Real Time, Onboard Landing Site Evaluation for Autonomous Drones

PhD Thesis Proposal

Joshua Springer

Reykjavík University

March 2022

Presentation Structure

(1) Introduction
- Problem description and motivation
- State of the Art

(2) Completed/ongoing projects
- Initial proof of concept attempt
  - Continuation of master thesis (tested in simulation)
- Fiducial marker modifications
- Proof of concept

(3) Research Plan
- Methods
- Challenges and risk analysis

Introduction

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"Human-assisted landing"

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- How can those methods execute in real time onboard a drone?

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Completed and Ongoing Projects

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- Two Tarot 680 hexacopters
- For real-world proof of concept of master thesis simulations.

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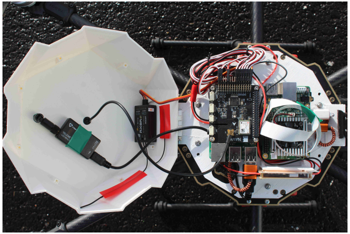
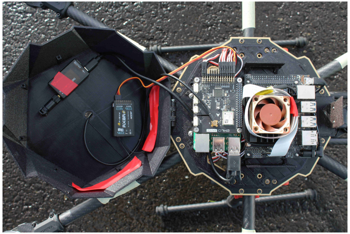
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo





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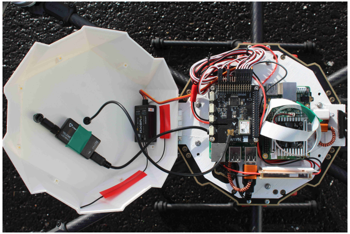

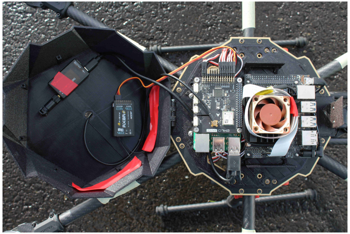

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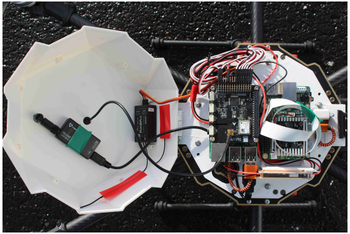

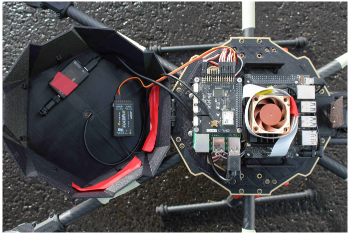

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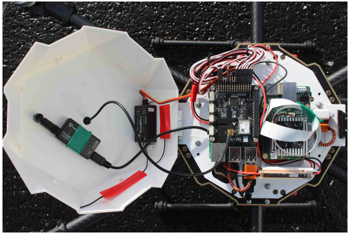

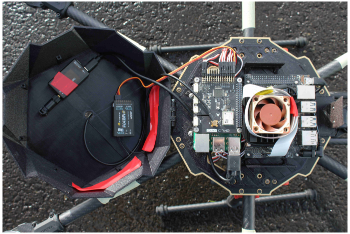

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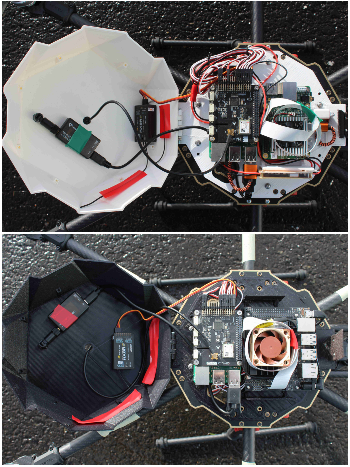

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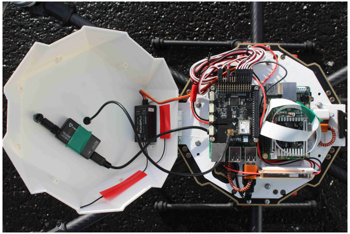

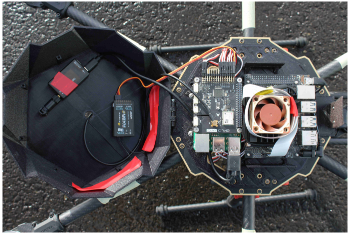

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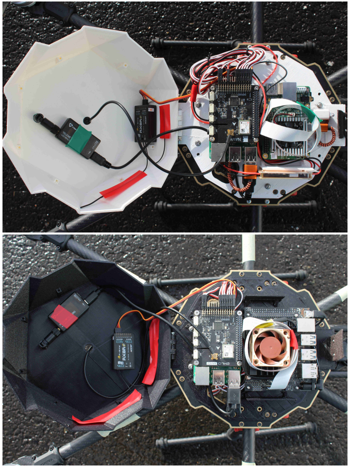

