Robust Visual Fiducials for Skin-to-Skin Relative Ship Pose Estimation

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Visual Ship Pose Estimation

We designed a system that uses an optical camera and fiducial tags to accurately estimate the relative position of two ships moored skin-to-skin in real-time.

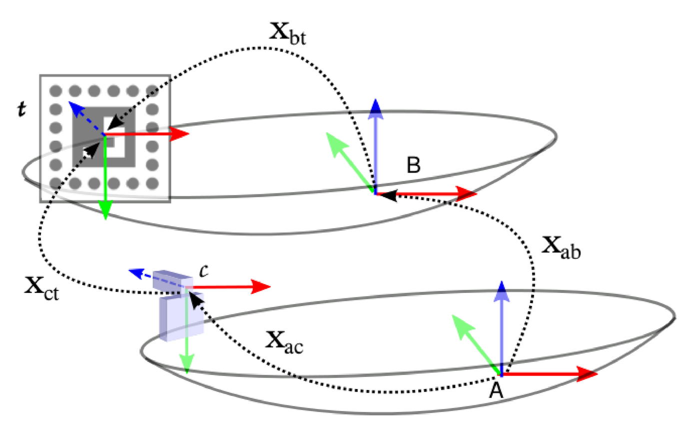
In order to do so we developed a fiducial design robust to CCD blooming caused by extreme lighting fluctuations prevalent at sea.

Bob Hope and a Mobile Landing Platform Skin-to-Skin

Current State-of-the-Art Fiducial Tags

- Provide consistent unique easily identifiable features
- Not robust to CCD blooming, designed and tested indoors

ARToolkit (Kato, 99) | ARTags (Fiala, 05) | Cantag (Rice, 06) | Circles (Pagani, 11) | AprilTag (Olson, 11) | PiTags (Bergamasco, 13)



Coordinate Transforms in our Designed System

Solving for the Tag Pose

Goal: Estimate the position and orientation (pose) of the tag relative to the camera coordinate frame, given 2D-3D point correspondences detected in the image.

Have:

$\mathbf{x}_i \longleftrightarrow {}^w\mathbf{X}_i$

Want:

$[\,{}^c_w\mathbf{R} \mid {}^c t_{cw}\,]$ or $\mathbf{x}_{ct}$

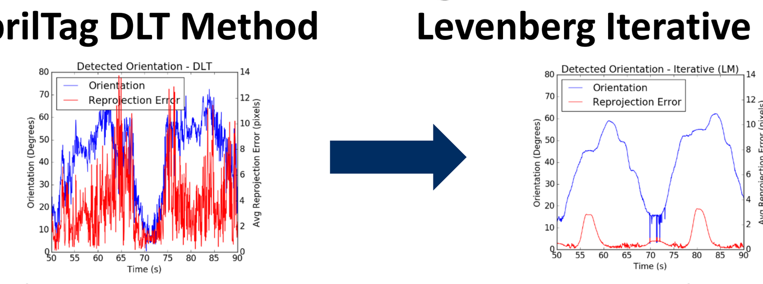
$\mathbf{x} = \mathbf{P}\,{}^w\mathbf{X}$

$= \mathbf{K}\,[\,{}^c_w\mathbf{R} \mid {}^c t_{cw}\,]\,{}^w\mathbf{X}$

Intrinsic   Extrinsic

Two Methods for Solving:

