

Real Time, Onboard-only 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 deep-dive and modifications
- Proof of concept

(3) Research Plan

- Methods
- Challenges and risk analysis



Introduction



Problem Description and Motivation

- Much of basic drone flight has been **automated**.



Problem Description and Motivation

- Much of basic drone flight has been **automated**.
 - Takeoff
 - Waypoint-to-waypoint-flight
 - Track/orbit objects,
take pictures, etc.



Problem Description and Motivation

- Much of basic drone flight has been **automated**.
 - Takeoff
 - Waypoint-to-waypoint-flight
 - Track/orbit objects,
take pictures, etc.
- Landing is still largely **manual**.



Problem Description and Motivation

- Much of basic drone flight has been **automated**.
 - Takeoff
 - Waypoint-to-waypoint-flight
 - Track/orbit objects,
take pictures, etc.
- Landing is still largely **manual**.
 - Problem in continuous, autonomous missions
 - Primitive, semi-autonomous methods are common
(still require human operator)
 - Hand-catching is common



Problem Description and Motivation

- Much of basic drone flight has been **automated**.
 - Takeoff
 - Waypoint-to-waypoint-flight
 - Track/orbit objects,
take pictures, etc.
- Landing is still largely **manual**.
 - Problem in continuous, autonomous missions
 - Primitive, semi-autonomous methods are common
(still require human operator)
 - Hand-catching is common



“Human-assisted landing”



Research Questions



Research Questions

- How can a drone autonomously land?



Research Questions

- How can a drone autonomously land?
- What data do autonomous drone landing methods need?



Research Questions

- How can a drone autonomously land?
- What data do autonomous drone landing methods need?
- How can those methods execute in real time onboard a drone?



State of the Art

- GPS-based landing



State of the Art

- GPS-based landing
 - RTK



State of the Art

- GPS-based landing
 - RTK
- Known landing locations:
 - Visual matching



State of the Art

- GPS-based landing
 - RTK
- Known landing locations:
 - Visual matching
 - Visual markers



State of the Art

- GPS-based landing
 - RTK
- Known landing locations:
 - Visual matching
 - Visual markers
 - IR beacons



State of the Art

- GPS-based landing
 - RTK
- Known landing locations:
 - Visual matching
 - Visual markers
 - IR beacons
- Terrain analysis
 - Optical flow



State of the Art

- GPS-based landing
 - RTK
- Known landing locations:
 - Visual matching
 - Visual markers
 - IR beacons
- Terrain analysis
 - Optical flow
 - RGBD, LIDAR



State of the Art

- GPS-based landing
 - RTK
- Known landing locations:
 - Visual matching
 - Visual markers
 - IR beacons
- Terrain analysis
 - Optical flow
 - RGBD, LIDAR
- Other methods



Completed and Ongoing Projects



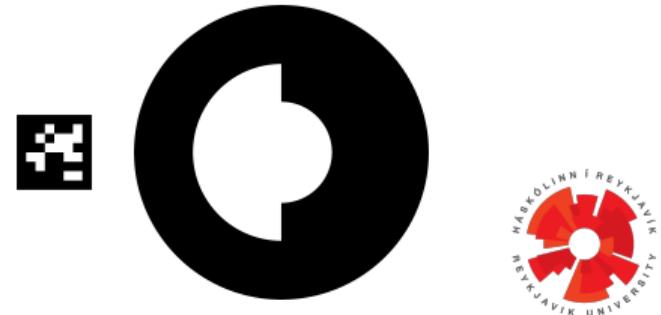
Test Hexacopters

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



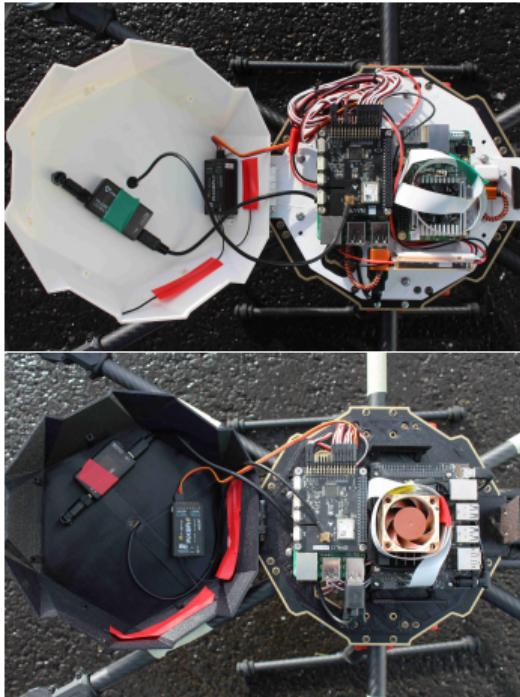
Test Hexacopters

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



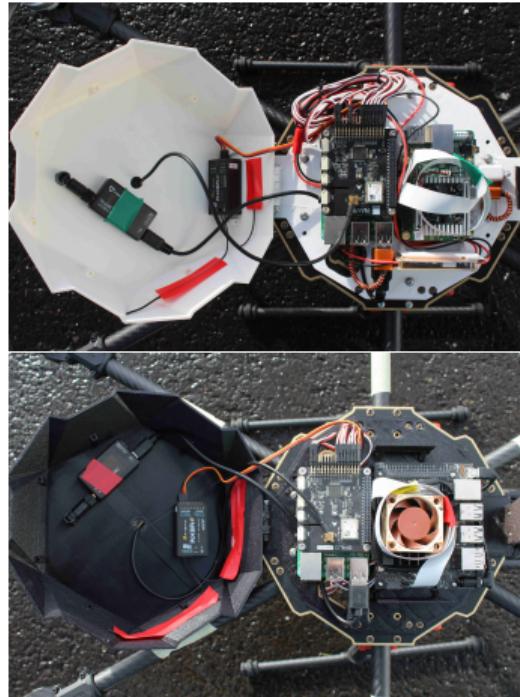
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo



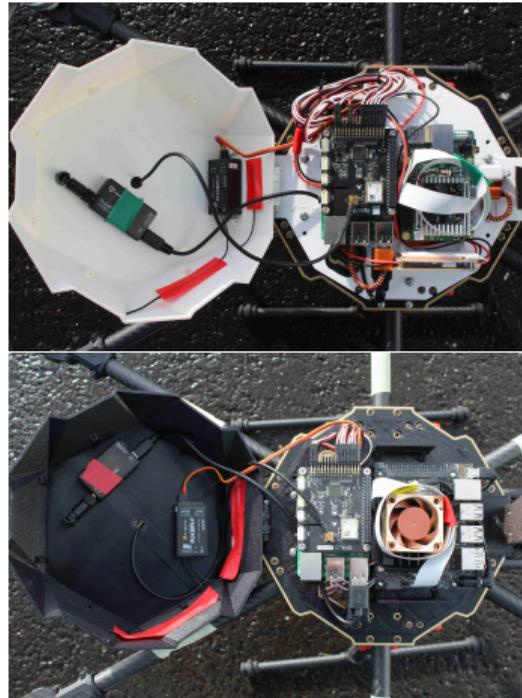
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):



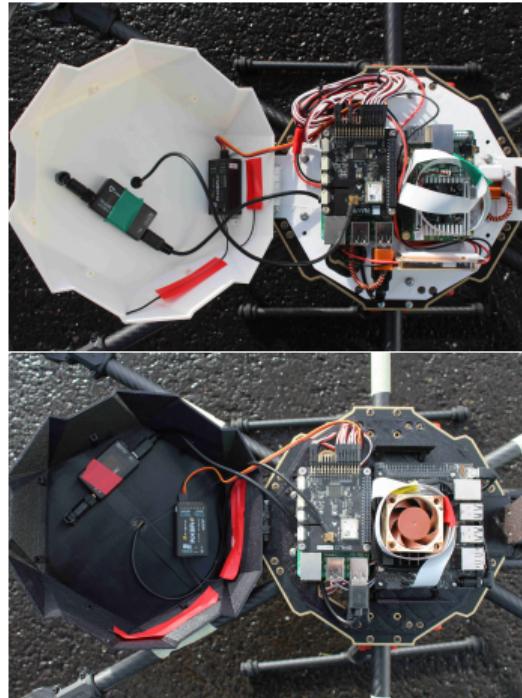
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)



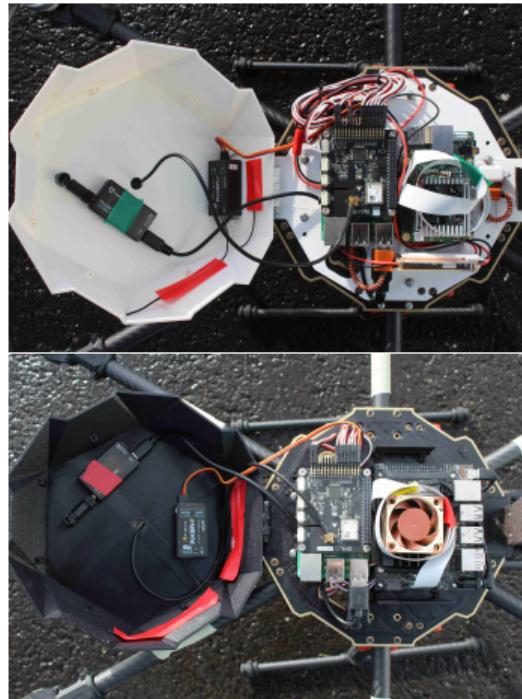
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)
 - Jetson Nano (embedded GPU)



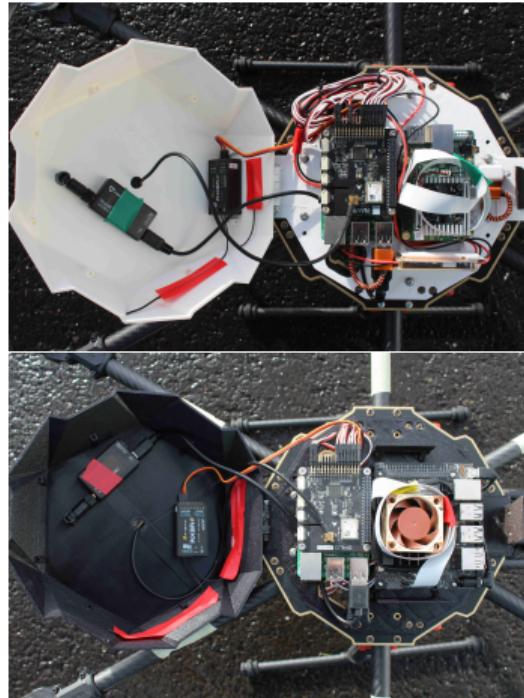
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)
 - Jetson Nano (embedded GPU)
- Gimbaled camera modules



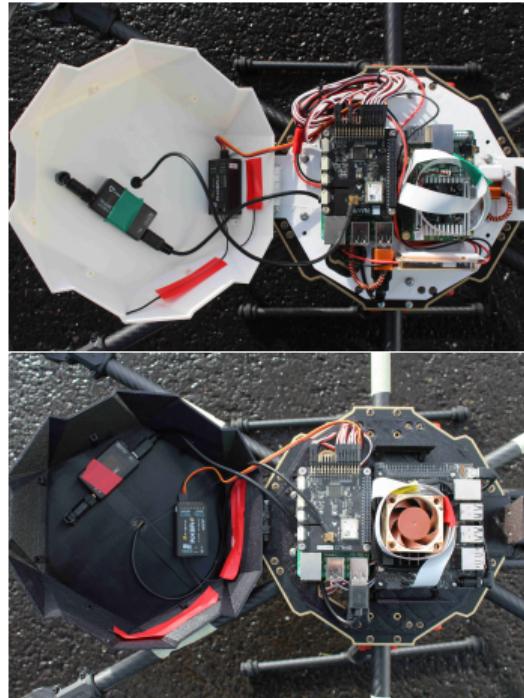
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)
 - Jetson Nano (embedded GPU)
- Gimbaled camera modules
- 433 MHz telemetry



