

# Controlling UAVs with Sensor Input Spoofing Attacks

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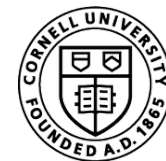
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# This Work In One Slide

- Introduce **sensor input spoofing attacks** to exercise an **implicit control channel** over an autonomous vehicle through its **sensors**
- Demonstrate an instance on **optical flow** for two consumer UAVs
- Propose mitigation techniques through **robust algorithms**

# Outline

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# Pop Quiz

**What is This?**



- ✗ A tile floor
- ✓ An *image of* a tile floor



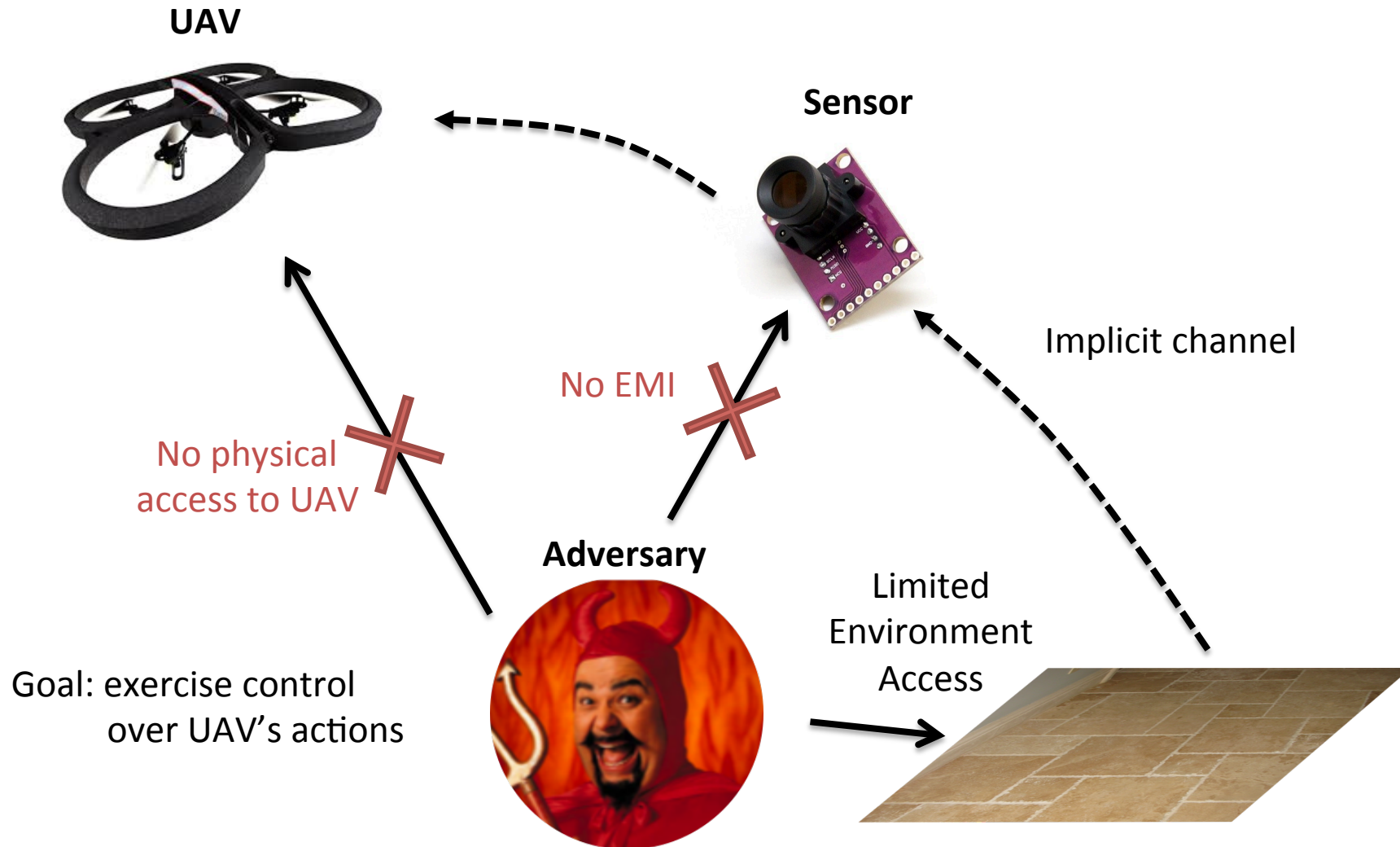
# What Happens if you Fool a Sensor?