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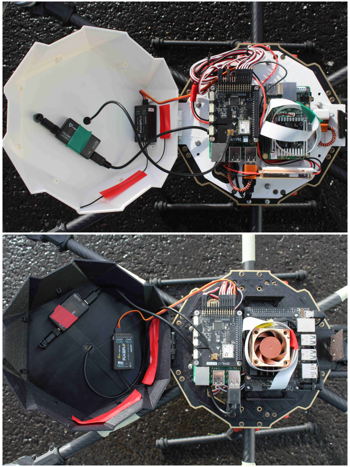

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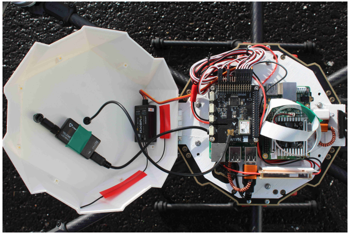
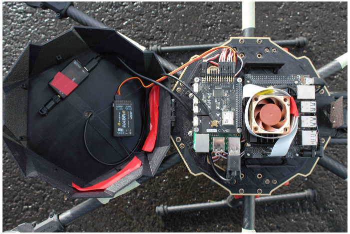
  - PX4 (not technically supported)





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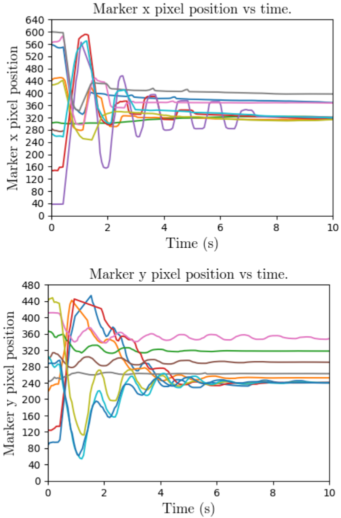
- Errors during approach
  - Monocular pose estimation ambiguity
  - GPS inaccuracy
- No successful autonomous landing (but almost)



Meanwhile...

Heavy Lift IR Drone

- Project with Christopher Hamilton (geologist, University of Arizona) and Baldur Björnsson

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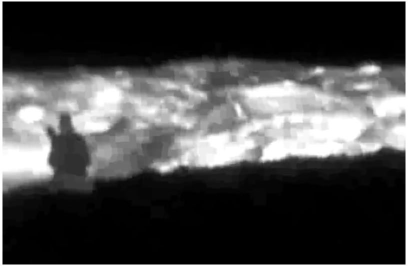
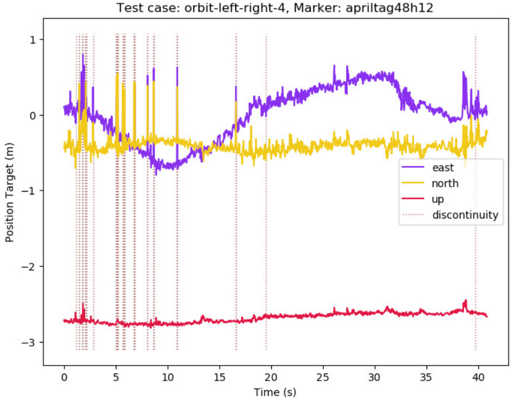
- Featured on BBC Click



Fiducial System Modifications

Necessary properties:

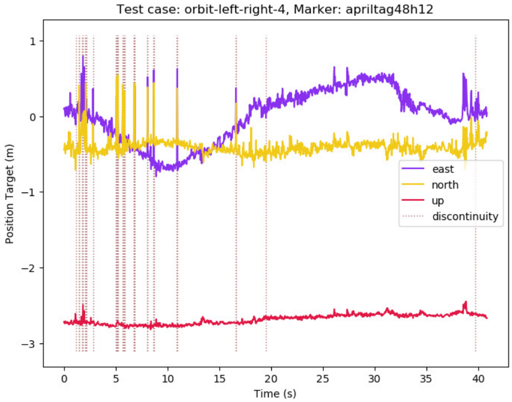
- Mitigates orientation ambiguity



Fiducial System Modifications

Necessary properties:

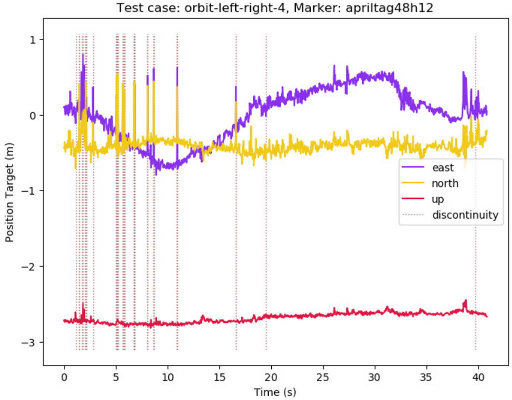
- Mitigates orientation ambiguity
- Detectable at long- and short-range