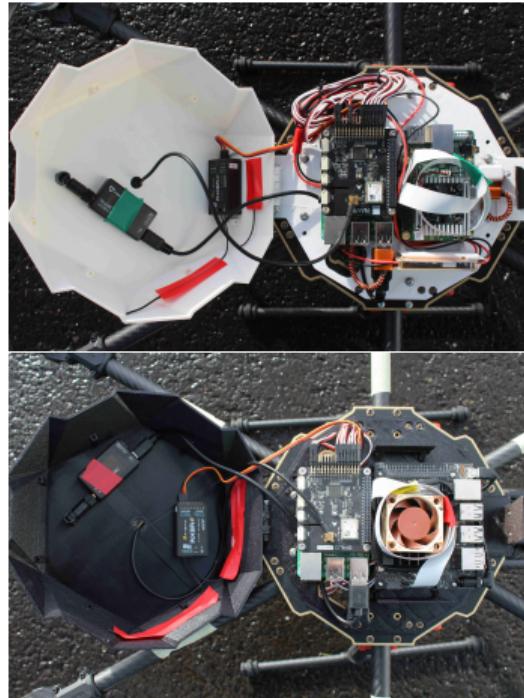
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)
 - Jetson Nano (embedded GPU)
- Gimbaled camera modules
- 433 MHz telemetry
- 2.4 GHz R/C control



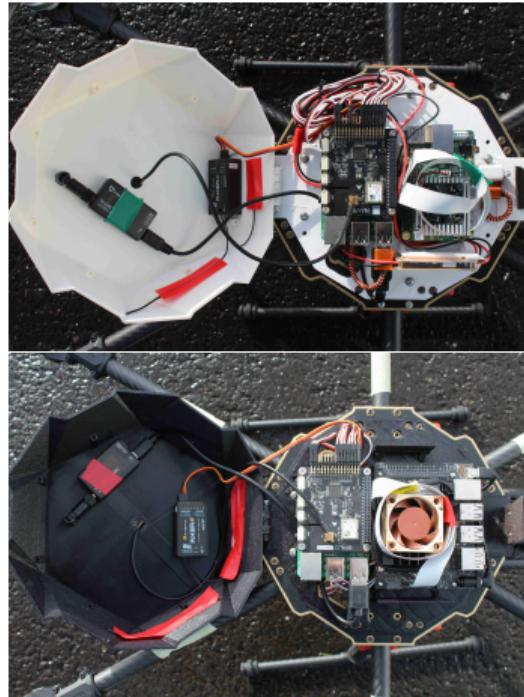
Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)
 - Jetson Nano (embedded GPU)
- Gimbaled camera modules
- 433 MHz telemetry
- 2.4 GHz R/C control
- Tested Autopilot Softwares
 - ArduPilot



Test Hexacopter Components

- Navio2 + RPi 3 autopilot combo
- Companion boards (for heavy onboard processing):
 - Google Coral (embedded TPU)
 - Jetson Nano (embedded GPU)
- Gimbaled camera modules
- 433 MHz telemetry
- 2.4 GHz R/C control
- Tested Autopilot Softwares
 - ArduPilot
 - PX4 (not technically supported)



Test Hexacopters' Performance

- Stable (manual) flight performance



Test Hexacopters' Performance

- Stable (manual) flight performance
- ~20 min flying time



Test Hexacopters' Performance

- Stable (manual) flight performance
- ~20 min flying time
- Successful marker tracking



Test Hexacopters' Performance

- Stable (manual) flight performance
- ~20 min flying time
- Successful marker tracking
- Errors during approach
 - Monocular pose estimation ambiguity



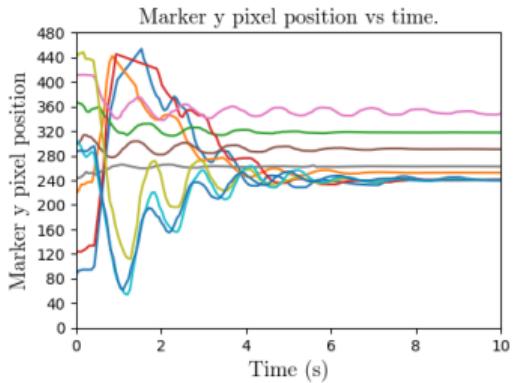
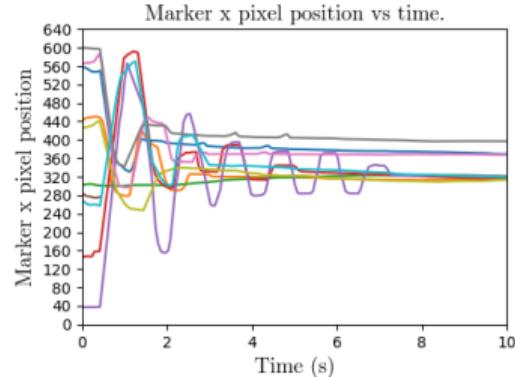
Test Hexacopters' Performance

- Stable (manual) flight performance
- ~20 min flying time
- Successful marker tracking
- Errors during approach
 - Monocular pose estimation ambiguity
 - GPS inaccuracy



Test Hexacopters' Performance

- Stable (manual) flight performance
- ~20 min flying time
- Successful marker tracking
- Errors during approach
 - Monocular pose estimation ambiguity
 - GPS inaccuracy
- No successful autonomous landing
(but almost)



Heavy Lift IR Drone

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



Heavy Lift IR Drone

- Project with Christopher Hamilton (geologist, University of Arizona) and Baldur Björnsson
- 1.3 m span, 25 kg lift



Heavy Lift IR Drone

- Project with Christopher Hamilton (geologist, University of Arizona) and Baldur Björnsson
- 1.3 m span, 25 kg lift
- FLIR camera



Heavy Lift IR Drone

- Project with Christopher Hamilton (geologist, University of Arizona) and Baldur Björnsson
- 1.3 m span, 25 kg lift
- FLIR camera
- Surveyed lava field at Fagradalsfjall



Heavy Lift IR Drone

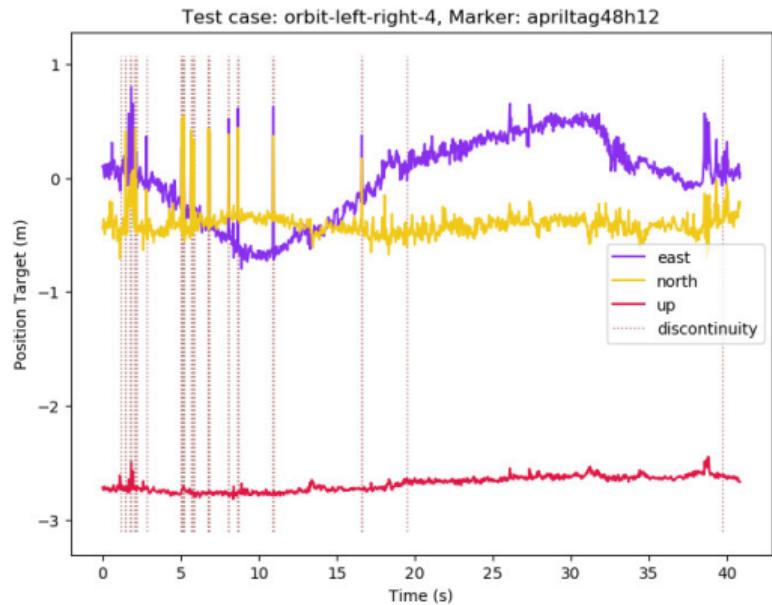
- Project with Christopher Hamilton (geologist, University of Arizona) and Baldur Björnsson
- 1.3 m span, 25 kg lift
- FLIR camera
- Surveyed lava field at Fagradalsfjall
- Featured on BBC Click



Fiducial System Modifications

Necessary properties:

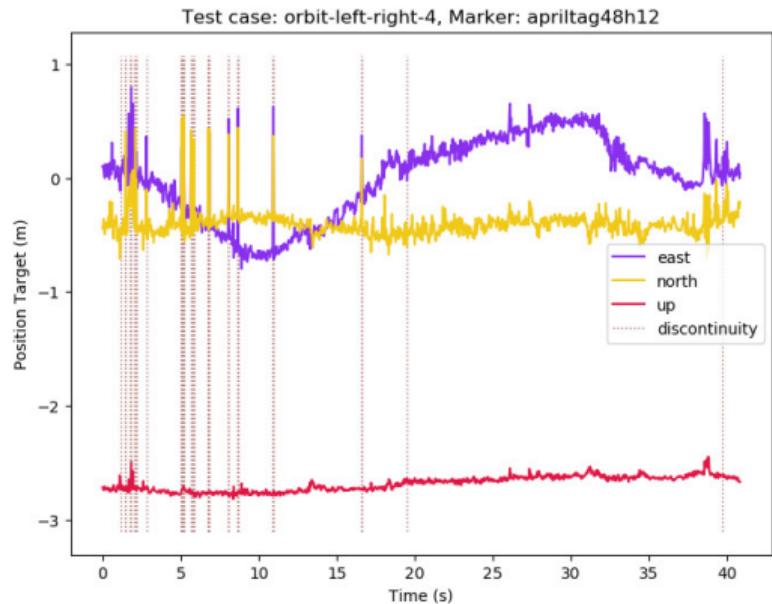
- Mitigates orientation ambiguity



Fiducial System Modifications

Necessary properties:

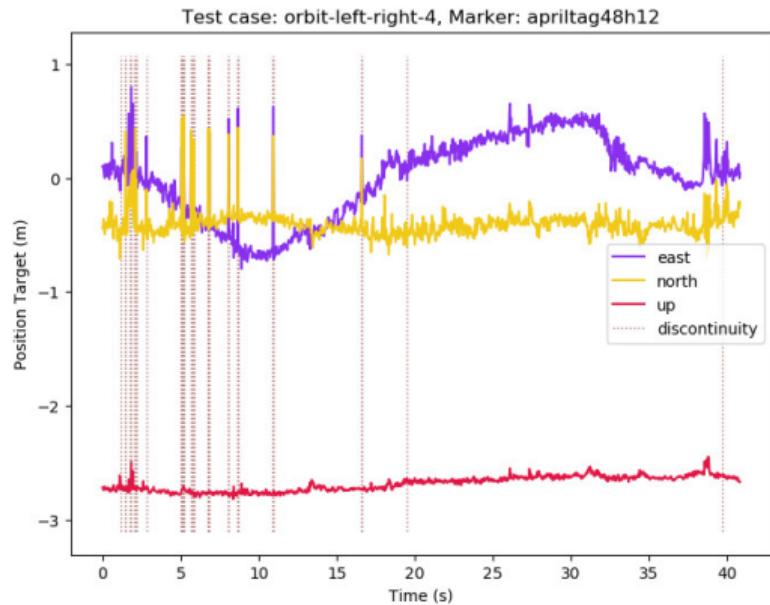
- Mitigates orientation ambiguity
- Detectable at long- and short-range