- Depends on how sensor is deployed
- Autonomous Vehicles
  - Self-driving cars (Google car)
  - UAVs (Drones)
    - Safety critical
    - Commodity sensors
    - Widely used
- Our work:
  - (To our knowledge) first to exercise **continuous control** over UAV motion

Our focus



# Sensor Input Spoofing Attacks

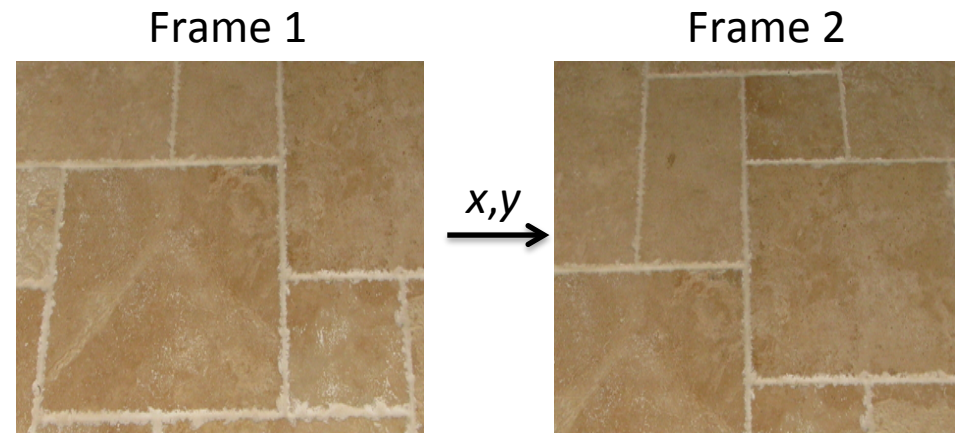


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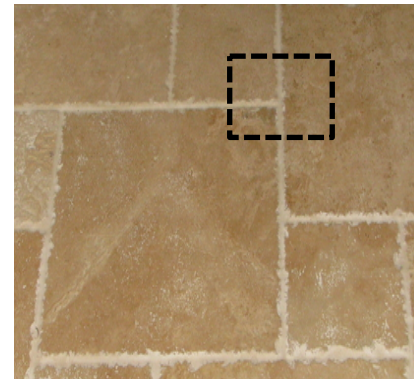
# Background: Optical Flow (OF)

- Goal: quantify motion between two temporally similar images
- Use in UAVs: lateral stabilization
  - Sensor: downward-facing camera
    - High framerate
    - Low resolution
- Sensor detects motion  $(x,y)$ 
  - UAV assumes drift  $(-x,-y)$
  - Corrects with motion  $(x,y)$



# Background: Feature Extraction

- *Sparse* OF – only tracking features rather than each pixel
- Classic: Shi-Tomasi **corner** detection
  - Sharp intensity falloff along both x and y dimensions