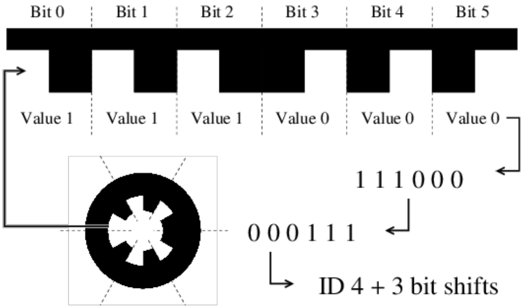
Fiducial System Modifications

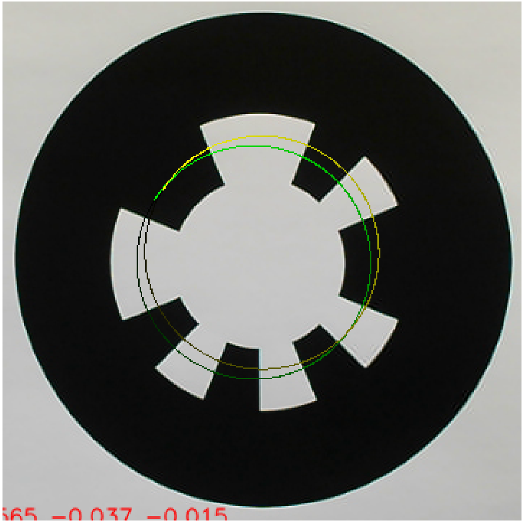
Necessary properties:

- Mitigates orientation ambiguity
- Detectable at long- and short-range
- Runs on embedded hardware



WhyCode Orig(inal)





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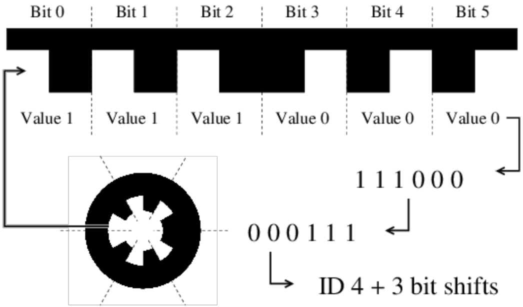
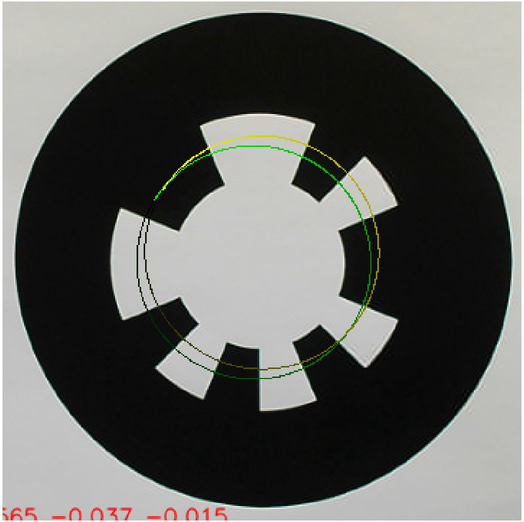


- Semi-axes $\rightarrow$ 2 possible orientations



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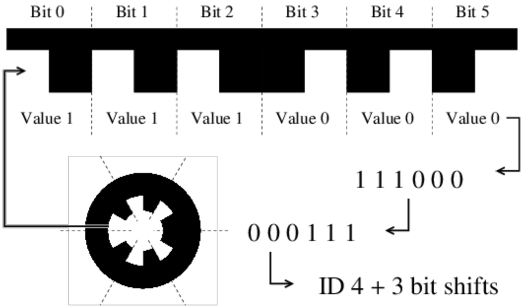

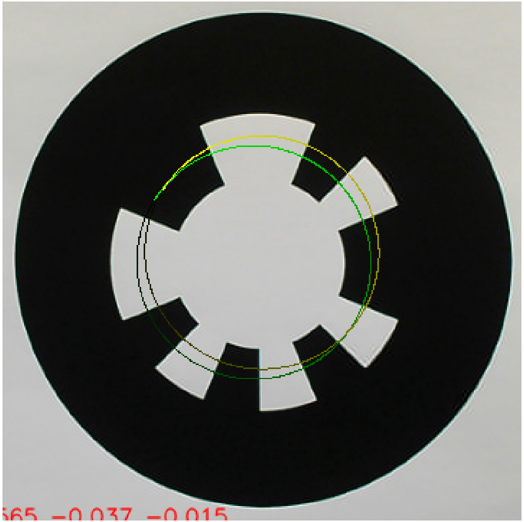

- Semi-axes → 2 possible orientations
- Better centered → correct

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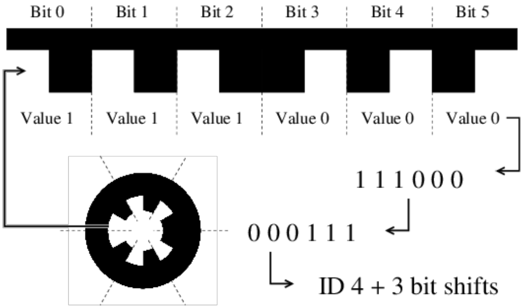