AprilTag DLT Method → **Levenberg Iterative Method**

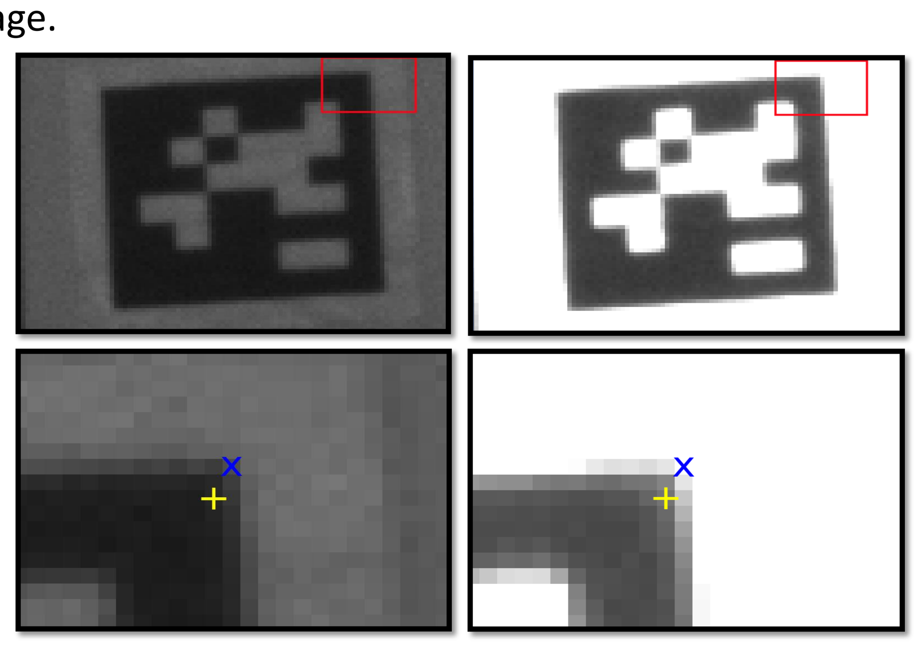


Iteratively minimizing reprojection error using the Levenberg Marquardt (Levenberg, 1944) algorithm results in a significantly less noisy estimate.

$$\hat{\mathbf{x}}_{ct} = \arg\min_{\mathbf{x}_{ct}} \sum_{i=1}^{N} \|\mathbf{x}_i - \hat{\mathbf{x}}_i\|^2$$

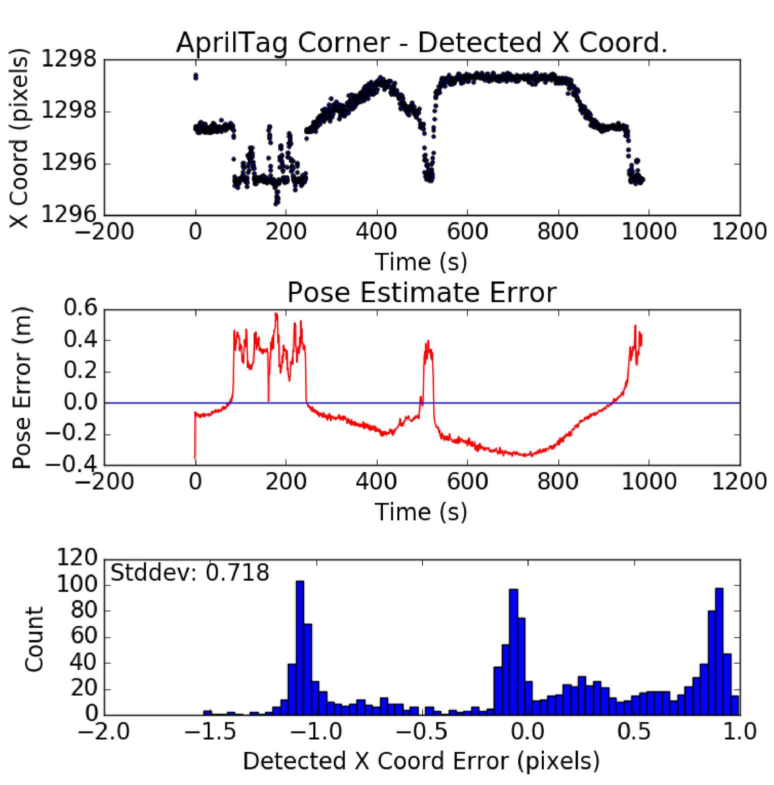
Blooming Bias In Outdoor Lighting

High lighting variations in outdoor environments causes blooming of the camera CCD and affects the observed image.