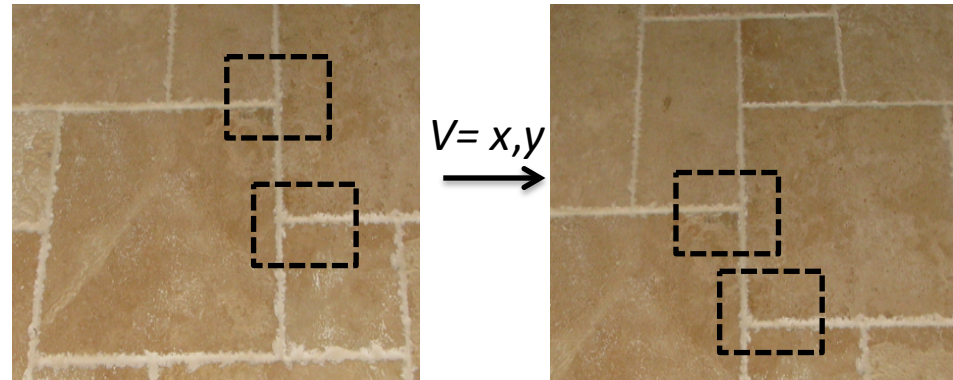
# Background: Sparse Lucas-Kanade

- Produce feature motion vector

$$V_1, \dots, V_n$$

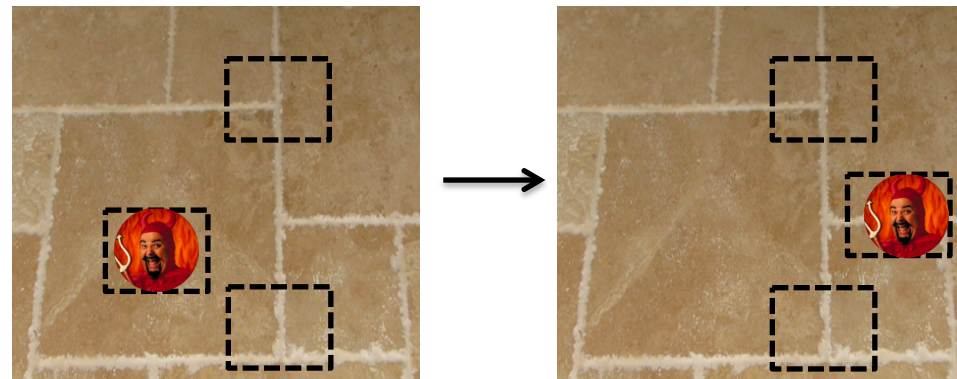
for each of the  $N$  features

- Final motion pair  $V$  is component-wise mean of  $V_1, \dots, V_n$



# Attack: Key Idea

- Adversary-controlled features
- Move *features* in the image by  $(x,y)$ 
  - UAV thinks the features are stationary and **it** is drifting by  $(-x,-y)$
  - UAV “corrects” by matching the adversary’s motion  $(x,y)$

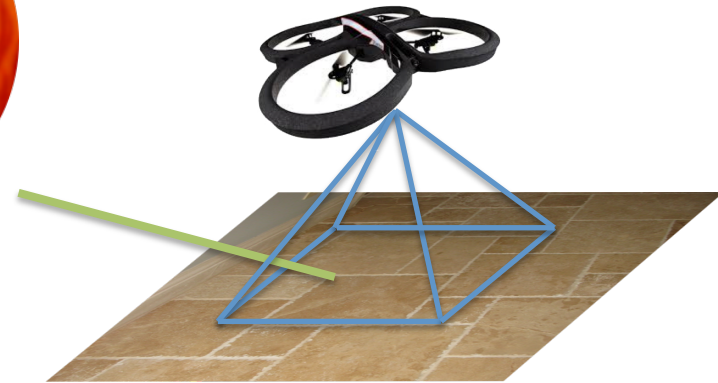


# Attack: Creating Features

- Project light onto the OF sensor's plane
  - Scenario 1: portable projector



- Scenario 2: laser pointer + filter







# Attack Evaluation: Methodology

- 2 popular UAVs
  - ArduCopter – open source control software, popular amongst UAV enthusiasts, primarily for outdoor use
  - AR.Drone 2.0 – closed source, popular amongst hobbyists, some use in professional indoor settings
- 4 real-world environments
  - Tile
  - Carpet
  - Grass
  - Concrete