Fiducial System Modifications

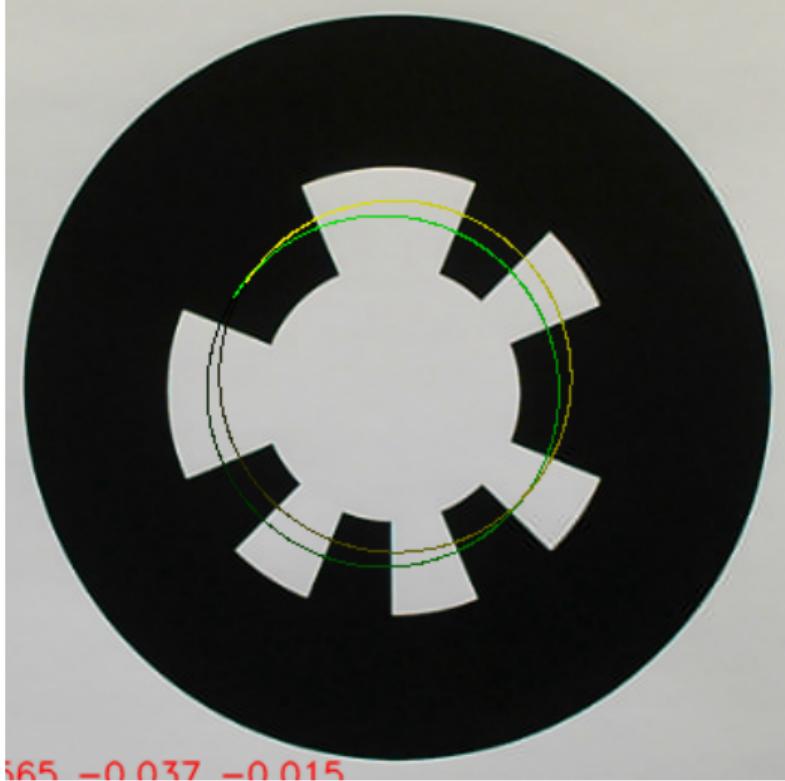
Necessary properties:

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



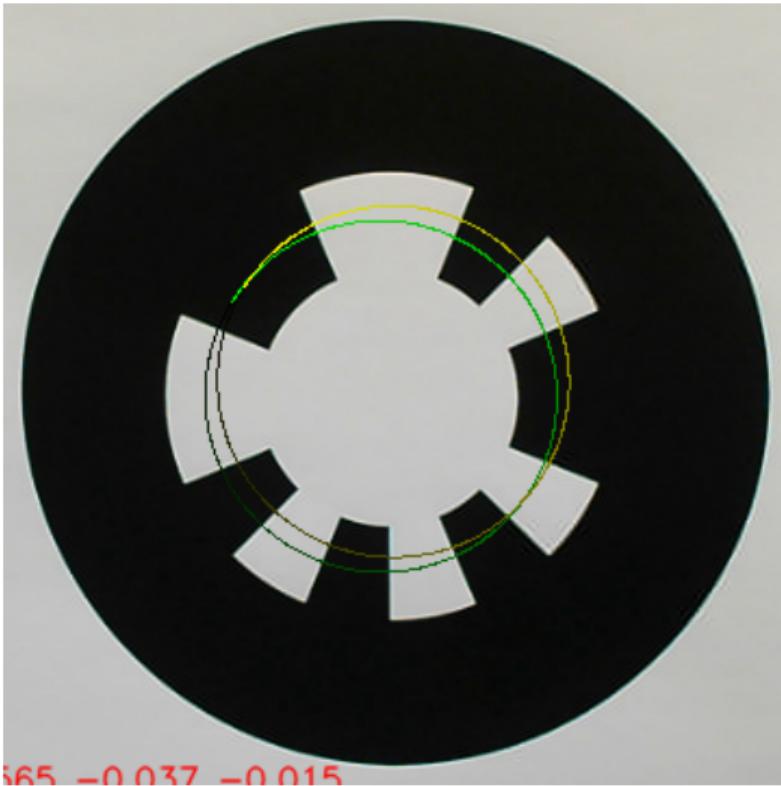
Orientation Ambiguity in WhyCode

- Semi-axes → 2 possible orientations



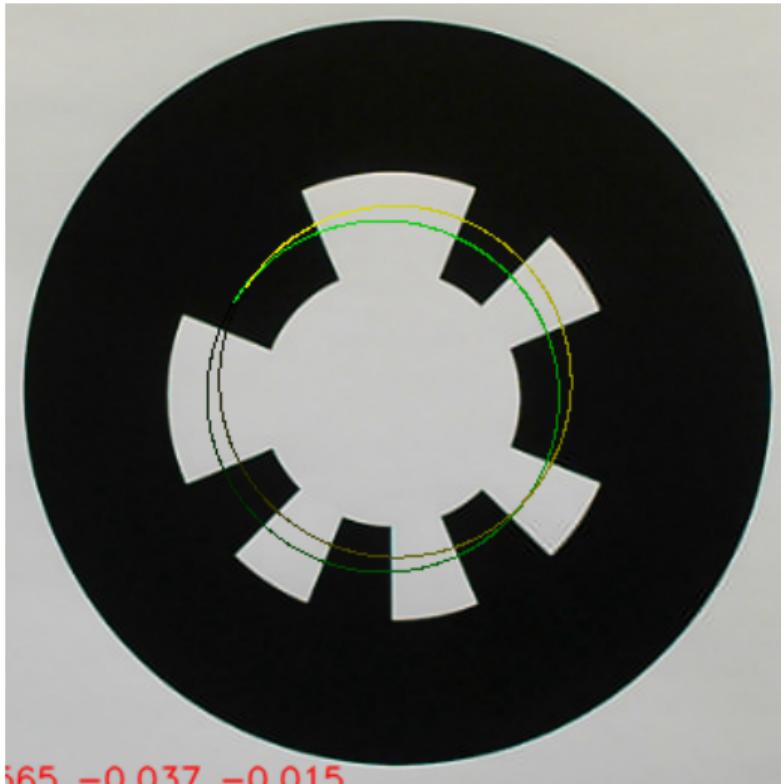
Orientation Ambiguity in WhyCode

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



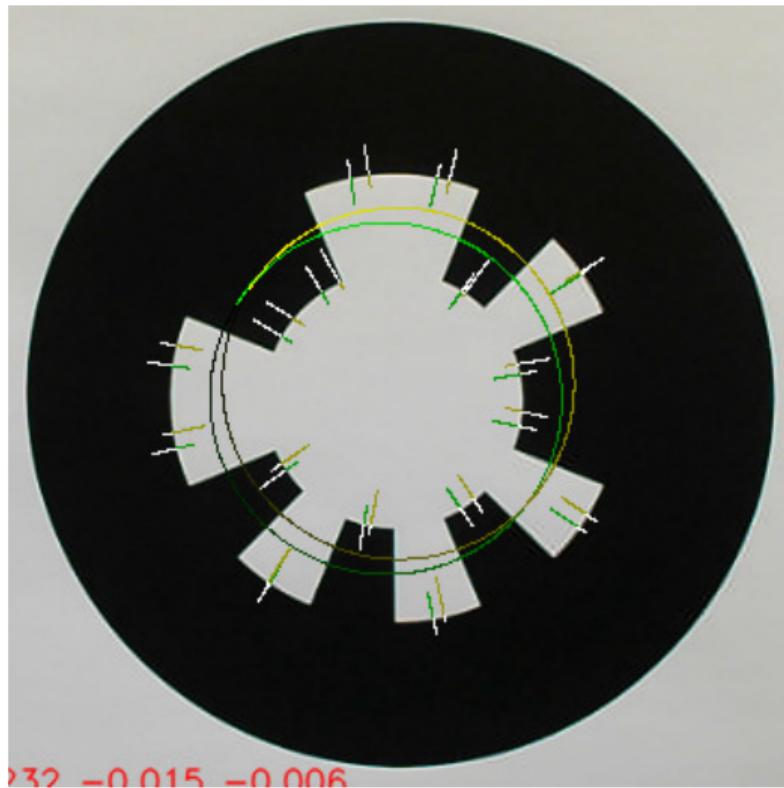
Orientation Ambiguity in WhyCode

- Semi-axes → 2 possible orientations
- Better centered → correct
- Arclength of intersections with ID “teeth”



Fiducial System Modifications: “WhyCode Ellipse”

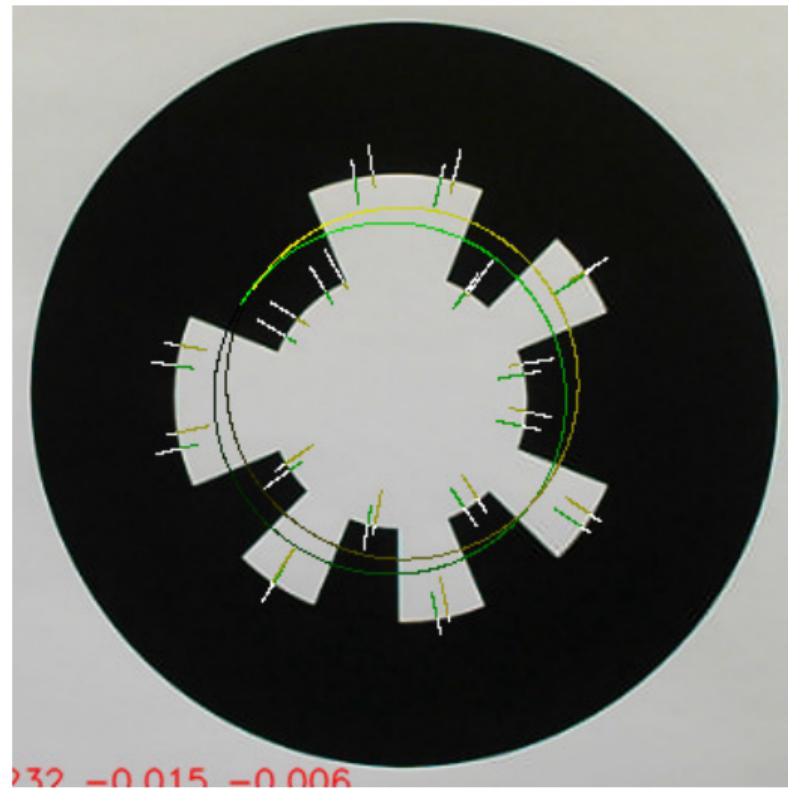
Approach 1: Extra tooth sampling



Fiducial System Modifications: “WhyCode Ellipse”

Approach 1: Extra tooth sampling

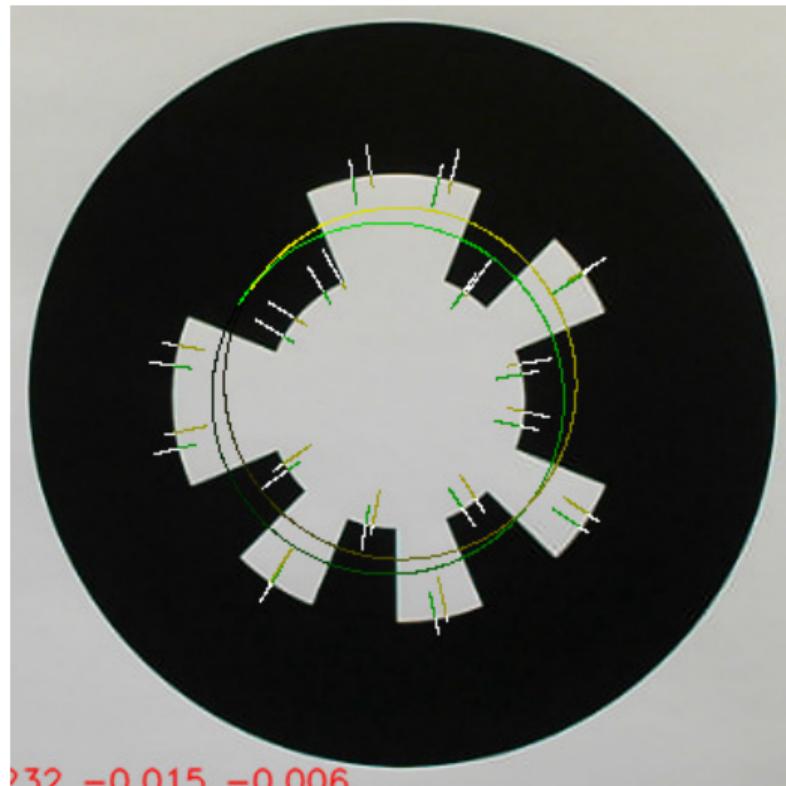
- Sample ID with original method.



