ROBUST INDOOR LOCALIZATION ON A CELL PHONE

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Sponsored by

Motivation

- Why indoor localization?
  - Navigating malls, airports, office buildings
  - Museum tours, context aware apps
  - Augmented reality and games
- Why cell phones?
  - Off the shelf hardware is more capable and cheaper
  - Vast array of sensors
  - Low barrier to entry

Scenarios

Capability	System Requirements
1. Tell a lost person where he or she is.	Automatic initialization
2. Guide a person to within sight of a target.	Room-level, ~10 meter accuracy

Localization Techniques

- **Dead Reckoning** – *Integrate measurements of motion*
  - Common in robotics via gyroscopes and wheel odometry
  - Shoes, helmets, and wearable modules for human use [Stirling et al. 2003, Beauregard 2006, Randell 2003]

- **Beacon-based** – *Use standard indicators from the environment*
  - Wifi, GPS, GSM, ultrasonic, RFID
  - Signal strength fingerprinting, time difference of arrival, angle of arrival

Cell-Phone Localization

- “Dead Reckoning from the Pocket” [Steinhoff, Schiele 2010]
- “Advanced Integration of WiFi and Inertial Navigation Systems for Indoor Mobile Positioning” [Evennou, Marx 2006]

- Contributions
  - Incorporation of magnetometer sensor for global orientation
  - Variance threshold method for detecting movement
  - Faster, higher density, and more accurate signal strength database using a robot to collect data
  - Implementation on cell phone rather than custom platform

Platform

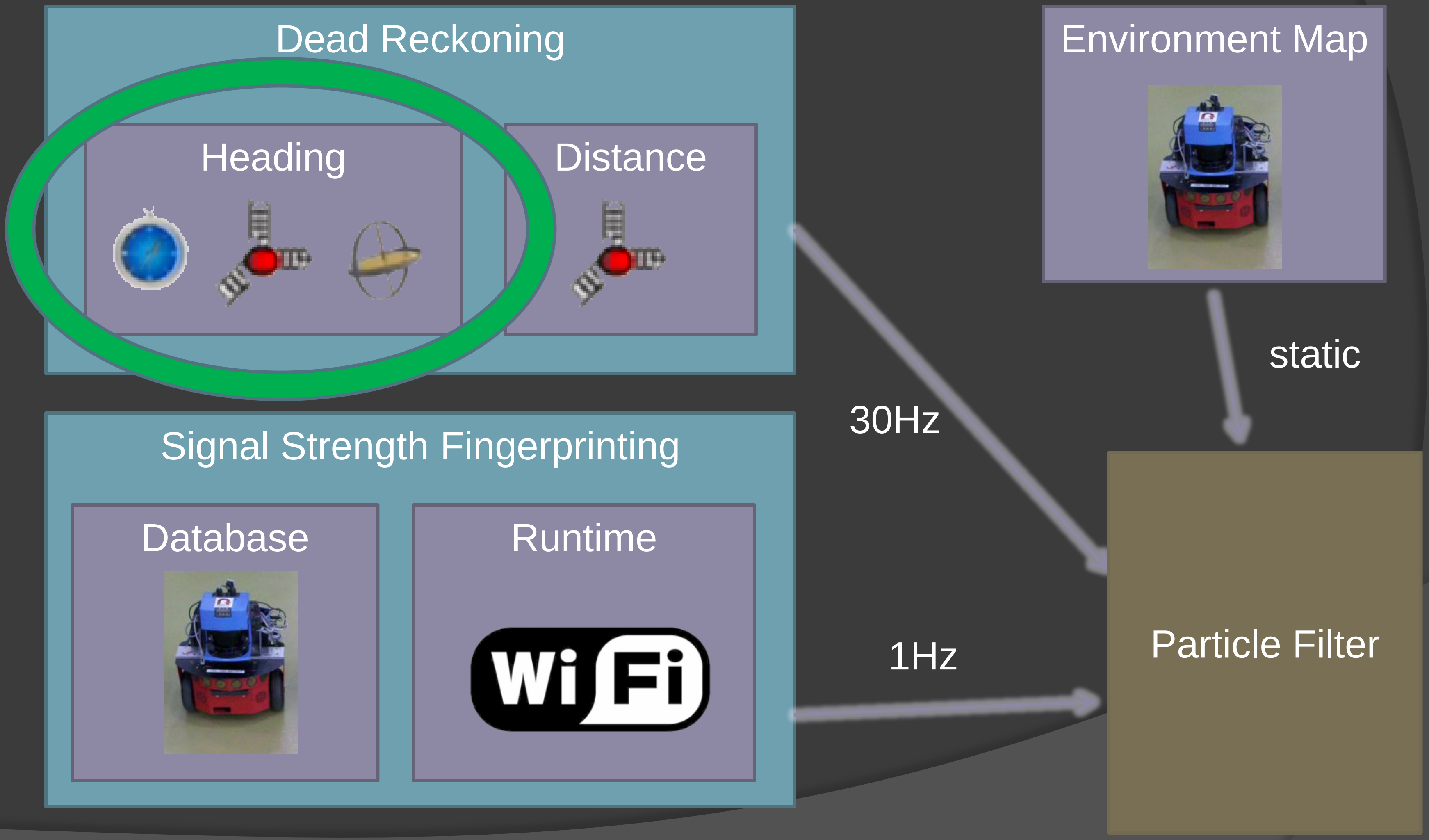
Current:
Google Nexus S

Prior:
Nexus One

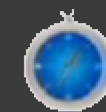
Prior:
G1

Sensor	Quantity Sensed
Accelerometer	gravity + linear acceleration
Magnetometer/ Compass	magnetic field vector
Gyroscope (Nexus S only)	angular rate
WiFi	access point signal strengths