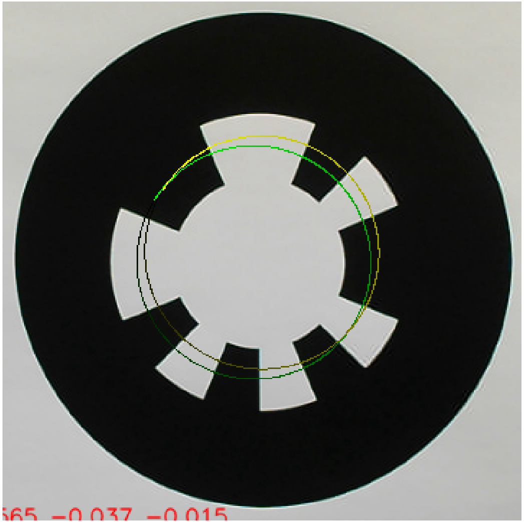

- Semi-axes $\rightarrow$ 2 possible orientations
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- Arclength of intersections with ID “teeth”

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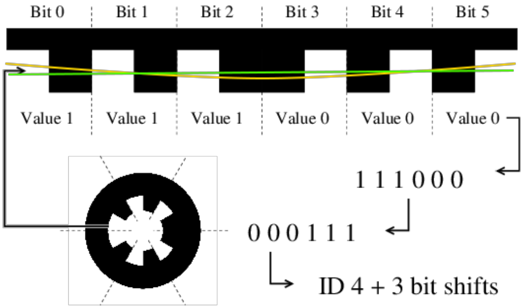

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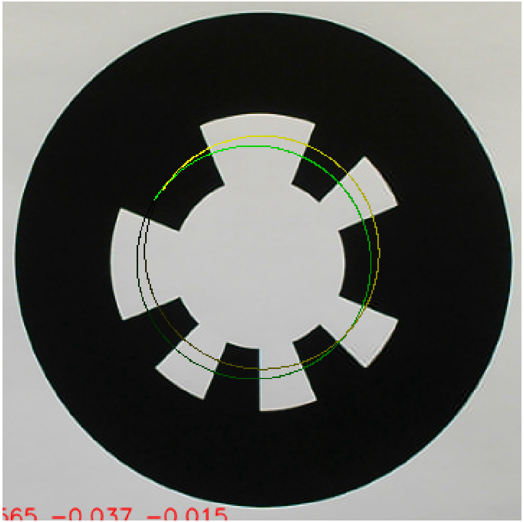
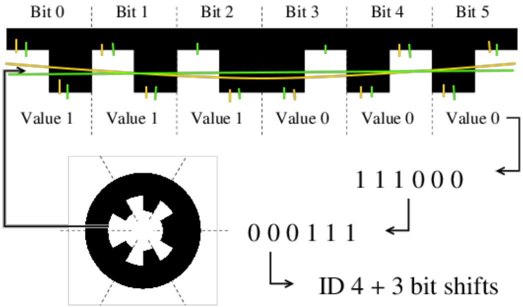
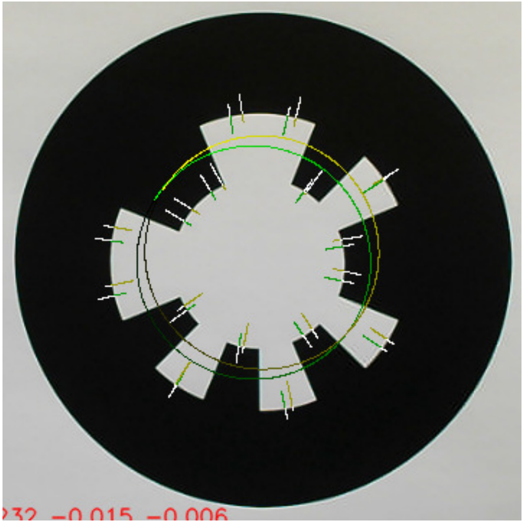


Fiducial System Modifications: “WhyCode Ellipse”





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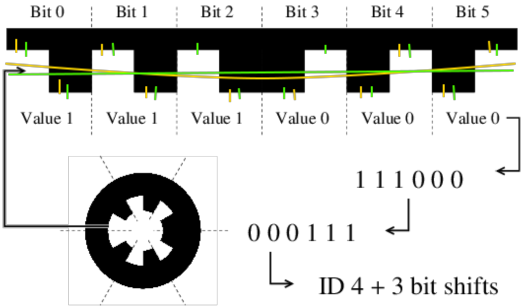

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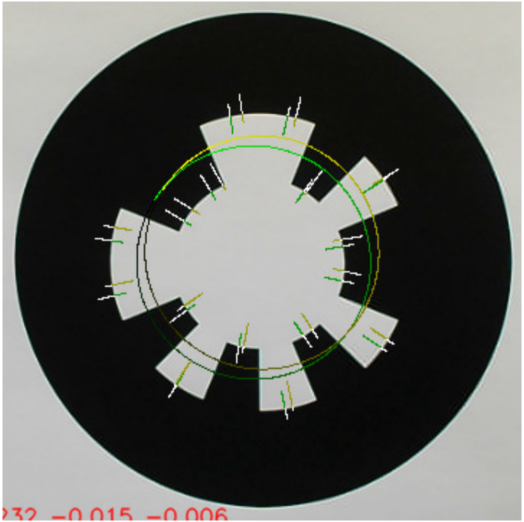