The above figure shows the effects of blooming on the detected image. The colored points mark static pixels in the detected image for reference. Blooming causes black areas of the image to recede causing a bias in the detection of corner coordinates.

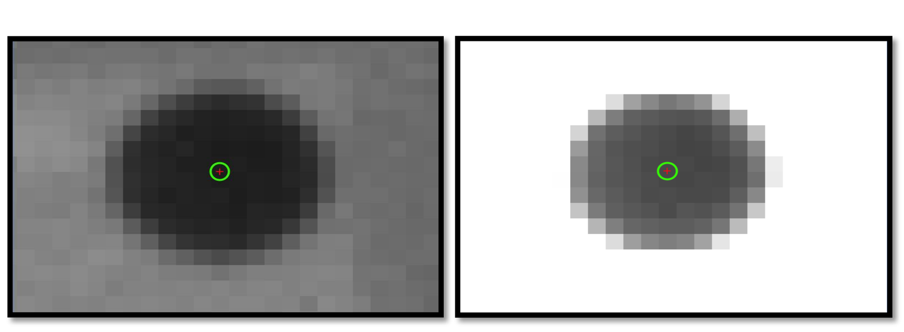
Blooming affects the detection of AprilTag corners needed for estimating the position and orientation of the tag in the camera frame. This bias in detected corners translates to a significant error in the calculated pose of the tag.



(Top) Given a static tag and camera, the detected x coordinate of a stationary AprilTag corner should be constant. However, the plot varies significantly with natural variations in outdoor lighting. (Middle) The resulting error of nearly 1 meter in the estimated pose. (Bottom) A histogram of the detected coordinate error from the mean.

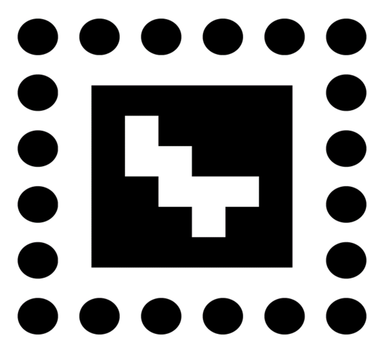
Detecting Ellipses instead of Corners

The effects of blooming are much less pronounced when detecting ellipse centers rather than corners.



New Tag Design

- Augment fiducial with a border of ellipses for accurate pose estimation
- Use original fiducial for initial detection, initial rotation estimate, and unique identification if applicable



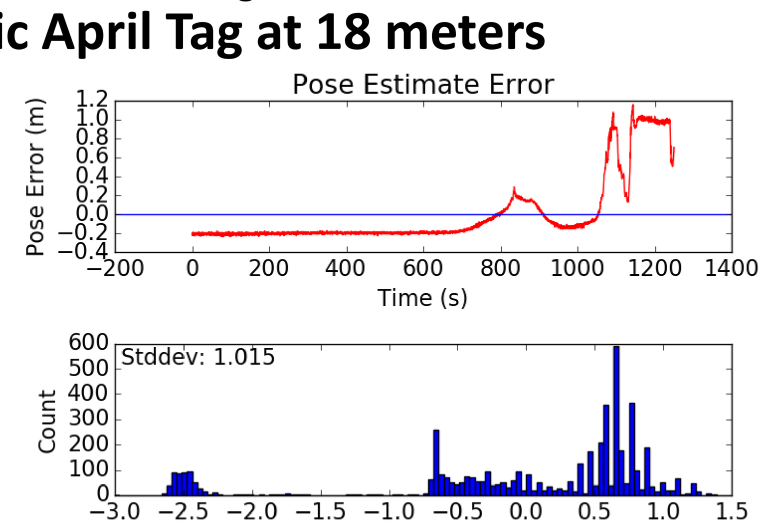
Detecting the New Tag and Estimating Pose

1. Estimate initial pose based on fiducial points
2. Re-project ellipse points into image
3. Detect and estimate ellipse centers
4. Perform Data Association
5. Estimate tag pose based only on unbiased ellipse center points.