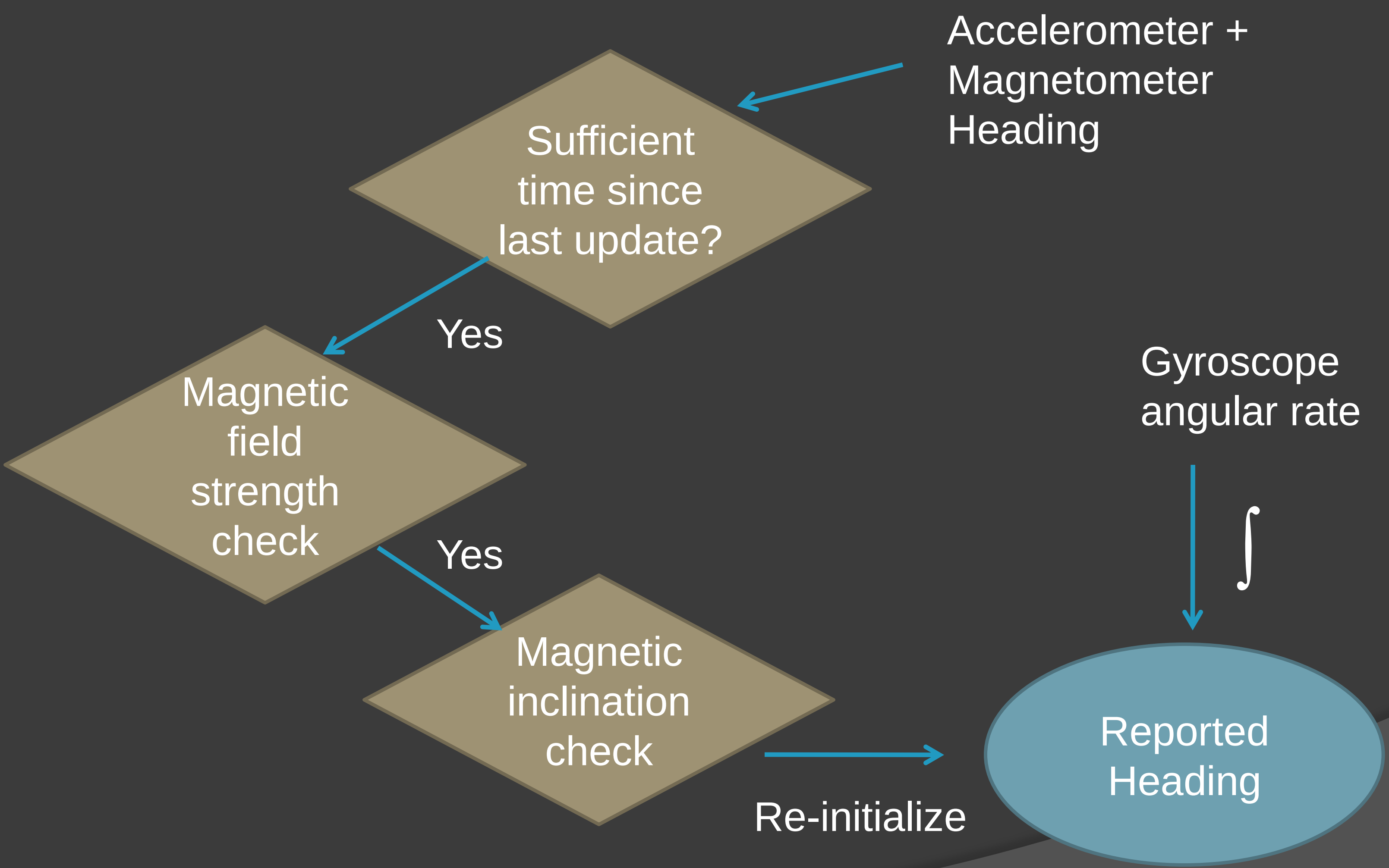
System Architecture



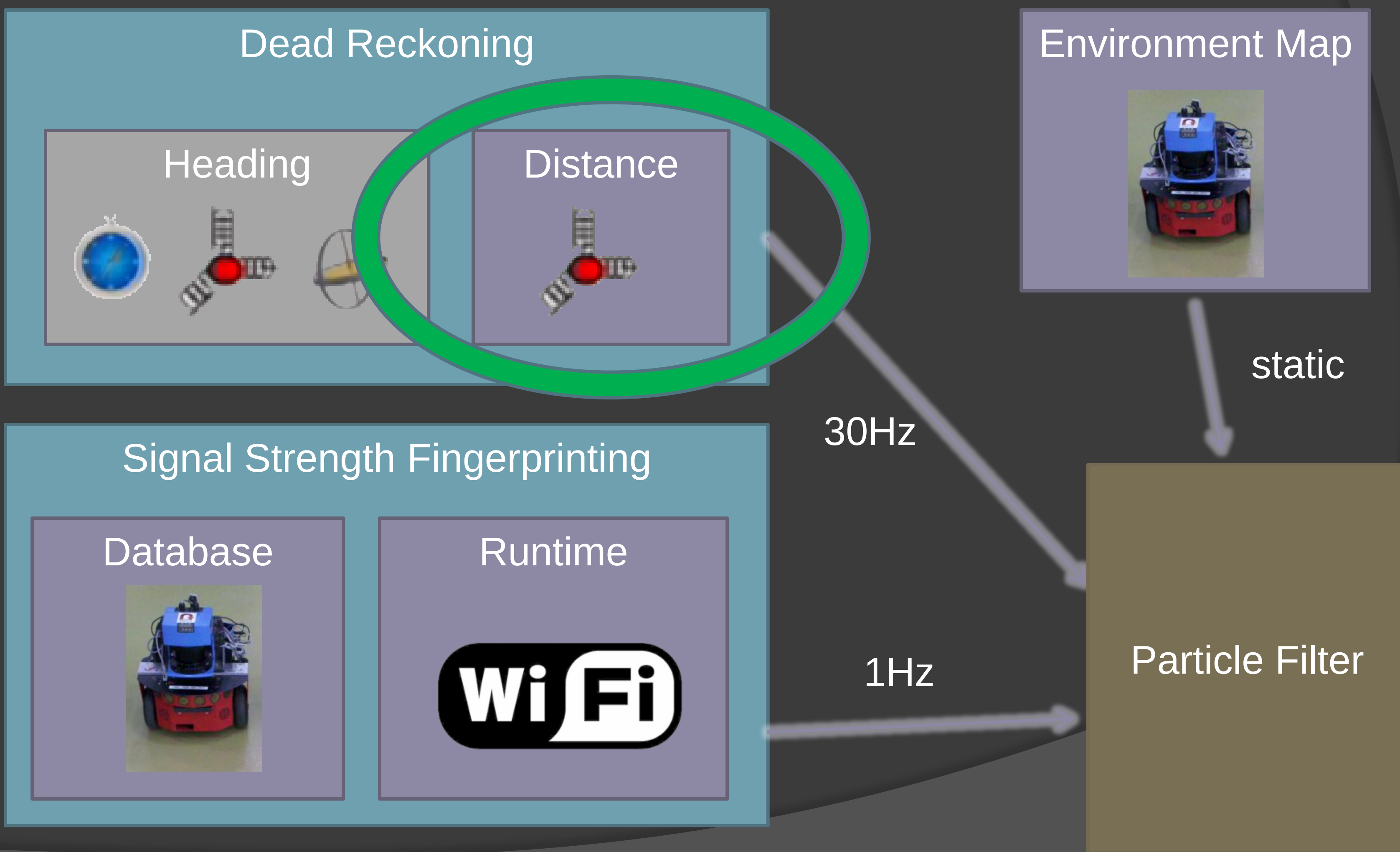
Dead Reckoning - Heading

- Accelerometer  + Magnetometer 
  - ✚ Externally referenced - bounded error
  - ▬ Magnetic interference very common indoors
- Gyroscope 
  - ✚ Low noise and high accuracy
  - ✚ Not susceptible to interference
  - ▬ Error growth is unbounded over time