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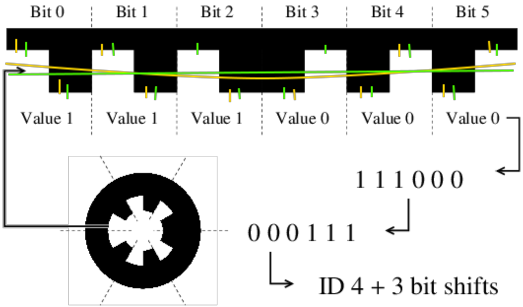
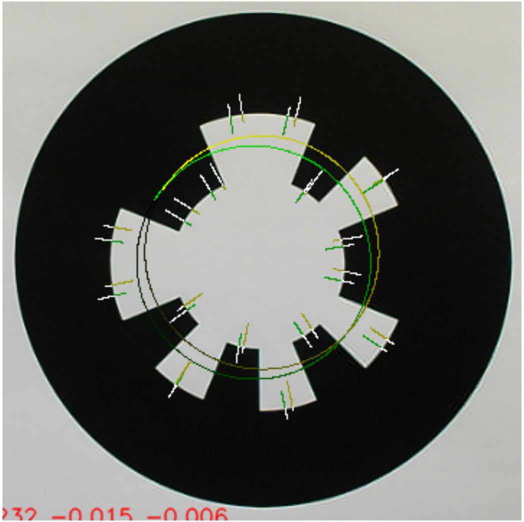


- Sample ID with original method.
- Add: radial sampling on tooth edges.



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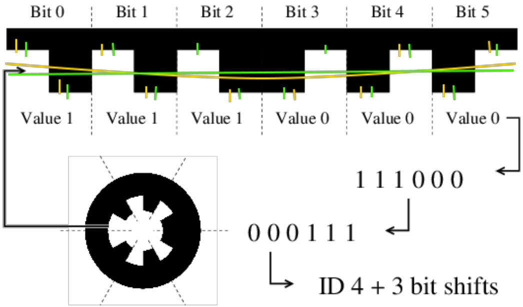
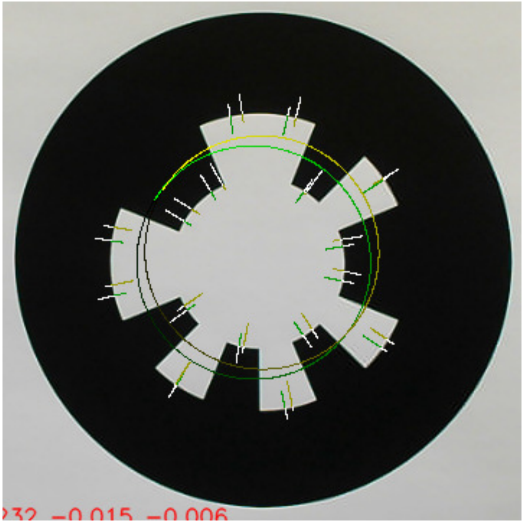
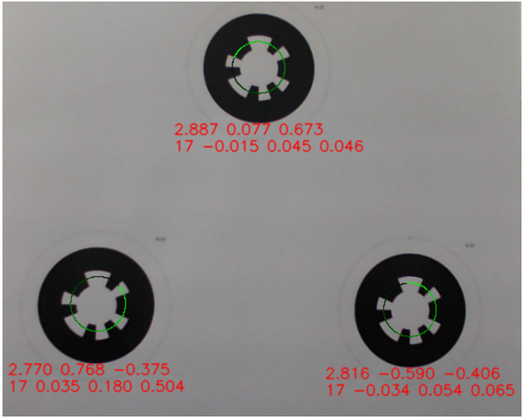




- Sample ID with original method.
- Add: radial sampling on tooth edges.
- Minimize variance on extra sample lines.

Fiducial System Modifications: “WhyCode Multi”

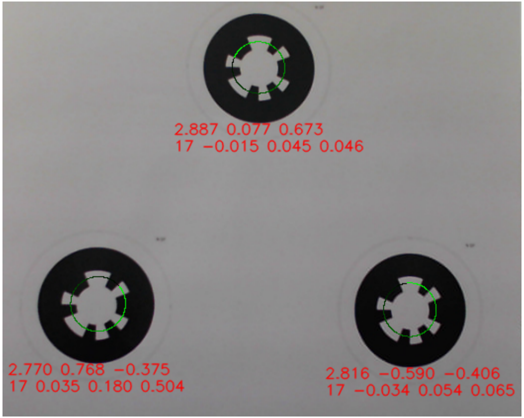
Approach 2: Coplanar marker arrangements