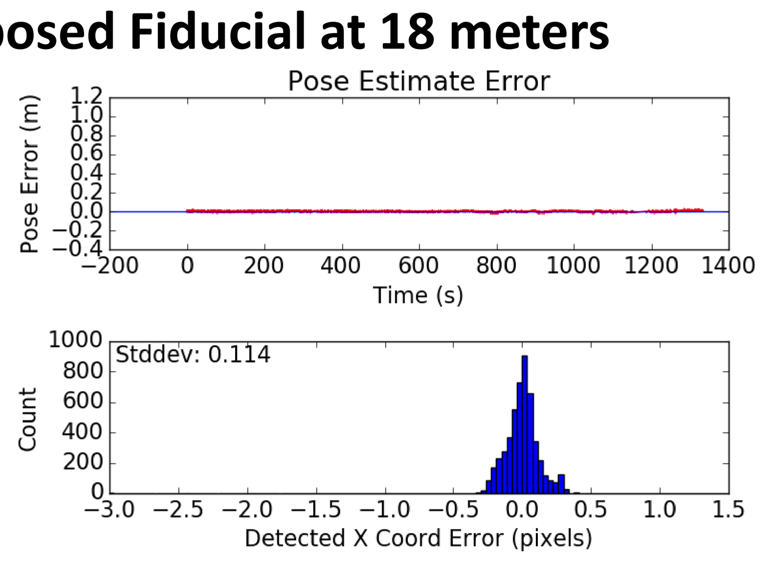
Robustness to Blooming

For a pair of stationary tags under the same lighting at 18 meters range from the camera, our method reduced pose estimate error from greater than 1 meter to +/- 2 cm.

Static April Tag at 18 meters

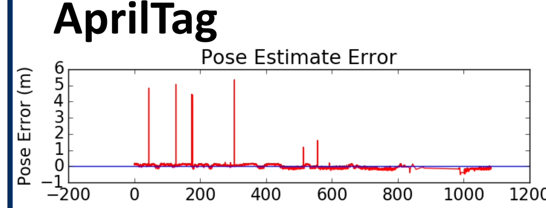


Proposed Fiducial at 18 meters

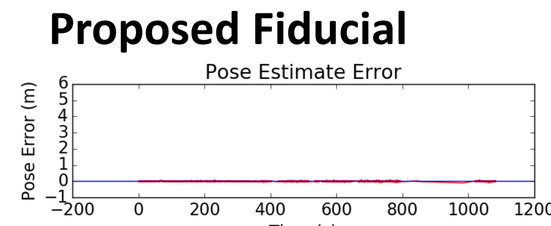


Comparison at 30 Meters

AprilTag



Proposed Fiducial



At 30 meters range, our method reduced the error from almost 5 meters to +/- 5 centimeters.

Estimating Measurement Covariance

In order to integrate these measurements into a filtering framework, an accurate estimate of the measurement covariance is needed.

We suggest two different methods for accomplishing this.

First Order Backward Propagation (FO)

The widely accepted approach attempts to approximate the non-linear estimation process up-to First Order through linearization (Hartley, Zisserman).

$$\Sigma_{ct} = (\mathbf{J}^\top\,\Sigma_p^{-1}\,\mathbf{J})^{-1}, \text{ where } \mathbf{J} = \left[\frac{\partial f}{\partial \mathbf{x}_{ct}}\right], \mathbf{X}_p = f(\mathbf{x}_{ct})$$

Where, $f(\mathbf{x}_{ct})$ is the reprojection function of the tag.