Dead Reckoning - Heading

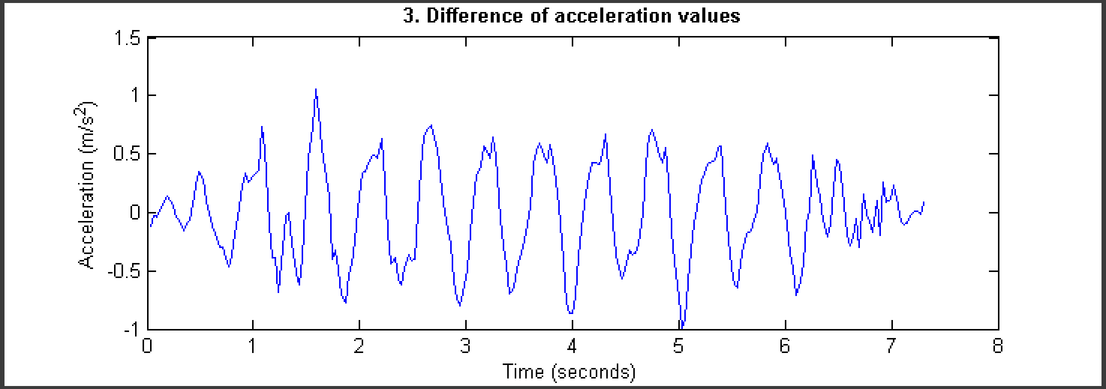


System Architecture



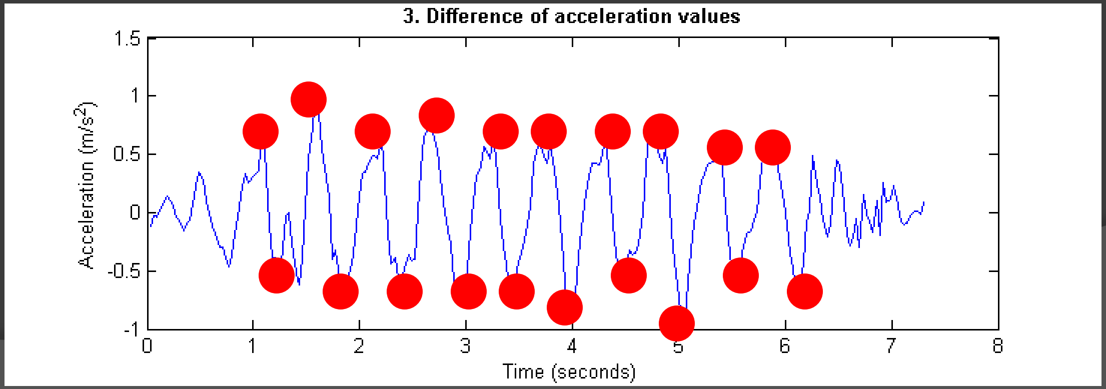
Dead Reckoning – Step Counting

- Peak detection filter [Randell, Djiallis, Muller 2003]



Acceleration

Detect peaks

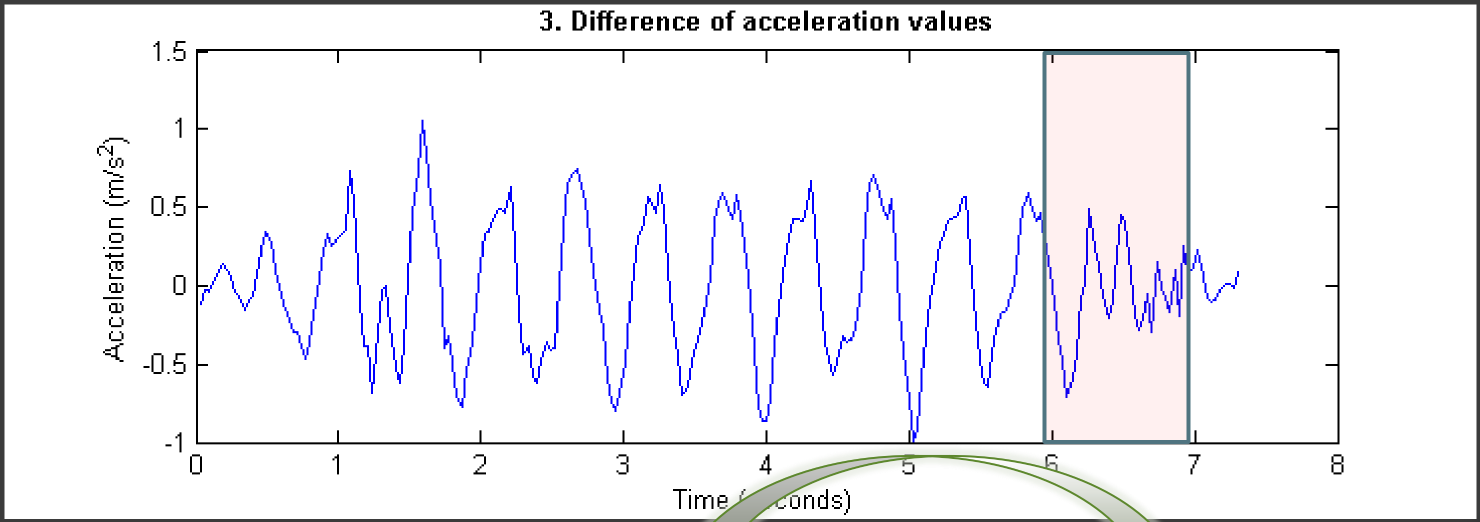


Each pair of peaks corresponds to a step.