Fiducial System Modifications: “WhyCode Ellipse”

Approach 1: Extra tooth sampling

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

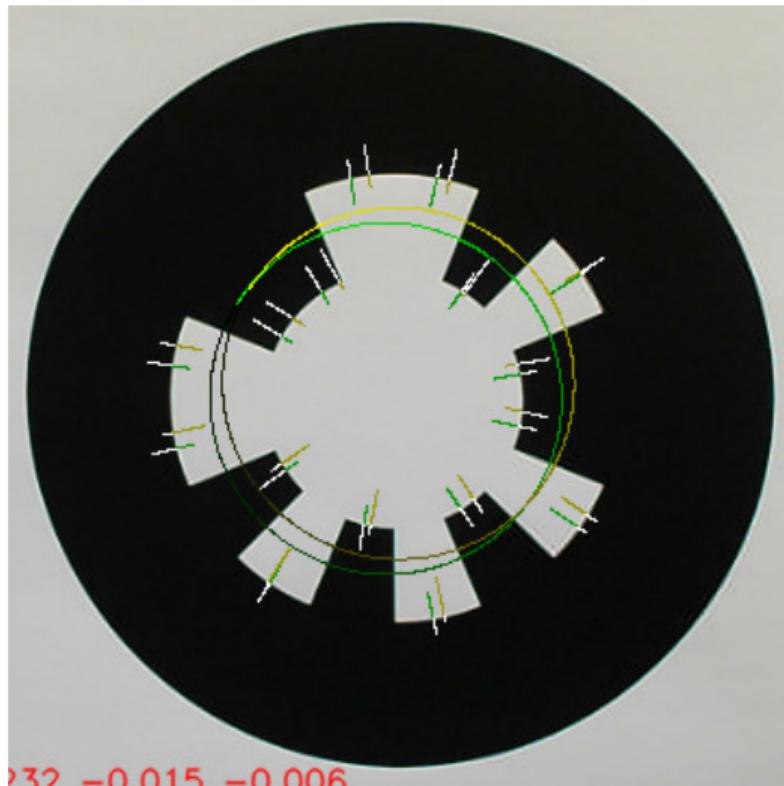


032 -0.015 -0.006

Fiducial System Modifications: “WhyCode Ellipse”

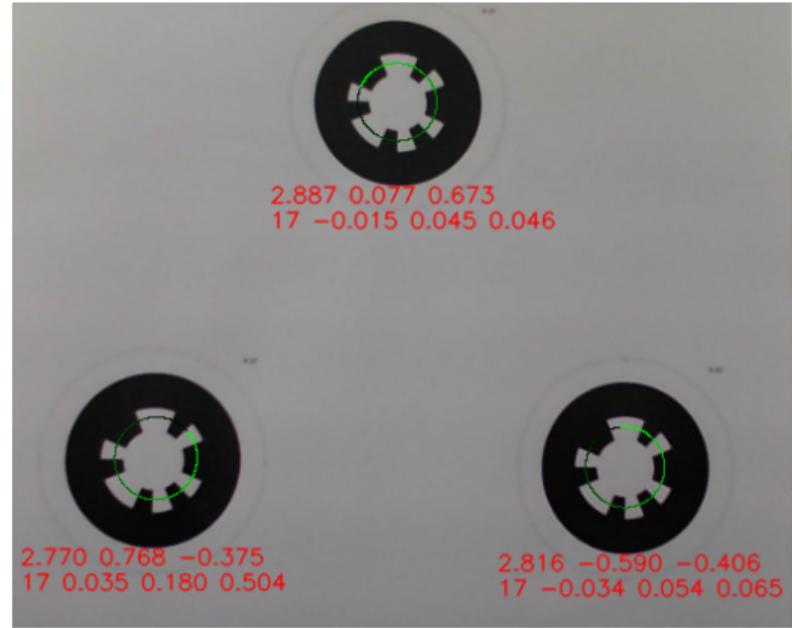
Approach 1: Extra tooth sampling

- Sample ID with original method.
- Add: radial sampling on tooth edges.
- Choose solution based on tooth edge predictions.



Fiducial System Modifications: “WhyCode Multi”

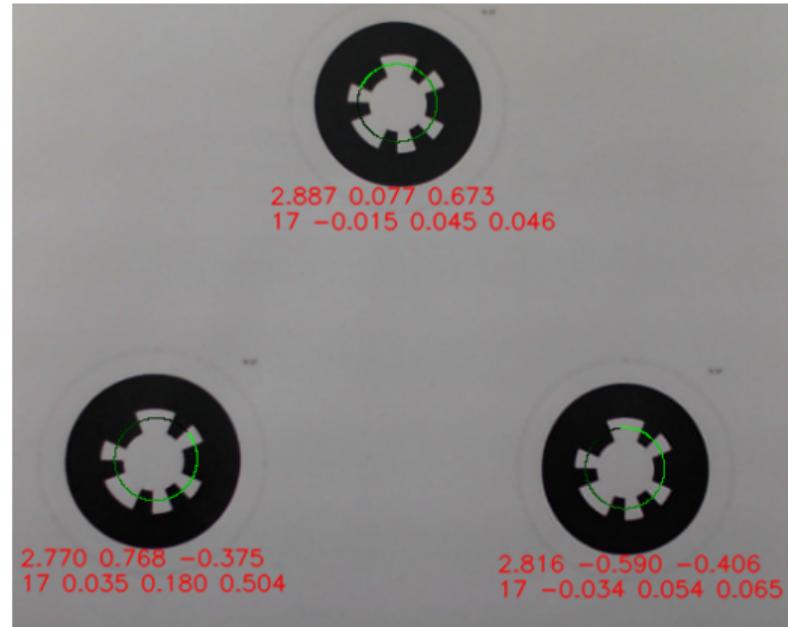
Approach 2: Coplanar marker arrangements



Fiducial System Modifications: “WhyCode Multi”

Approach 2: Coplanar marker arrangements

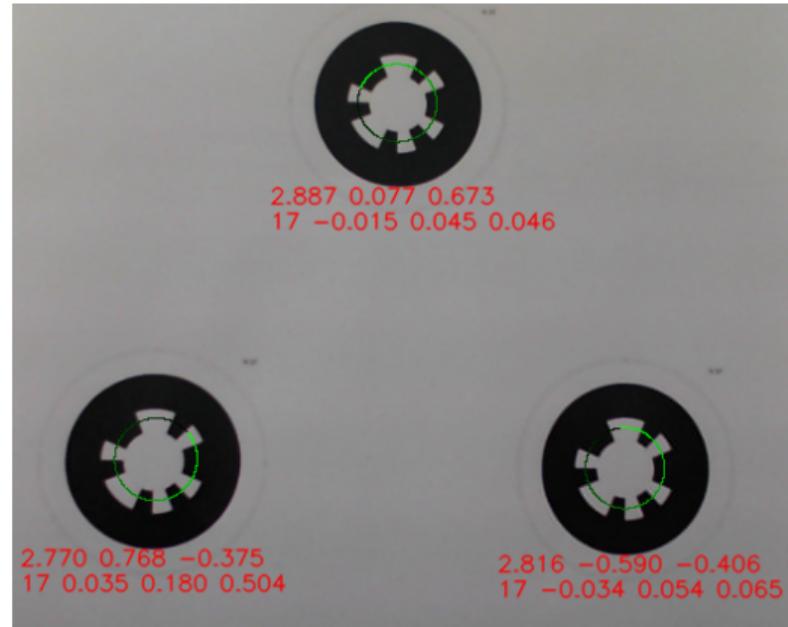
- Ignore individual marker orientations



Fiducial System Modifications: “WhyCode Multi”

Approach 2: Coplanar marker arrangements

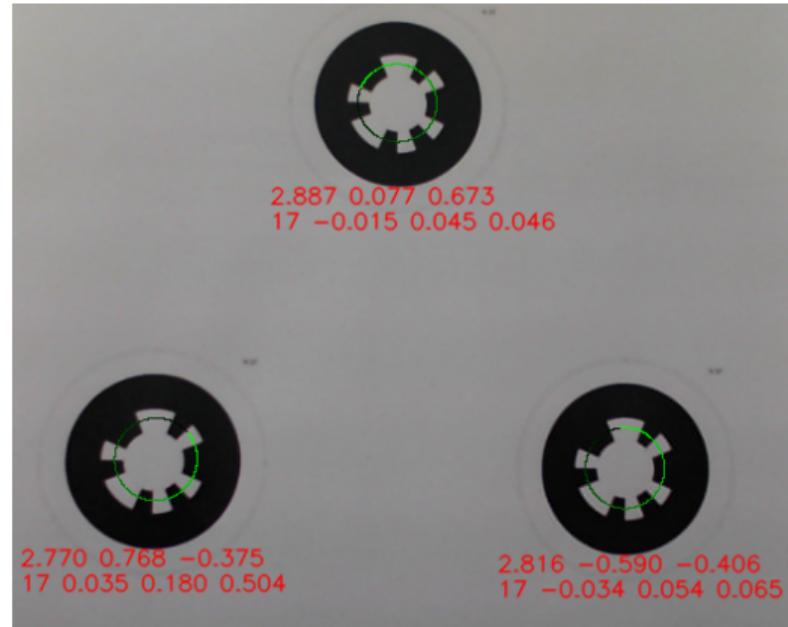
- Ignore individual marker orientations
- Calculate normal vector to the plane connecting the markers.



Fiducial System Modifications: “WhyCode Multi”

Approach 2: Coplanar marker arrangements

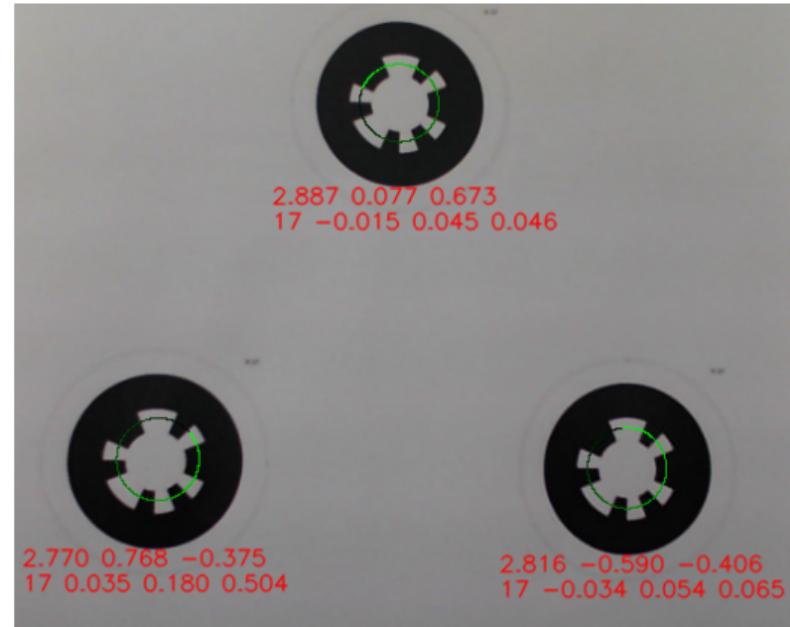
- Ignore individual marker orientations
- Calculate normal vector to the plane connecting the markers.
- Extract pitch and roll from the normal vector.