Fiducial System Modifications: “WhyCode Multi”

Approach 2: Coplanar marker arrangements

- Ignore individual marker orientations



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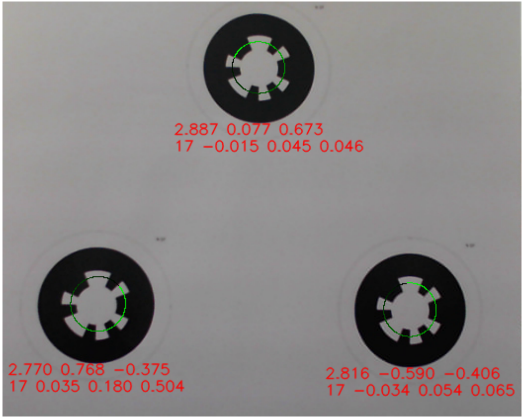
- Ignore individual marker orientations
- Calculate normal vector to the plane connecting the markers.



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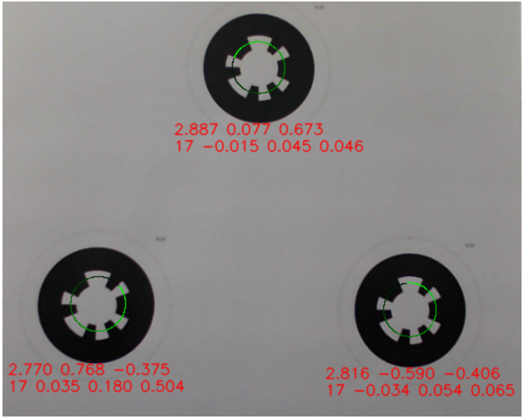
- Extract pitch and roll from the normal vector.



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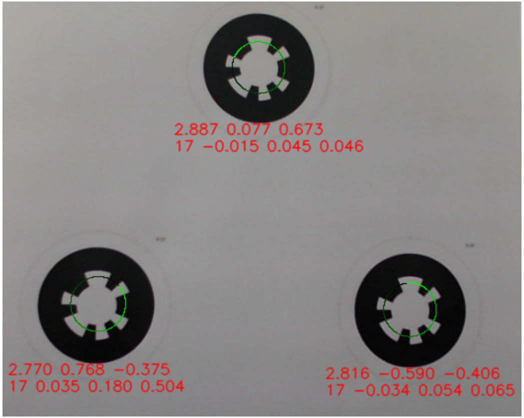

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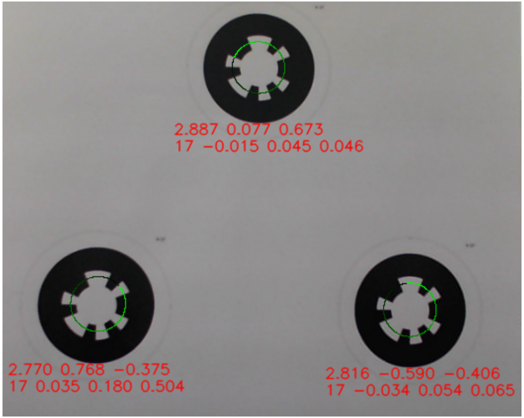
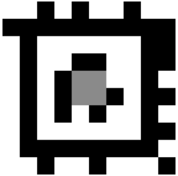
- Extract pitch and roll from the normal vector.
- Extract yaw from the marker IDs.
- Takes advantage of WhyCode’s efficiency.



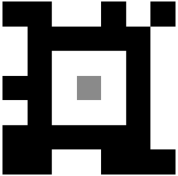
Fiducial System Modifications: April Tag

April Tag: less orientation ambiguity, but less computationally efficient.

April Tag 48h12: more sophisticated, “recursive.”