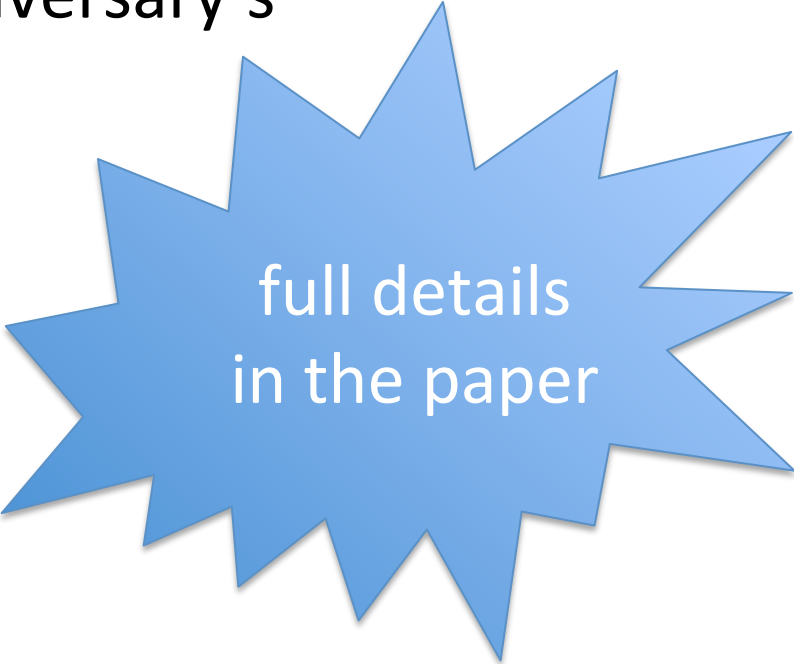
# Attack: Evaluation

Environment	Illuminance (lux)	ArduCopter			AR.Drone		
		Benign	Projector	Laser	Benign	Projector	Laser
Tile	200	Drift	Fail	Control	Drift	Fail	Control
Carpet	150	Drift	Fail	Control	Drift	Fail	Control
Concrete	138	Stable	Control	Control	Stable	Control	Control
Grass	438	Stable	Fail	Fail	Stable	Fail	Fail

- Portable projector
  - Only works in low-light at close range
- Laser pointer
  - Effective in all but the most feature-rich environments
  - Unbounded motion
  - Rapid enough motion with AR.Drone to cause damage to UAV

# Attack: Refinement

- Performed experiments in simulation and practice
- Considered the effect of adversary's
  - feature light intensity
  - feature pattern
  - feature shape
  - feature size



full details  
in the paper

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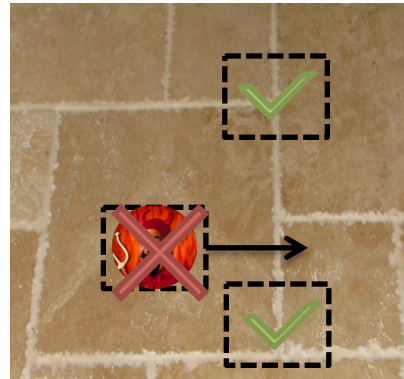
# Defenses

- Enhance OF to deal with adversarial features
- Intuition: address the algorithmic limitations of sparse-LK in OF



# Random Sample Consensus: RANSAC

- Assume data contains correct “inliers” and bad “outliers”
- Randomly sample  $k$  features, each with a “motion hypothesis”
  - Other features vote for each hypothesis based if their own motion is close
- Use the winning hypothesis



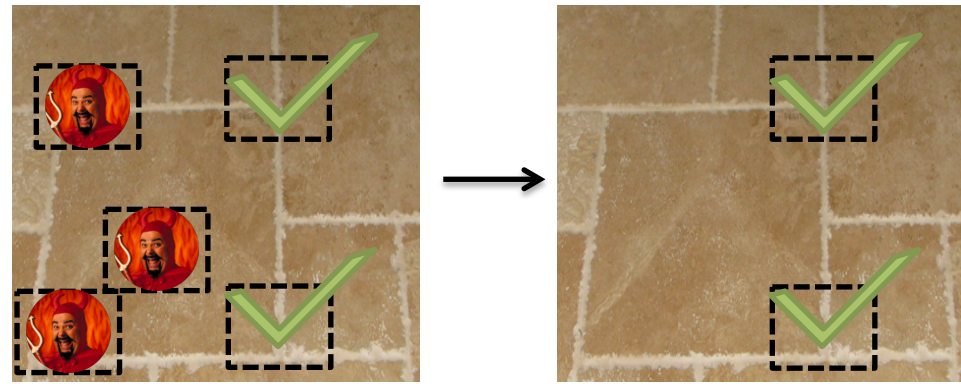
Breaks down when  
the adversary  
overwhelms  
benign features