Fiducial System Modifications: “WhyCode Multi”

Approach 2: Coplanar marker arrangements

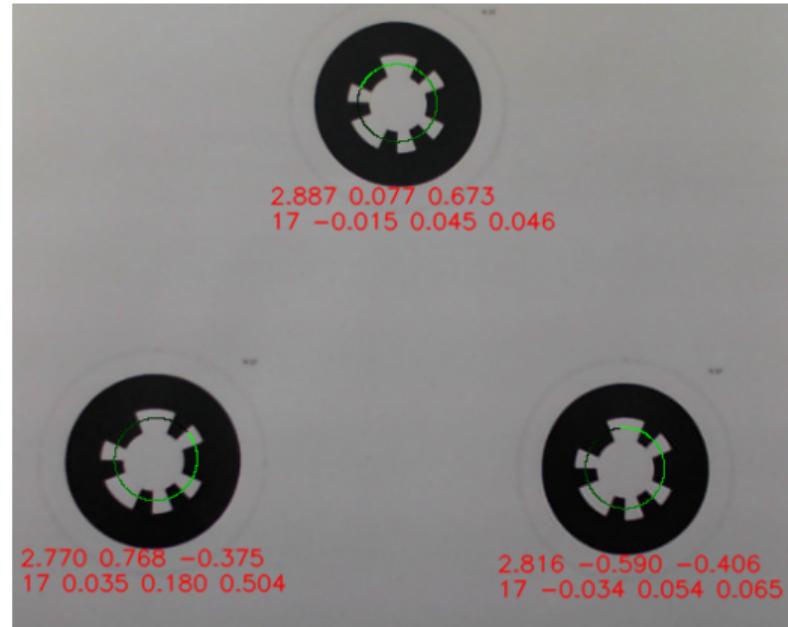
- Ignore individual marker orientations
- Calculate normal vector to the plane connecting the markers.
- Extract pitch and roll from the normal vector.
- Extract yaw from the marker IDs.



Fiducial System Modifications: “WhyCode Multi”

Approach 2: Coplanar marker arrangements

- Ignore individual marker orientations
- Calculate normal vector to the plane connecting the markers.
- Extract pitch and roll from the normal vector.
- Extract yaw from the marker IDs.
- Takes advantage of WhyCode’s efficiency.



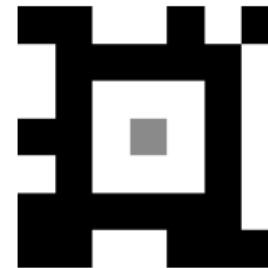
Fiducial System Modifications: April Tag

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

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

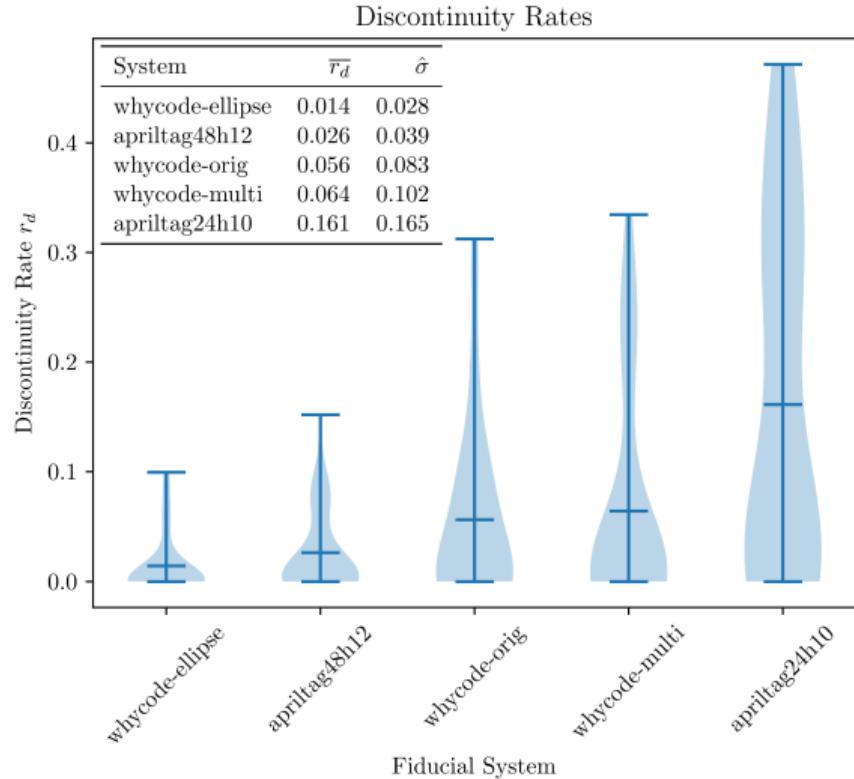


April Tag Custom 24h10: “recursive,” smaller definition



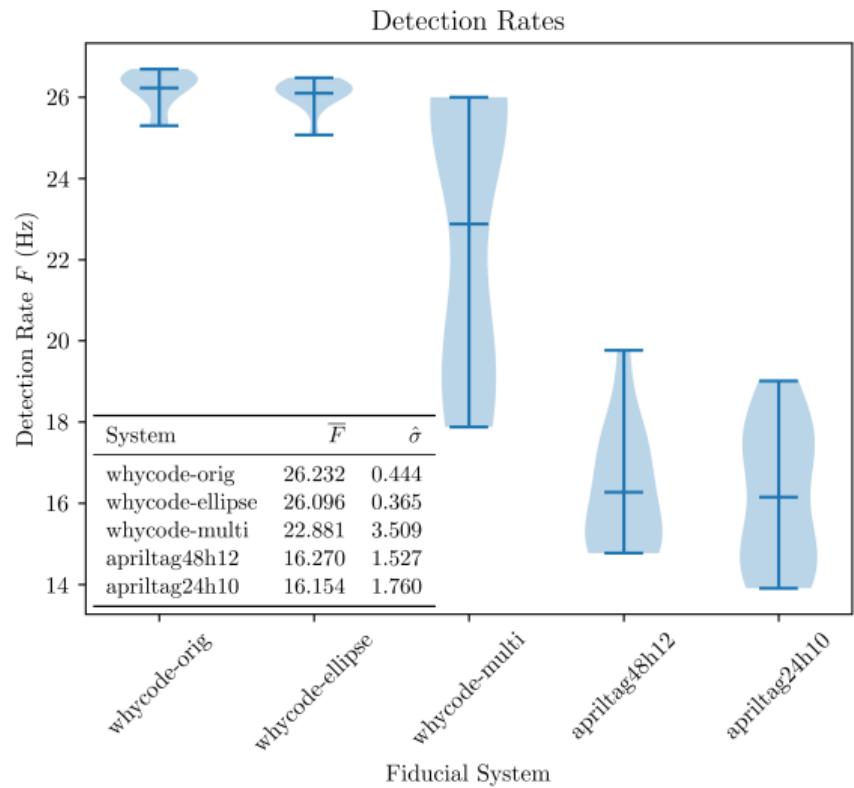
Performance Analysis: Discontinuity Rates

- Orientation ambiguity → discontinuities.
- Discontinuity rate \bar{r}_d is the number of discontinuities per detection.
- Lower is better.



Performance Analysis: Detection Rates

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



Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark



(Banana for scale.)

Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark
 - Reduces logistical considerations: transportation, weather



(Banana for scale.)

Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark
 - Reduces logistical considerations: transportation, weather
 - Stable out-of-the-box autonomous flight



(Banana for scale.)

Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark
 - Reduces logistical considerations: transportation, weather
 - Stable out-of-the-box autonomous flight
 - Doesn't require GPS (uses other sensors)



(Banana for scale.)

Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark
 - Reduces logistical considerations: transportation, weather
 - Stable out-of-the-box autonomous flight
 - Doesn't require GPS (uses other sensors)
- Requires DJI Mobile SDK, Custom Android App, and **lots** of workarounds.



(Banana for scale.)

Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark
 - Reduces logistical considerations: transportation, weather
 - Stable out-of-the-box autonomous flight
 - Doesn't require GPS (uses other sensors)
- Requires DJI Mobile SDK, Custom Android App, and **lots** of workarounds.
- Video frames are offloaded (via WiFi) to Raspberry Pi 4 for processing



(Banana for scale.)

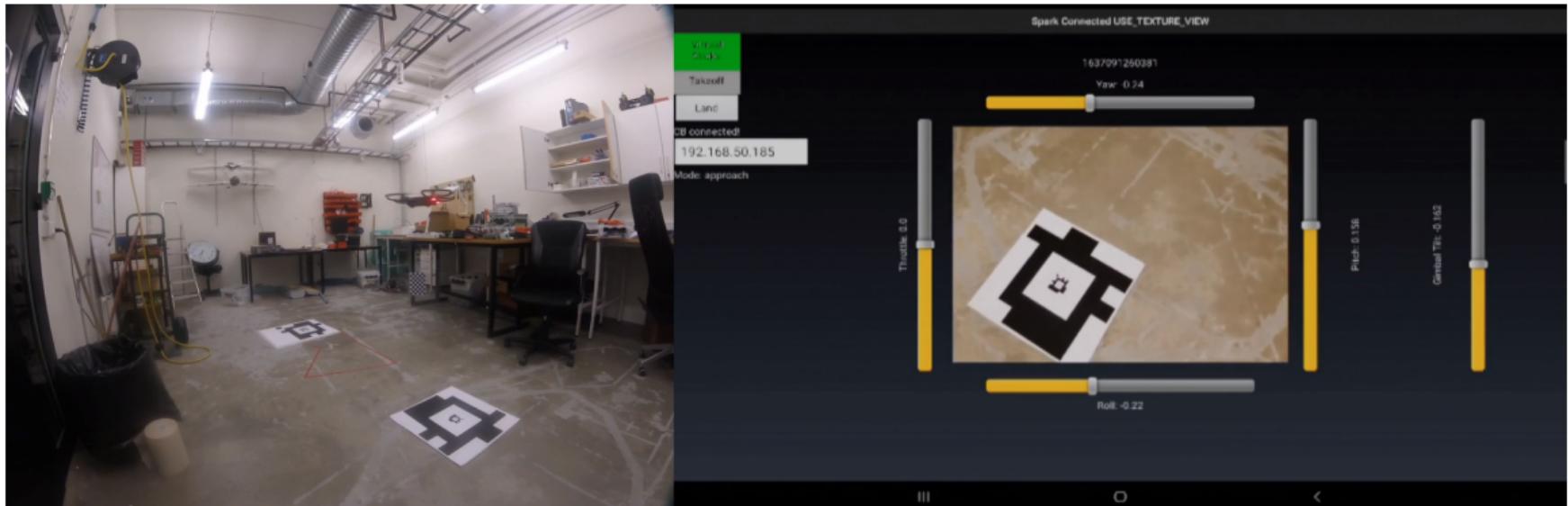
Autonomous Landing Proof of Concept (**FINALLY!**)