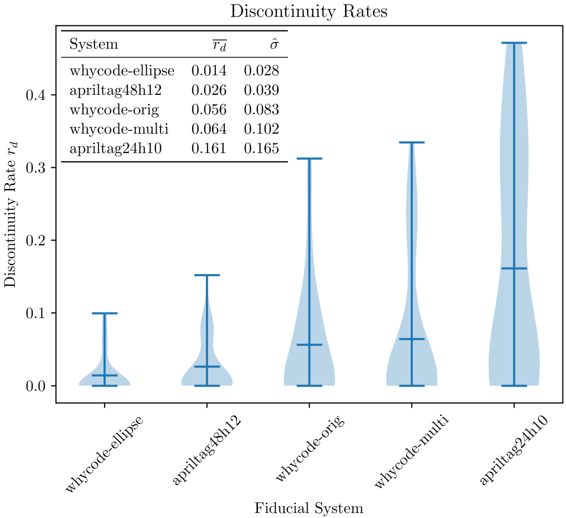


April Tag Custom 24h10: “recursive,” smaller definition



Performance Analysis: Discontinuity Rates

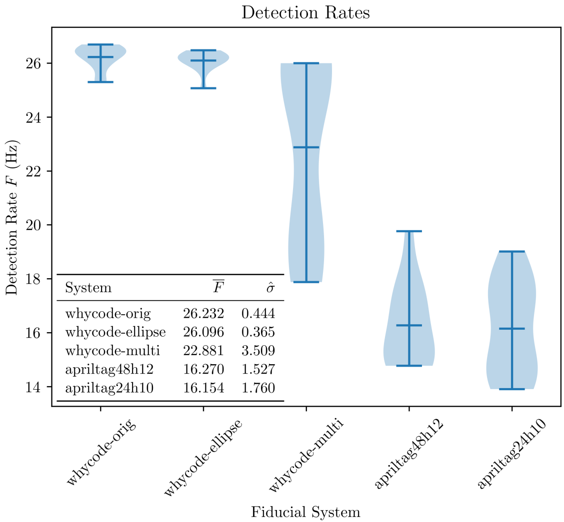
- Orientation ambiguity $\rightarrow$ discontinuities.
- Discontinuity rate $\overline{r_d}$ is the number of discontinuities per detection.
- Lower is better.



System	$\overline{r_d}$	$\hat{\sigma}$
whycode-ellipse	0.014	0.028
apriltag48h12	0.026	0.039
whycode-orig	0.056	0.083
whycode-multi	0.064	0.102
apriltag24h10	0.161	0.165

Performance Analysis: Detection Rates

- Detection rate $\overline{F}$ is the number of detections per second.
- Tested on Raspberry Pi 4.
- Higher is better.



System	$\overline{F}$	$\hat{\sigma}$
whycode-orig	26.232	0.444
whycode-ellipse	26.096	0.365
whycode-multi	22.881	3.509
apriltag48h12	16.270	1.527
apriltag24h10	16.154	1.760

Autonomous Landing Proof of Concept

- Indoor experiments with DJI Spark

(Banana for scale.)

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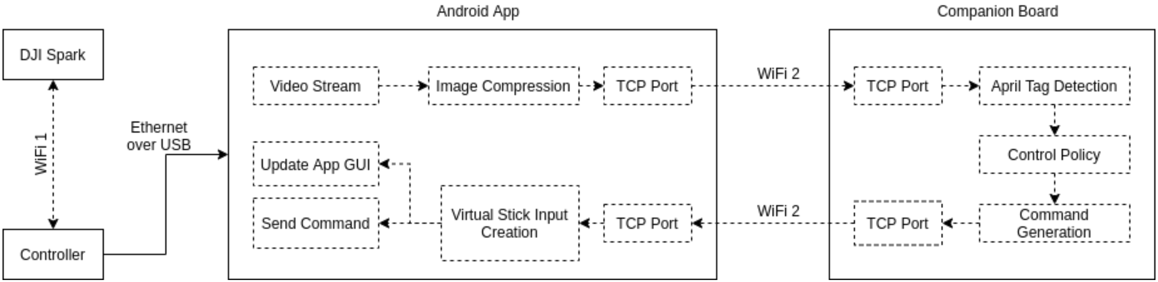
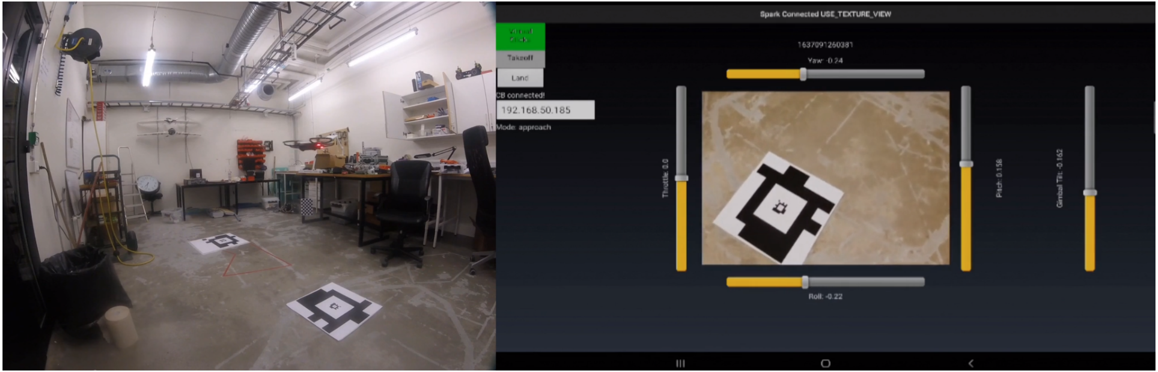
Autonomous Landing Proof of Concept: System Architecture



Demo with worst-performing April Tag 24h10



Works with every system except WhyCode Multi.