Dead Reckoning – Variance Threshold

Calculate running standard deviation for last N measurements or T seconds

Std dev = 12
Std dev = 18



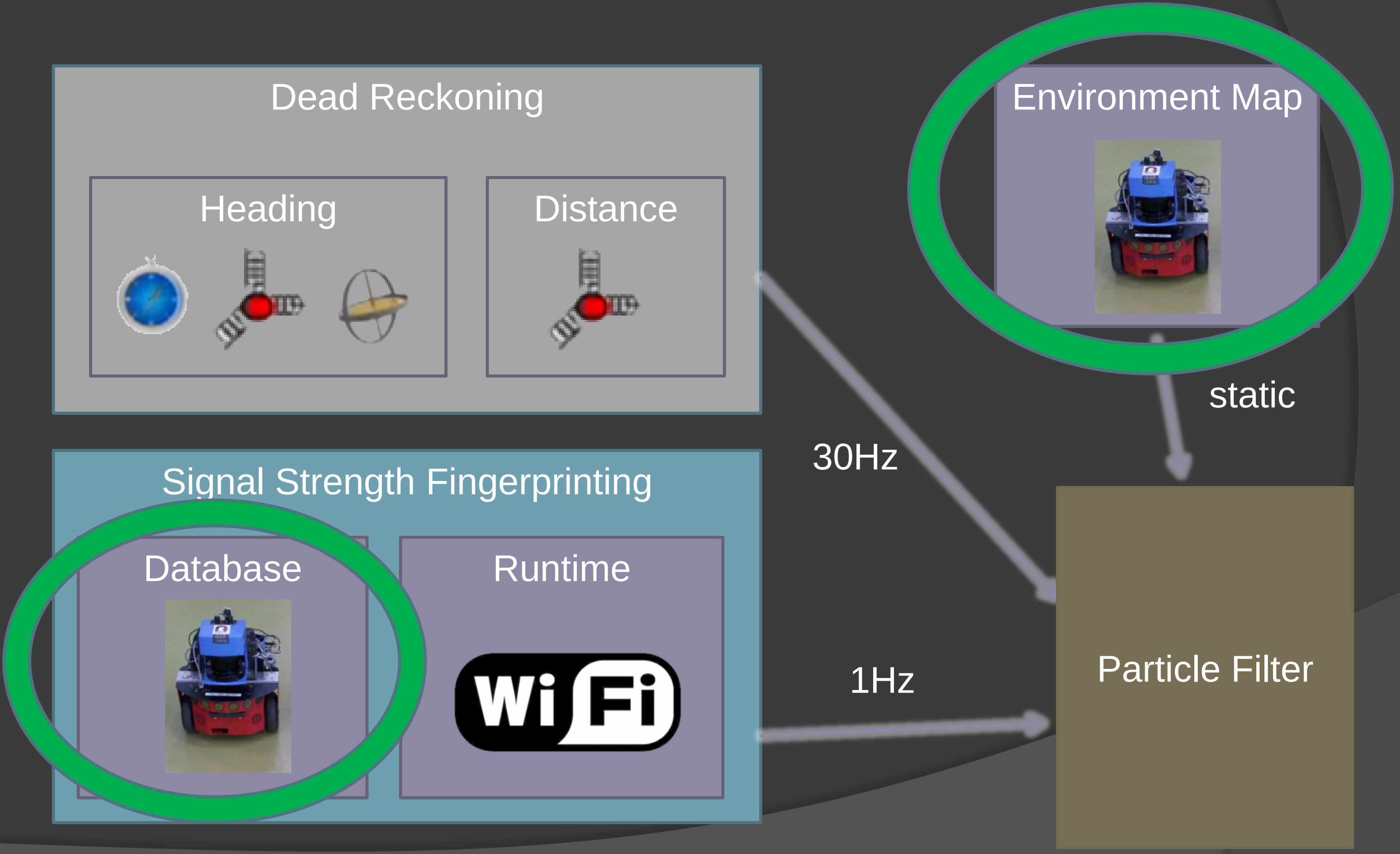
Std. Dev. = 12

<THRESHOLD?