- Indoor experiments with DJI Spark
 - Reduces logistical considerations: transportation, weather
 - Stable out-of-the-box autonomous flight
 - Doesn't require GPS (uses other sensors)
- Requires DJI Mobile SDK, Custom Android App, and **lots** of workarounds.
- Video frames are offloaded (via WiFi) to Raspberry Pi 4 for processing
- Limiting factor: pre-transmission image compression on tablet (6-7 Hz)

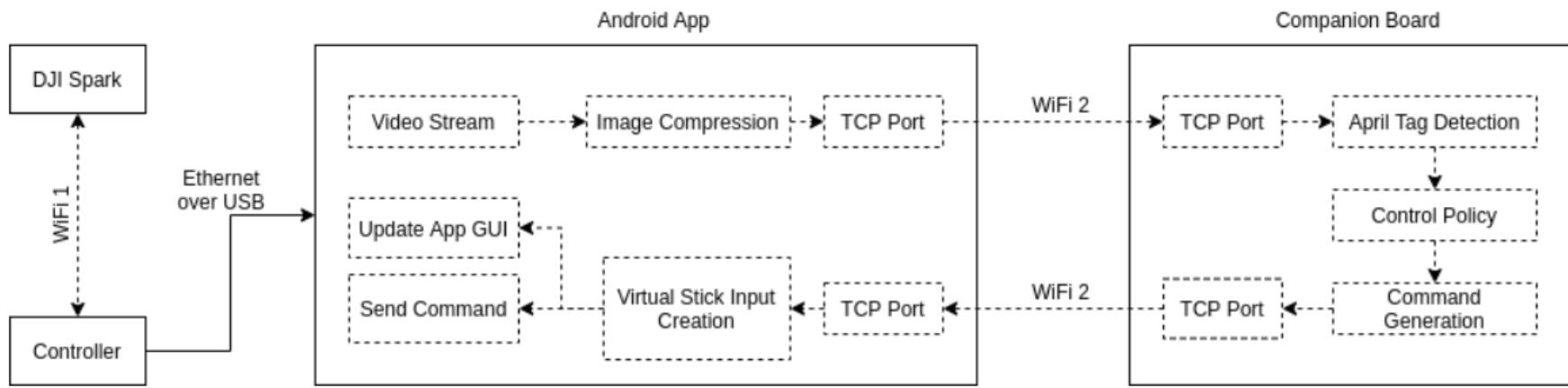


(Banana for scale.)

Demo with worst-performing April Tag 24h10!



Autonomous Landing Proof of Concept: System Architecture



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



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)
 - classify according to predicted safety: (safe, questionable, unsafe, etc.)



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)
 - classify according to predicted safety: (safe, questionable, unsafe, etc.)
- Focus on real time performance



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)
 - classify according to predicted safety: (safe, questionable, unsafe, etc.)
- Focus on real time performance
 - Minimize computational requirements



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)
 - classify according to predicted safety: (safe, questionable, unsafe, etc.)
- Focus on real time performance
 - Minimize computational requirements
 - Target specific hardware platforms



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)
 - classify according to predicted safety: (safe, questionable, unsafe, etc.)
- Focus on real time performance
 - Minimize computational requirements
 - Target specific hardware platforms
- Overall structure:
 - Input: sensor data
 - Process (quickly): ??
 - Output: safe landing sites (e.g. heat map)



Overview: Unstructured Autonomous Landing

- Focus on terrain analysis
 - Topographical analysis
 - Semantic segmentation
 - terrain type classification: (snow, ice, water, grass, rock, etc.)
 - classify according to predicted safety: (safe, questionable, unsafe, etc.)
- Focus on real time performance
 - Minimize computational requirements
 - Target specific hardware platforms
- Overall structure:
 - Input: sensor data
 - Process (quickly): ??
 - Output: safe landing sites (e.g. heat map) → flight control commands



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets

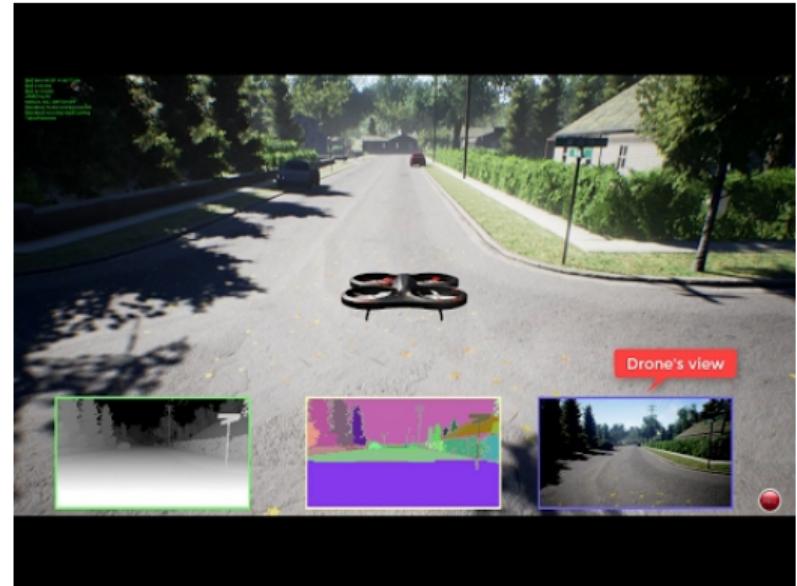


Image source



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets
- Synthetic sensor data (LIDAR, RGBD cameras)

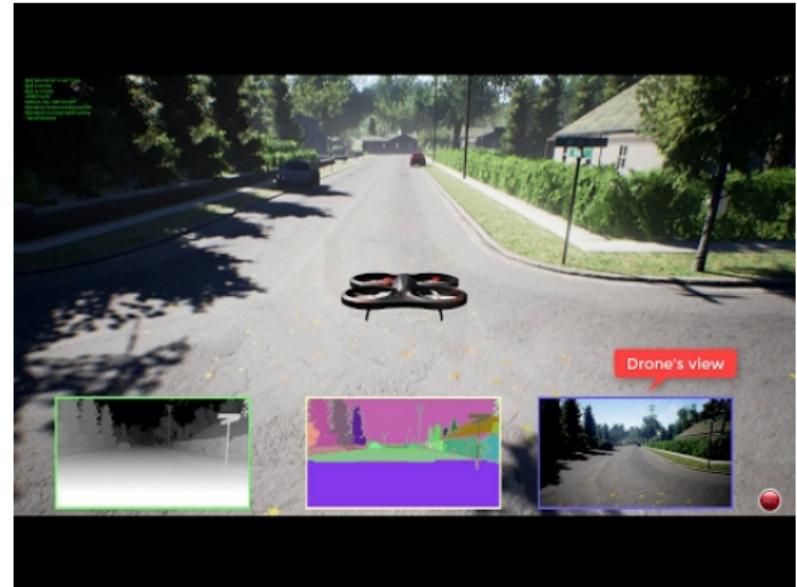


Image source



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets
- Synthetic sensor data (LIDAR, RGBD cameras)
- Tag with IMU data

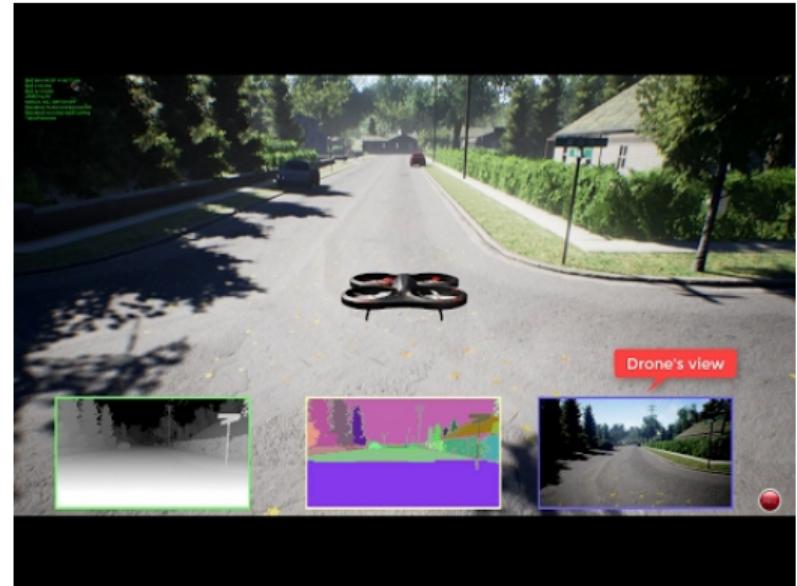


Image source



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets
- Synthetic sensor data (LIDAR, RGBD cameras)
- Tag with IMU data
 - LIDAR → RADAR

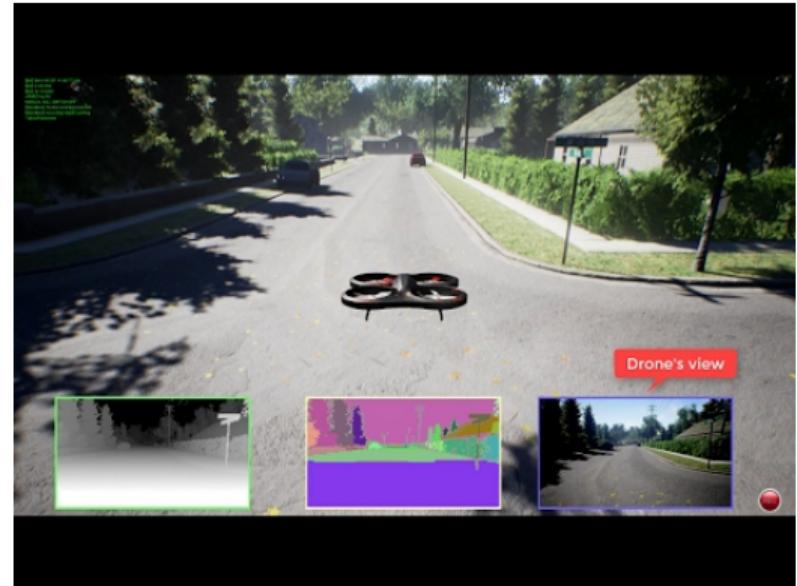


Image source



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets
- Synthetic sensor data (LIDAR, RGBD cameras)
- Tag with IMU data
 - LIDAR → RADAR
- Specify realistic sensor parameters

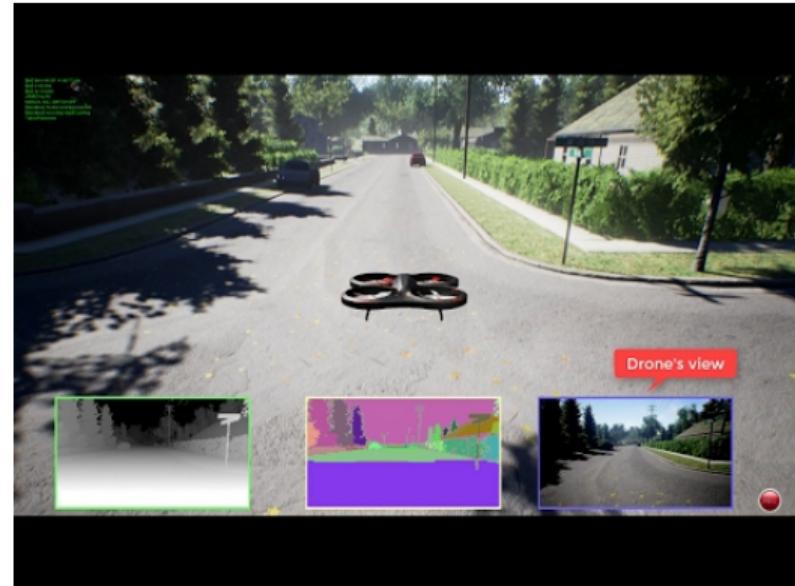


Image source



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets
- Synthetic sensor data (LIDAR, RGBD cameras)
- Tag with IMU data
 - LIDAR → RADAR
- Specify realistic sensor parameters
- Segmentation masks for high-level label generation