Works when  
adversary lacks  
majority of  
features



# Weighted RANSAC w/ Momentum

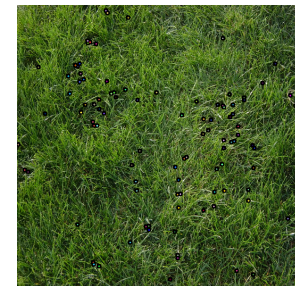
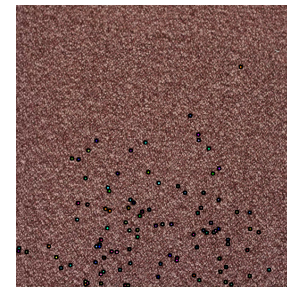
- Goal: assign more weight to trusted features
  - Features accrue weight
  - Fits the scenario of attacker entering scene
- Smaller number of trusted features can still form correct hypothesis





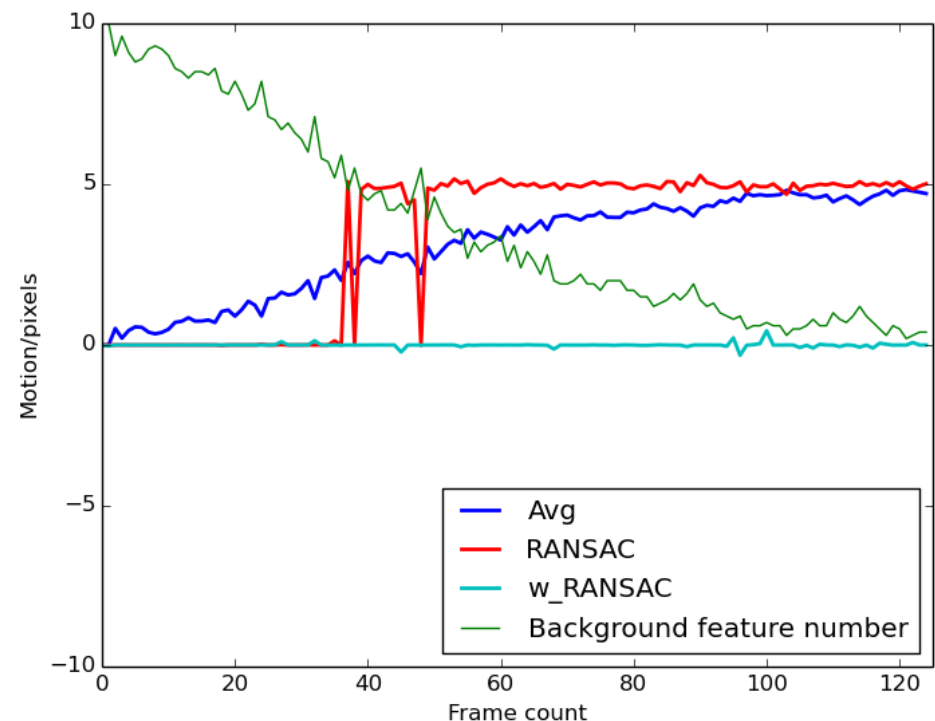
# Defense Evaluation: Methodology

- Evaluation via simulation
  - Add moving grid of laser “dots” across real image frames
- Several environments
  - Asphalt
  - Carpet
  - Grass
- Used the strongest adversary from our attack strategy



# Evaluation

- Tested three variants:
  - Lucas-Kanade (avg): blue
  - RANSAC: red
  - Weighted RANSAC: teal
- LK moves reliably
- RANSAC initially strong until overwhelmed
- WRANSAC fairly steady

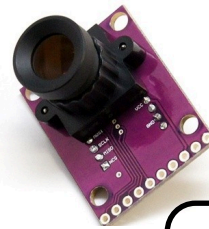


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# Sensor Firmware Robustness

- RANSAC and Weighted RANSAC are a good first step
  - Likely much better performance to be had
- Key insight: safety-critical sensors need to go beyond random noise