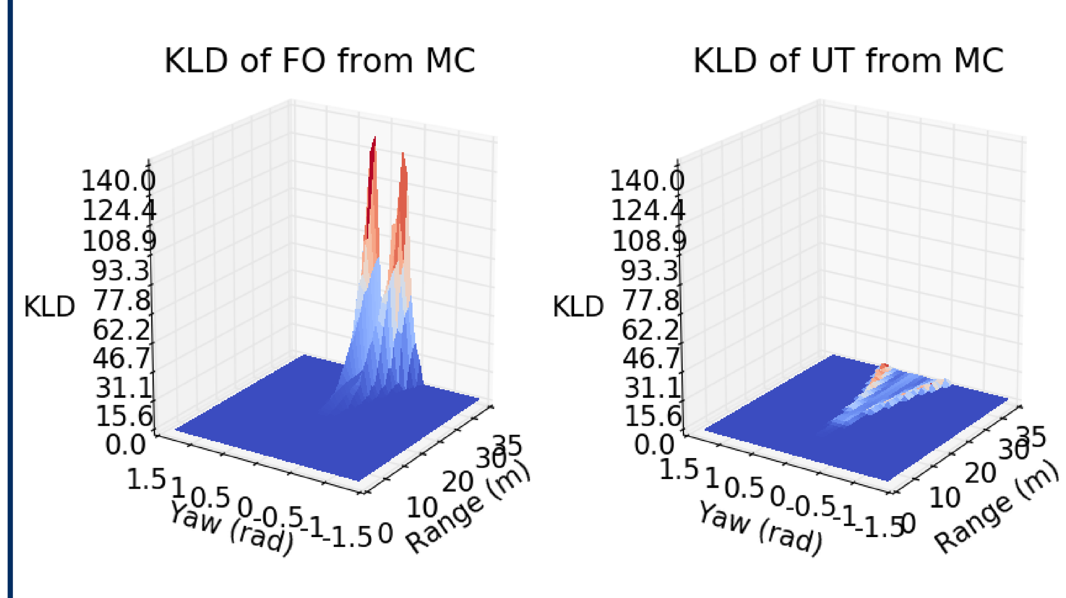
Unscented Transform (UT) (Julier 2002)

We can better approximate the effects of non-linearities in the pose estimation function by propagating sample pixel points through the pose estimation function and using a weighted average to estimate the covariance.

$$\boldsymbol{\Sigma_{ct}} = \sum_{i=0}^{2n} \omega_c^{[i]}(\boldsymbol{x}_{ct}^{[i]} - \boldsymbol{\mu}')(\boldsymbol{x}_{ct}^{[i]} - \boldsymbol{\mu}')^\top$$

Simulated Monte-Carlo Comparison

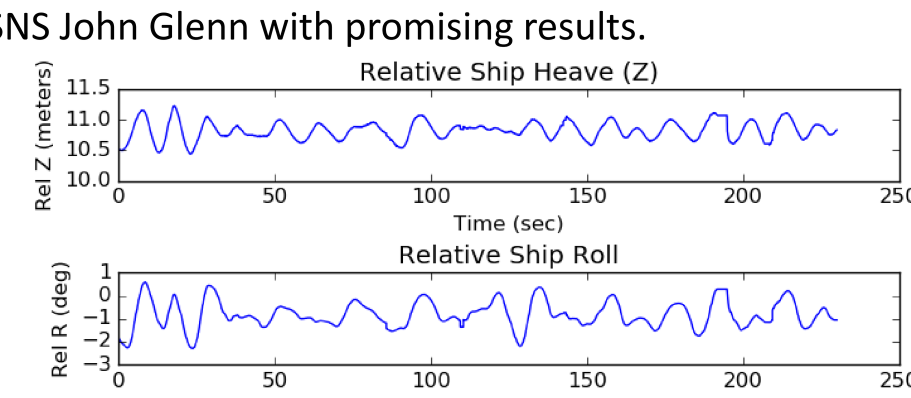
In Monte-Carlo simulation we measured the divergence (KLD) of the estimated uncertainty from the true uncertainty for both the first order and unscented transform methods.



Comparison results show that the unscented transform method is dramatically more accurate than the first order method.

Preliminary Skin-to-Skin Field Trials

We performed preliminary field testing of our system during to skin-to-skin field trials aboard the USNS Bob Hope and USNS John Glenn with promising results.



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