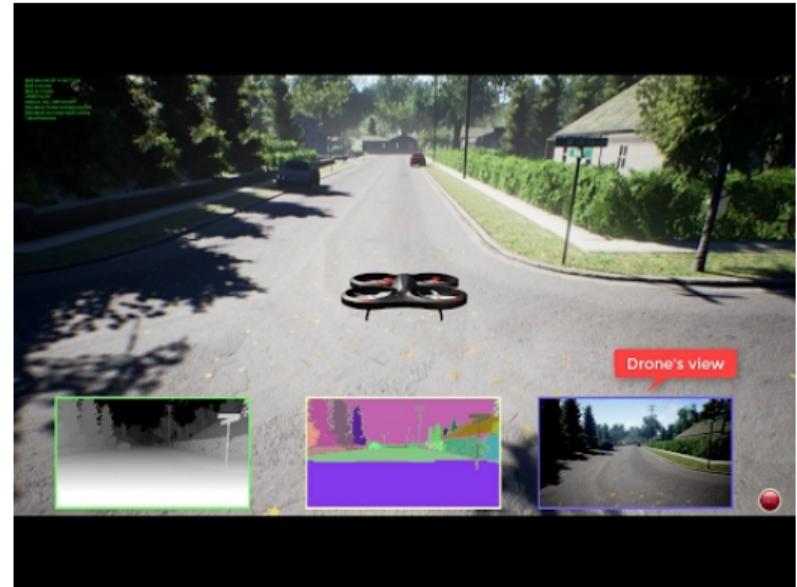


Image source



Data Set Generation

AirSim: realistic simulator

- Automatic generation of large data sets
- Synthetic sensor data (LIDAR, RGBD cameras)
- Tag with IMU data
 - LIDAR → RADAR
- Specify realistic sensor parameters
- Segmentation masks for high-level label generation
- Labeling method can be slow, hand-tuned

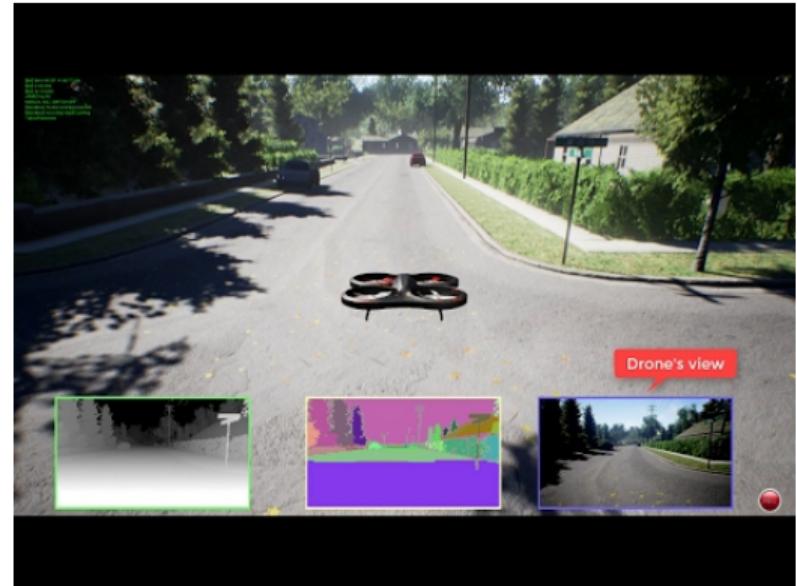


Image source



Terrain Classifier Creation

- Test several methods



Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing



Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing
 - Deep learning methods



Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing
 - Deep learning methods
 - Combination



Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing
 - Deep learning methods
 - Combination
- Pre-processing wrappers:
 - Rectification/calibration



Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing
 - Deep learning methods
 - Combination
- Pre-processing wrappers:
 - Rectification/calibration
 - Downsampling/resizing



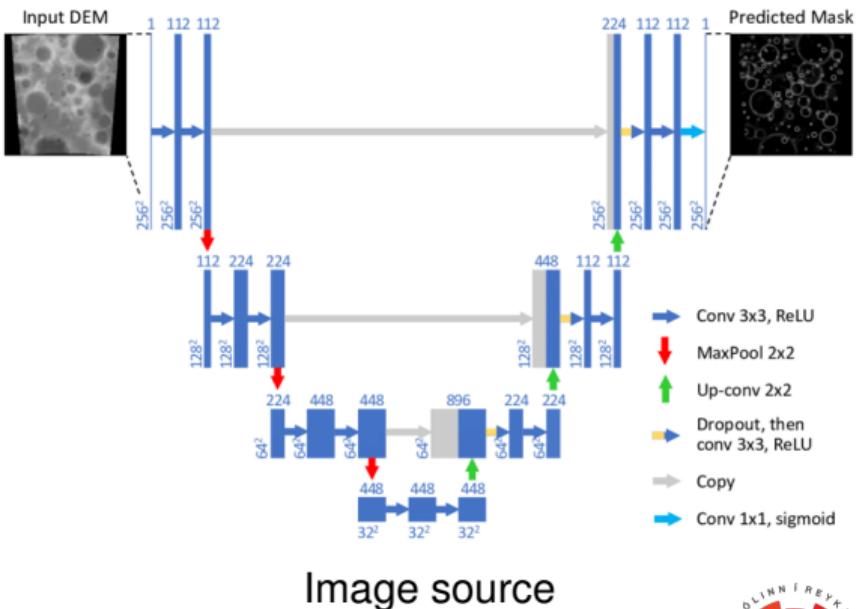
Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing
 - Deep learning methods
 - Combination
- Pre-processing wrappers:
 - Rectification/calibration
 - Downsampling/resizing
- Performance comparison
 - Reduce false positives



Terrain Classifier Creation

- Test several methods
 - Conventional signal/image processing
 - Deep learning methods
 - Combination
- Pre-processing wrappers:
 - Rectification/calibration
 - Downsampling/resizing
- Performance comparison
 - Reduce false positives



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking
 - Translation to flight commands



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking
 - Translation to flight commands
- Integration with ArduPilot/PX4 SITL



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking
 - Translation to flight commands
- Integration with ArduPilot/PX4 SITL
- Simulated autonomous missions in AirSim



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking
 - Translation to flight commands
- Integration with ArduPilot/PX4 SITL
- Simulated autonomous missions in AirSim
- Qualitative analysis:
 - Does the drone land at all?



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking
 - Translation to flight commands
- Integration with ArduPilot/PX4 SITL
- Simulated autonomous missions in AirSim
- Qualitative analysis:
 - Does the drone land at all?
 - Does the safe region tracking work?



Testing in Simulation

- Post-processing wrappers:
 - Safe region tracking
 - Translation to flight commands
- Integration with ArduPilot/PX4 SITL
- Simulated autonomous missions in AirSim
- Qualitative analysis:
 - Does the drone land at all?
 - Does the safe region tracking work?
 - Does the autopilot software accept the commands?



Simulation is not enough!



Testing in the Real World

- Offline
 - Accuracy on real world data

Testing in the Real World

- Offline
 - Accuracy on real world data
- Lab scenarios
 - Runtime framerate on embedded hardware
 - Power requirements on embedded hardware



Testing in the Real World

- Offline
 - Accuracy on real world data
- Lab scenarios
 - Runtime framerate on embedded hardware
 - Power requirements on embedded hardware
- Real world landing scenarios



Drone Upgrades

- New flight controller: Pixhawk Cube Orange



Drone Upgrades

- New flight controller: Pixhawk Cube Orange
- Here3



Drone Upgrades

- New flight controller: Pixhawk Cube Orange
- Here3
- Supplement GPS



Drone Upgrades

- New flight controller: Pixhawk Cube Orange
- Here3
- Supplement GPS
 - Optical Flow
 - LIDAR rangefinder



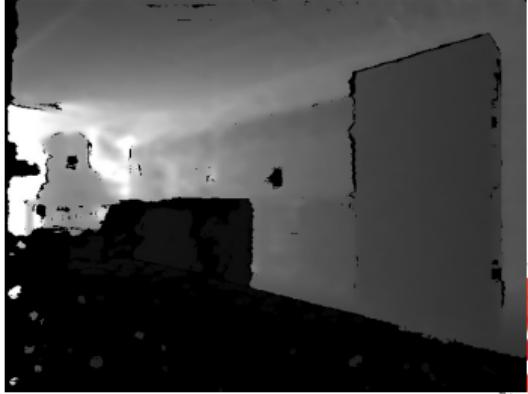
Drone Upgrades

- New flight controller: Pixhawk Cube Orange
- Here3
- Supplement GPS
 - Optical Flow
 - LIDAR rangefinder
- Protective sensor cases, gimbal mounts



Drone Upgrades

- New flight controller: Pixhawk Cube Orange
- Here3
- Supplement GPS
 - Optical Flow
 - LIDAR rangefinder
- Protective sensor cases, gimbal mounts
 - Intel RealSense D435 RGBD camera
 - Intel RealSense D455 RGBD camera (IMU)
 - Intel RealSense L515 LIDAR (IMU)
 - Texas Instruments IWR6843 60 GHz RADAR



Main Risks

- The synthetic data does not accurately represent the real world!



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data → no segmentation masks.



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data → no segmentation masks.
- The embedded hardware is too slow!



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data → no segmentation masks.
- The embedded hardware is too slow!
 - Reduce computational needs



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data → no segmentation masks.
- The embedded hardware is too slow!
 - Reduce computational needs → prune network, decrease input data size



Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data → no segmentation masks.
- The embedded hardware is too slow!
 - Reduce computational needs → prune network, decrease input data size
 - Use non-embedded hardware



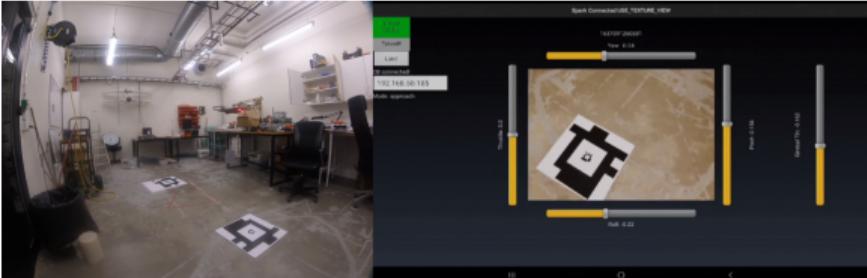
Main Risks

- The synthetic data does not accurately represent the real world!
 - Show results in simulation.
 - Use real world data → no segmentation masks.
- The embedded hardware is too slow!
 - Reduce computational needs → prune network, decrease input data size
 - Use non-embedded hardware → generate reliable flight commands on real world data