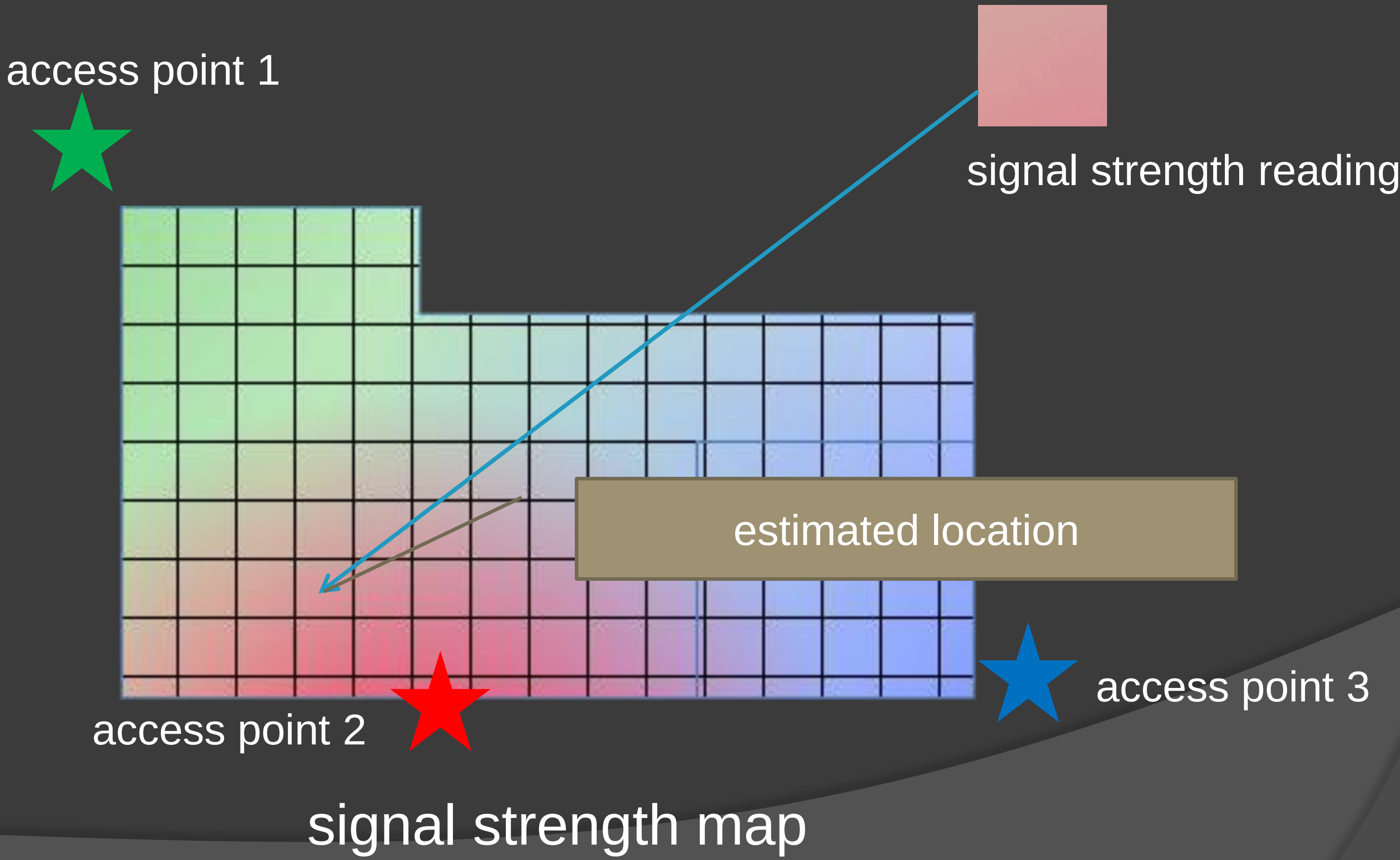
Stopped

Movement State

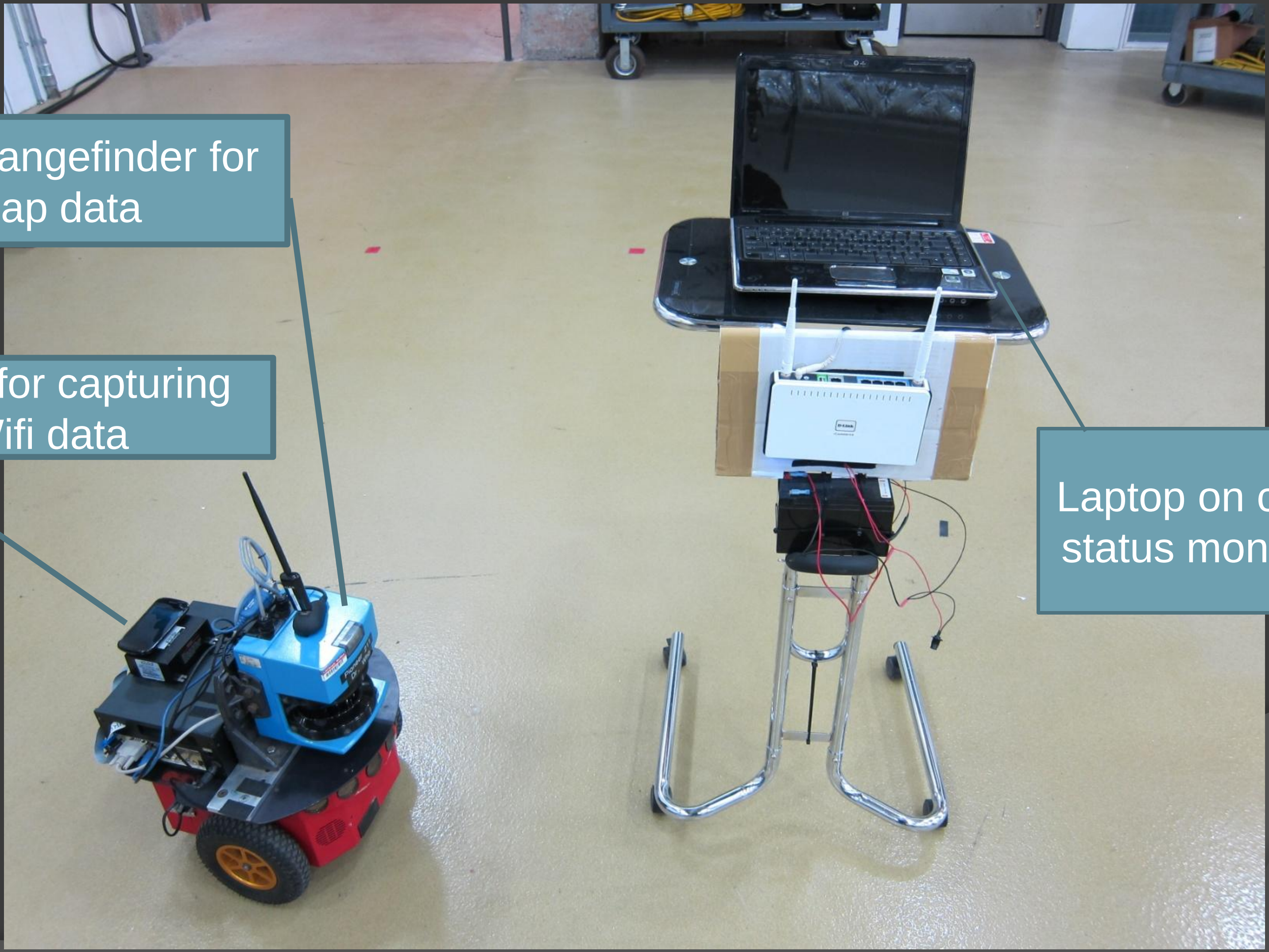
System Architecture



Signal Strength - Overview



Signal Strength - Database

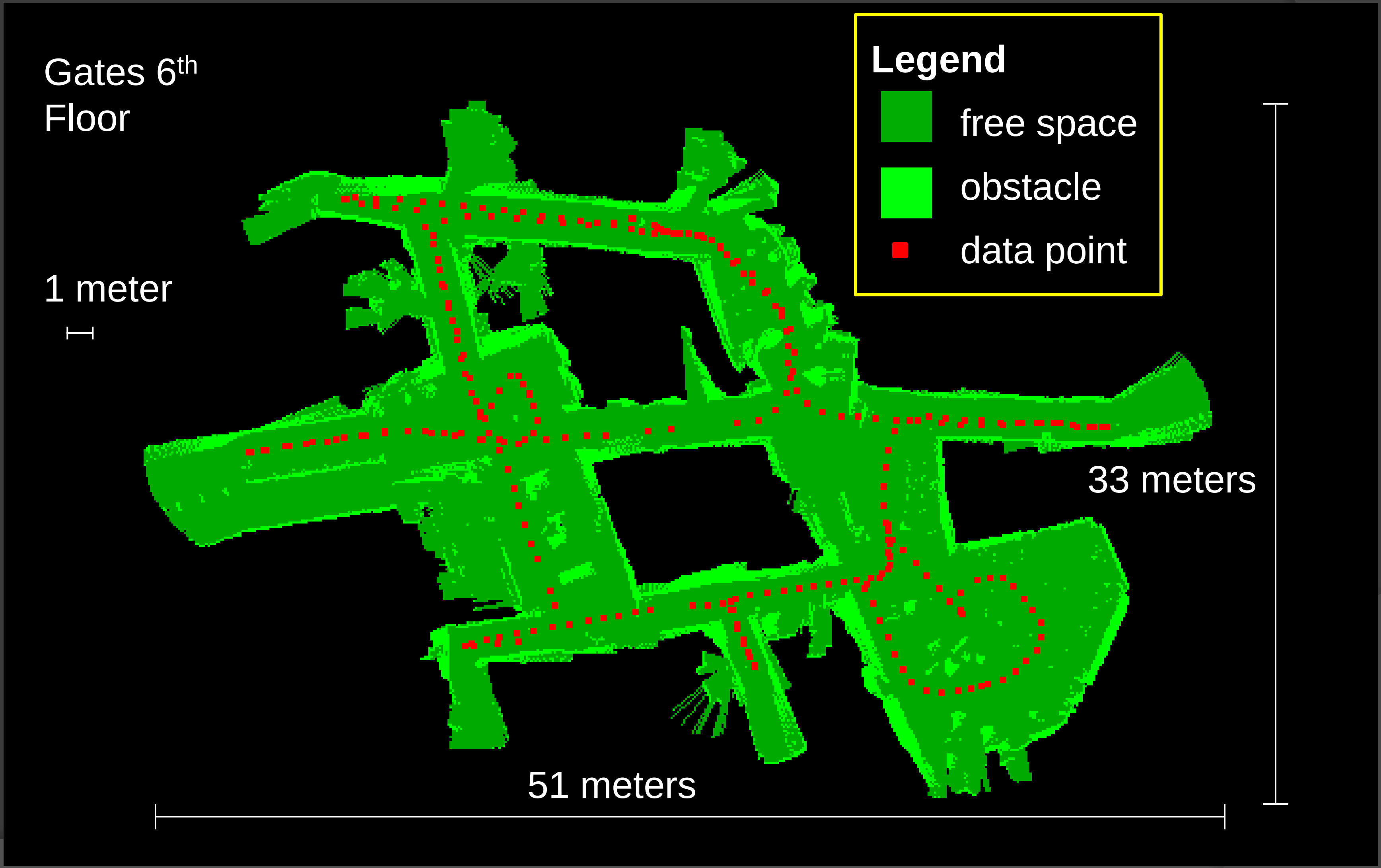


Laser Rangefinder for map data

