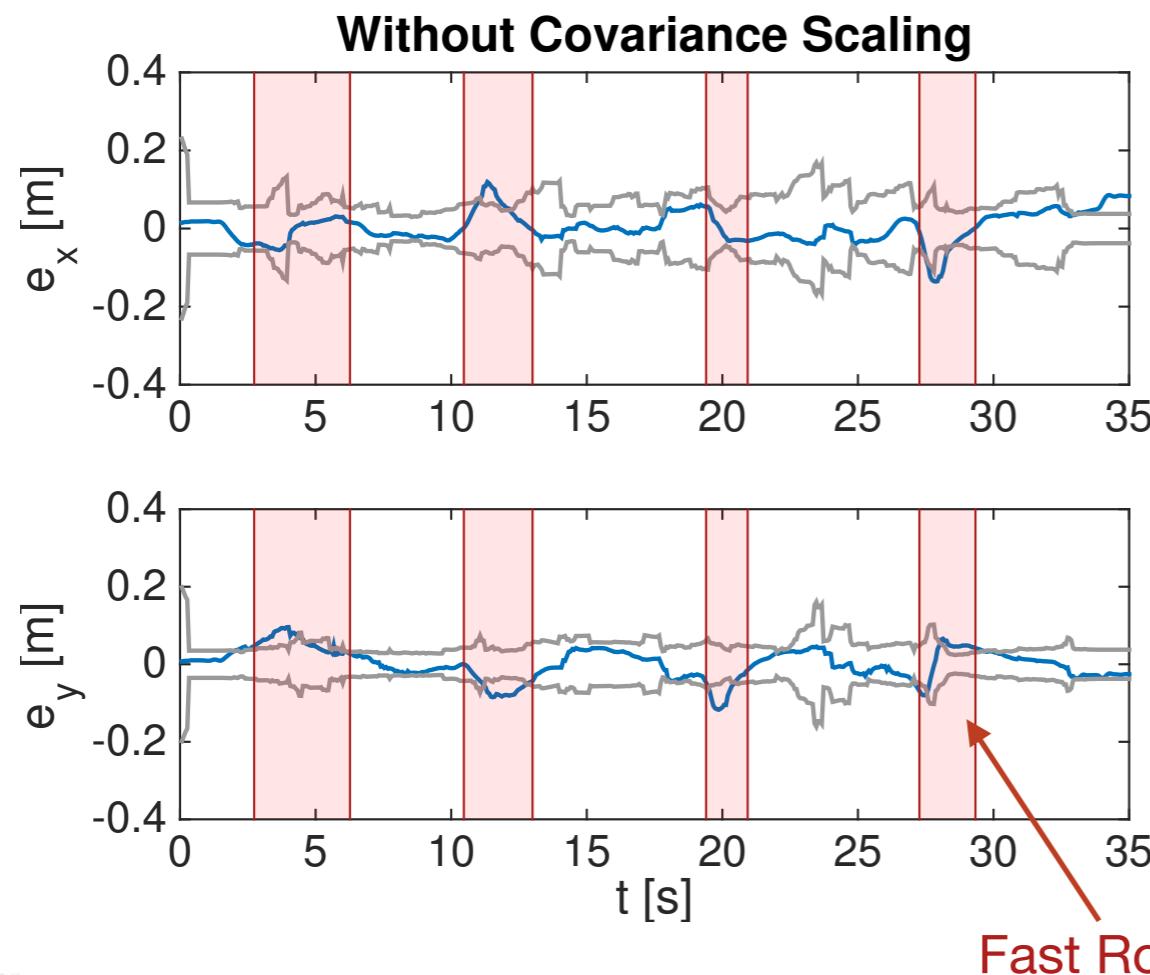
GTSAM Pose Graph

Accounting For Blur: Stereo Visual Odometry



~20 m planar route with VICON ground truth with sharp turns that induce motion blur

Estimator consistency improves with covariance scaling.



Thanks!

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Active Covariance Scaling for Feature Tracking Through Motion Blur
Valentin Peretroukhin, Lee Clement, and Jonathan Kelly

Introduction
For rapidly moving platforms such as micro aerial vehicles, legged robots, and human first responders, it is important to track visual features through fast motions with **substantial motion blur**.

Results
Perceived motion blur can be clearly correlated to camera pan speed. As pan speed increases, KLT tracking error remains approximately zero mean and Gaussian, but with increasing variance.

Visual Odometry Experiment
For stereo **visual odometry**, feature covariance scaling during fast turns makes the estimator **more consistent** compared to static covariance.

Discussion and Conclusions
When features are successfully tracked, KLT tracking error is zero-mean and approximately Gaussian. The effect of motion blur on feature tracking accuracy can be captured by inflating the covariance of image reprojection error as a function of rotational speed. Vision-based blur metrics are texture-dependent, but an IMU can be used to predict blur independent of texture.

Method

- Feature Extraction**
Extract point features from the textured region in the first image of the sequence.
- KLT Tracking**
Track features from frame to frame with Kanade-Lucas-Tomasi tracker.
- Error Computation**
Compute frame-to-frame tracking error using ground-truth homographies.

$$\mathbf{e}_n = \mathbf{p}_n - \hat{\mathbf{p}}_n = \mathbf{H}_{n,n-1} \mathbf{p}_{n-1} - \hat{\mathbf{p}}_n$$

Dataset
We use the dataset of Gauglitz et al.¹, in which a camera on a pan-tilt head observes one of **six textures** while panning at **nine angular rates**.

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