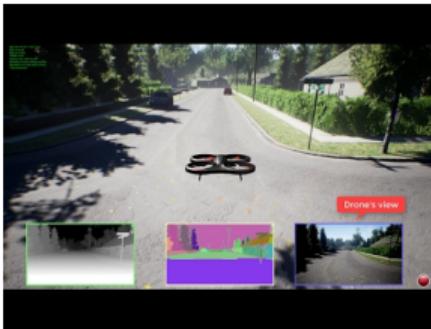


Summary

- Goal: autonomous drone landing

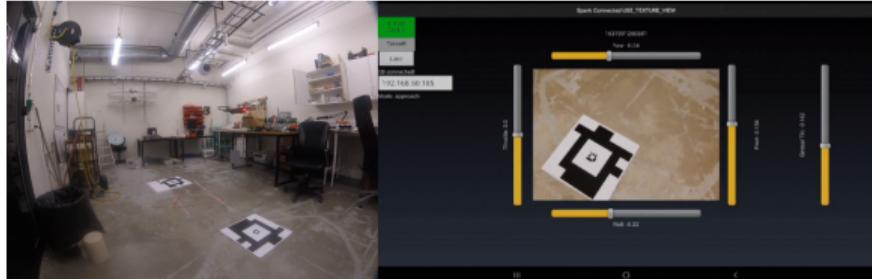


[Click to watch on Vimeo](#)



Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants

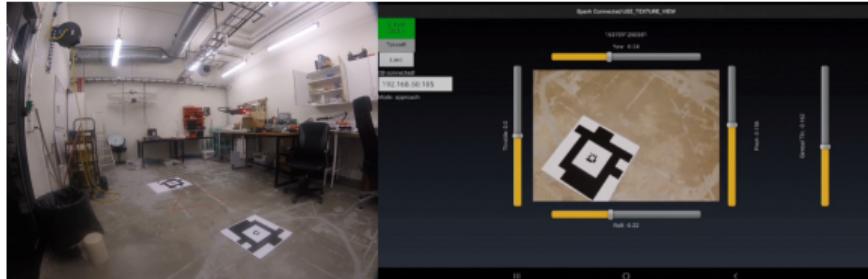


[Click to watch on Vimeo](#)

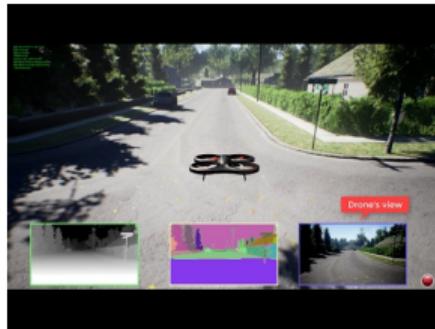


Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing

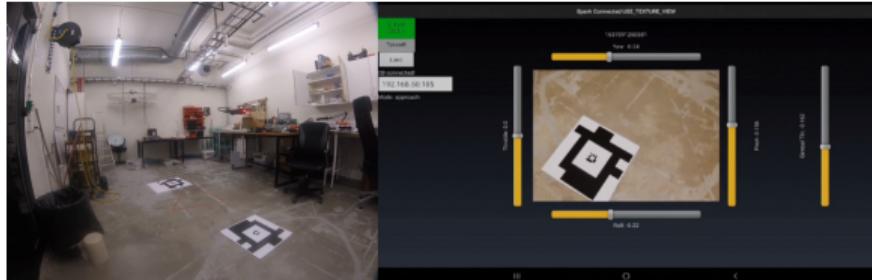


[Click to watch on Vimeo](#)



Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR

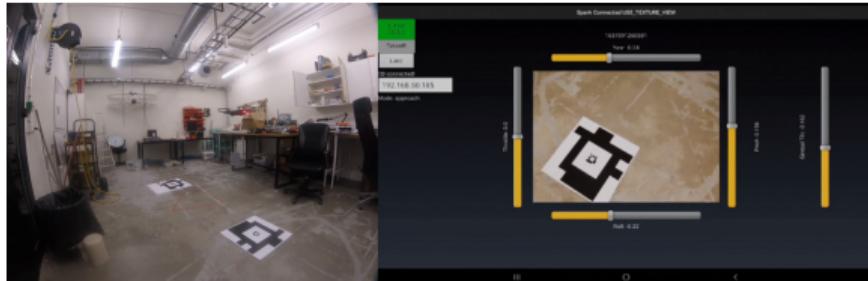


[Click to watch on Vimeo](#)

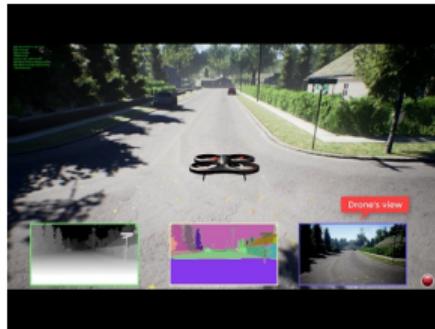


Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR
 - Topological/semantic terrain analysis

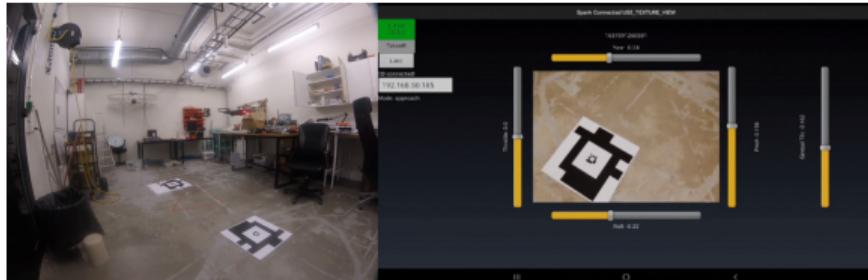


[Click to watch on Vimeo](#)



Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR
 - Topological/semantic terrain analysis
 - Synthetic data

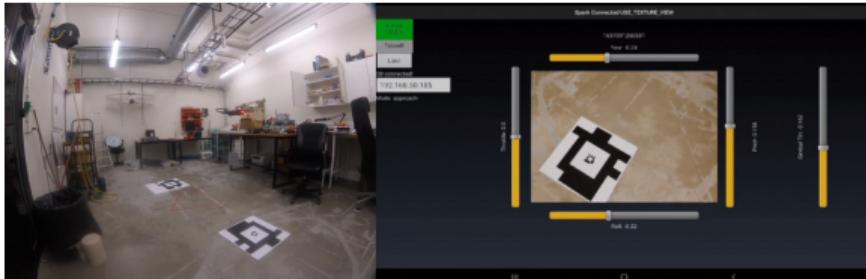


[Click to watch on Vimeo](#)

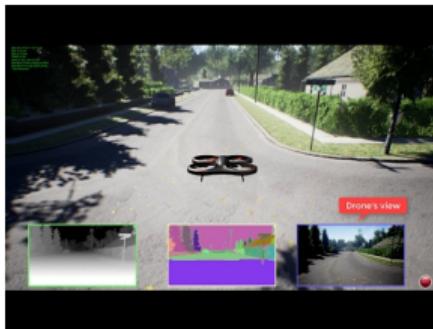


Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR
 - Topological/semantic terrain analysis
 - Synthetic data
 - Testing in simulation

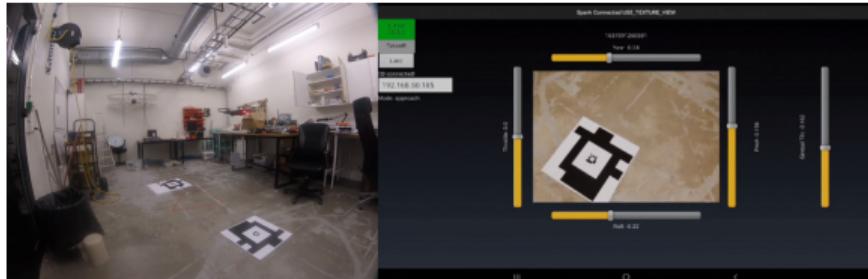


[Click to watch on Vimeo](#)

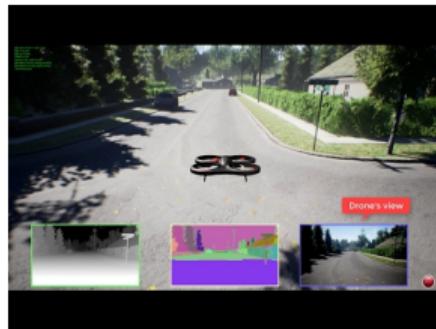


Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR
 - Topological/semantic terrain analysis
 - Synthetic data
 - Testing in simulation
 - Real world tests: power/framerate

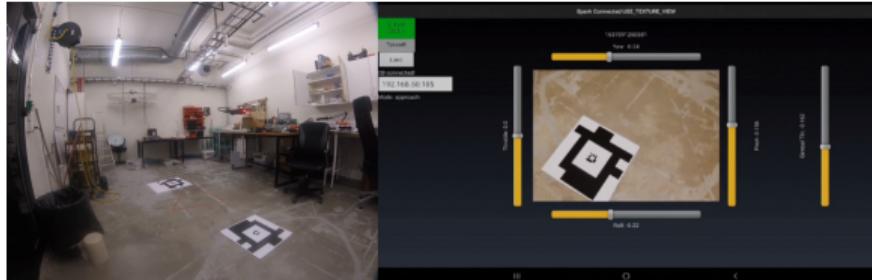


[Click to watch on Vimeo](#)

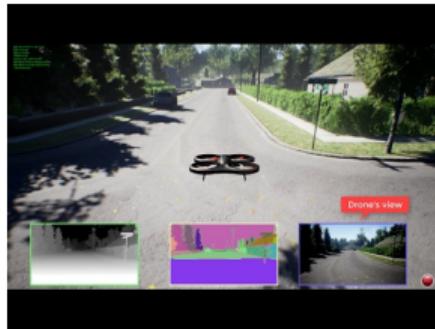


Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR
 - Topological/semantic terrain analysis
 - Synthetic data
 - Testing in simulation
 - Real world tests: power/framerate
 - Real world tests: landing with a physical drone

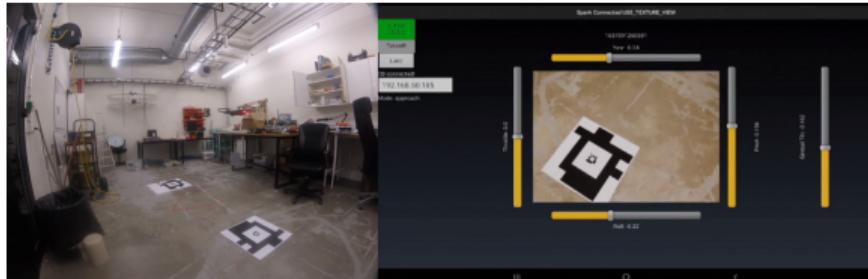


[Click to watch on Vimeo](#)

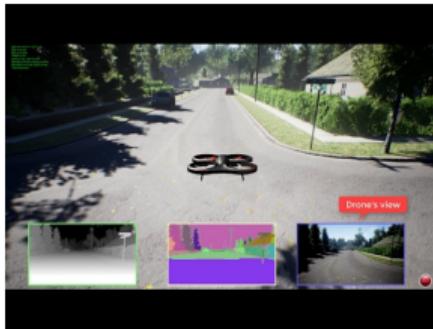


Summary

- Goal: autonomous drone landing
- Past work: landing via fiducial markers at *known* landing pads
 - Contribution: gimbal-mounted camera setup, new marker variants
- Research plan: unstructured landing
 - Sensors: RGBD, LIDAR/RADAR
 - Topological/semantic terrain analysis
 - Synthetic data
 - Testing in simulation
 - Real world tests: power/framerate
 - Real world tests: landing with a physical drone
- Thank you! Are there any questions?



[Click to watch on Vimeo](#)



References