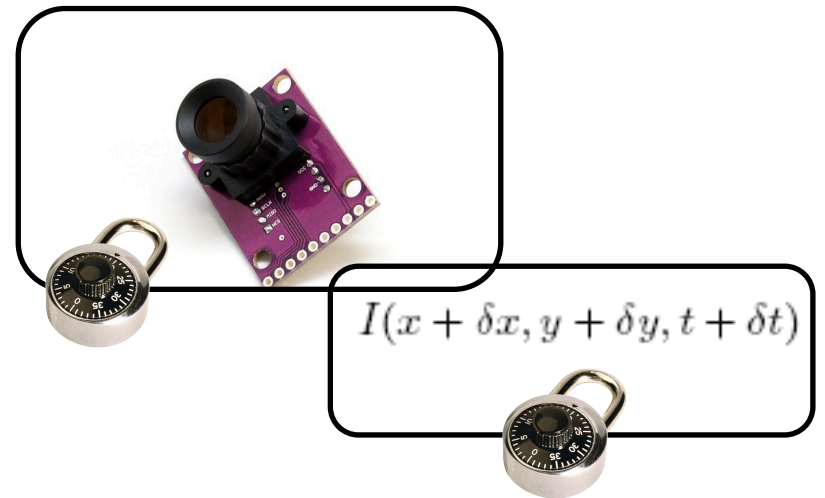


$$I(x + \delta x, y + \delta y, t + \delta t)$$



# Hardware-level Robustness

- Better cameras mean more features
  - More features complicate the attacker's goal
- IR illumination + IR cameras for low-light conditions



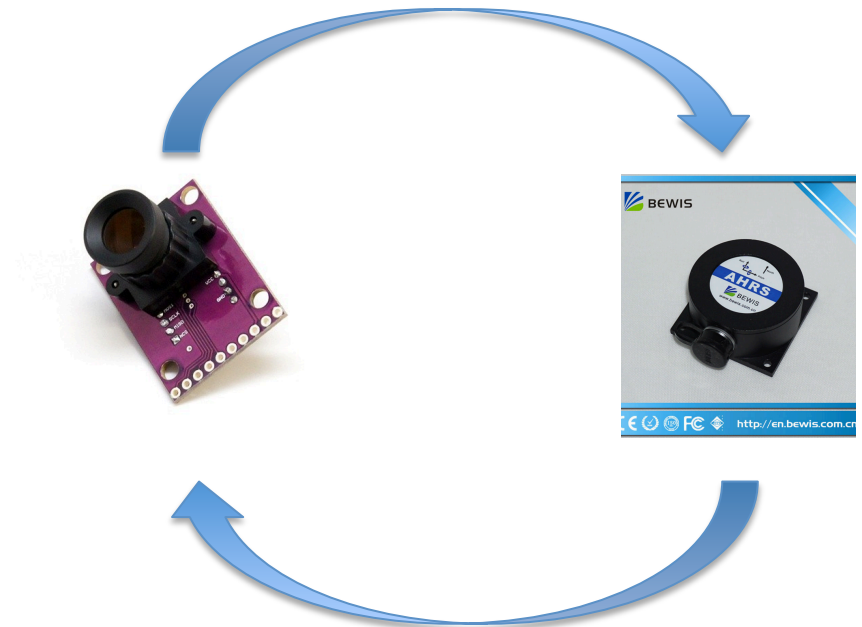
# Beyond Robust Sensing

- Consider a stronger adversary
- The “Sombrero Attack”
  - Adversary obscures the entire ground plane
  - Beyond the limits of algorithmic hardening



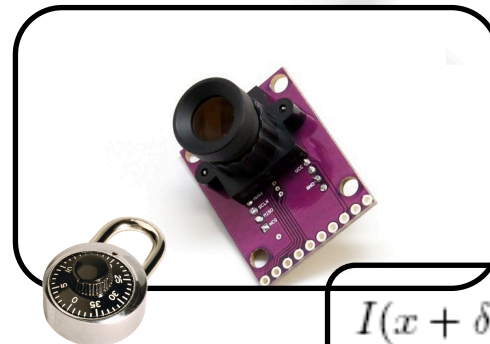
# Sensor Fusion

- Consider *plausible input* requirement
  - Cross-check the results of multiple sensors
  - Drift should be accompanied by acceleration



# Future Work: Verifying Sensor Fusion

- Dataflow on firmware
  - Sources: function containing sensor reading
  - Sinks: function containing response
- Policy for desired sensor fusion
- Prototype static analysis on LLVM



$$I(x + \delta x, y + \delta y, t + \delta t)$$



## Future Work: Considering other SISAs

- Combine SISA with jamming attacks from the literature
- Attack other sensors

# Summary

- Introduced Sensor Input Spoofing Attacks on passive sensors
- Crafted attack against Optical Flow on two commercial UAVs
- Developed defenses with robust algorithms
- Recommended future work by hardening the entire sensor pipeline

# Thanks

- Questions?
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