Publications

- Submitted: Evaluation of April Tag and WhyCode Fiducial Systems for Autonomous Precision Drone Landing with a Gimbal-Mounted Camera
- In Progress: results from autonomous landing proof of concept

Research Plan

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AirSim: realistic simulator

- Automatic generation of large data sets

Image source

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Image source

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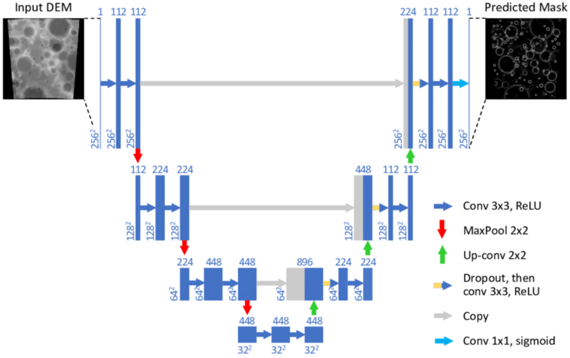

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Simulation is not enough!

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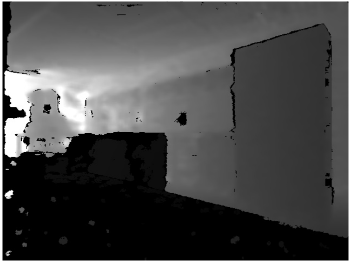

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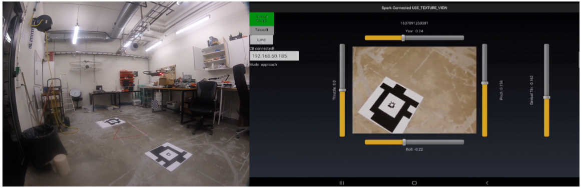
Summary

- Goal: autonomous drone landing



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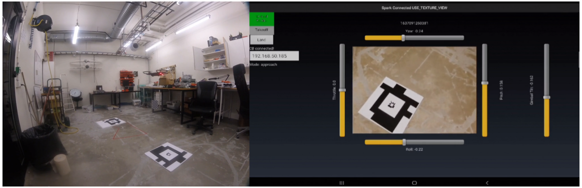

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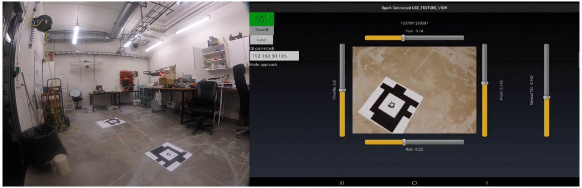

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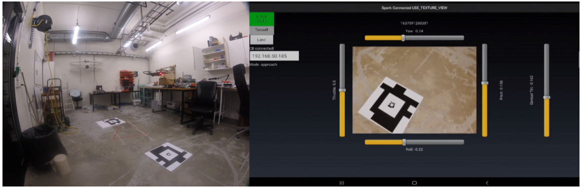

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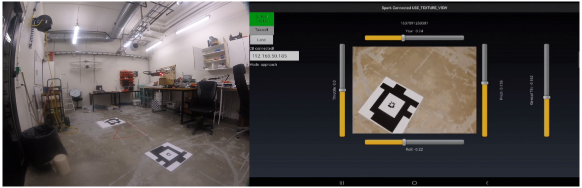

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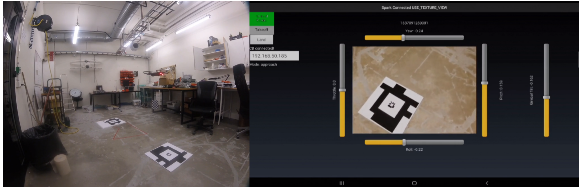

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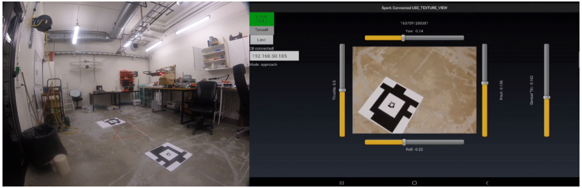

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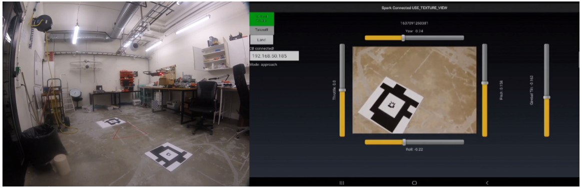

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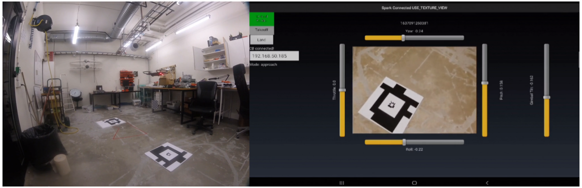

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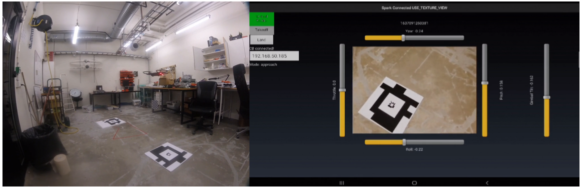

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Misc

- Google Coral Benchmarks
- Jetson Nano Benchmarks