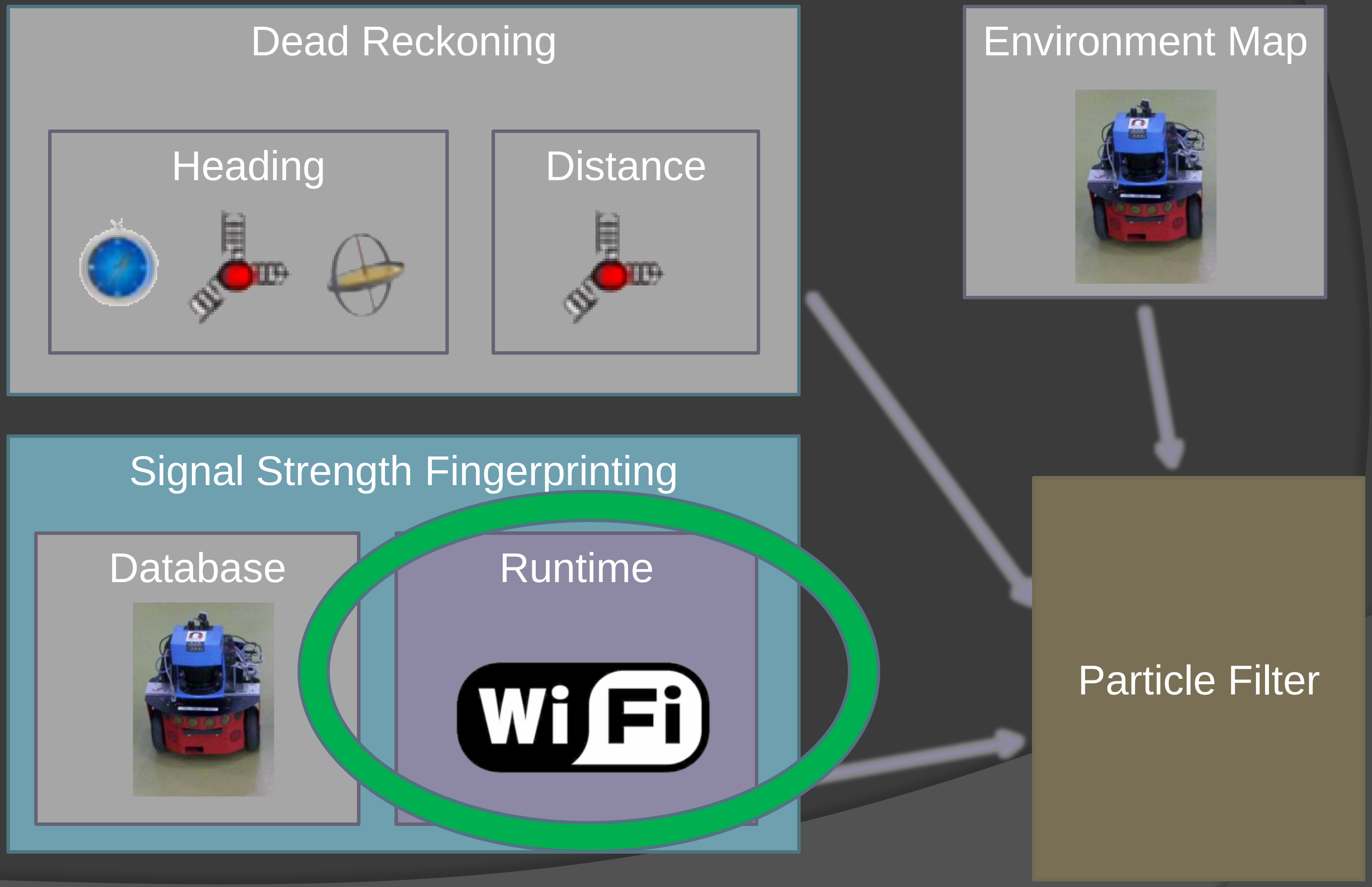
Phone for capturing Wifi data

Laptop on cart for status monitoring

Signal Strength - Database



System Architecture



Signal Strength - Runtime

Measured Reading:

AP1: 53 dBm
AP2: 42 dBm
AP3: 85 dBm

Readings from Database

AP1: 60 dBm
AP2: 0 dBm
AP3: 90 dBm

Dist = 43

signal space distance

signal space distance

Dist = 52

AP1: 45 dBm
AP2: 37 dBm
AP3: 34 dBm

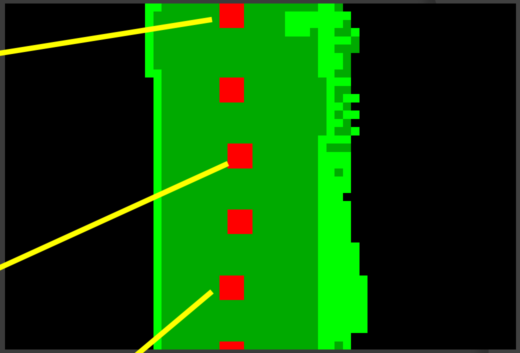
signal space distance

Most similar

Dist = 18

AP1: 41 dBm
AP2: 33 dBm
AP3: 77 dBm

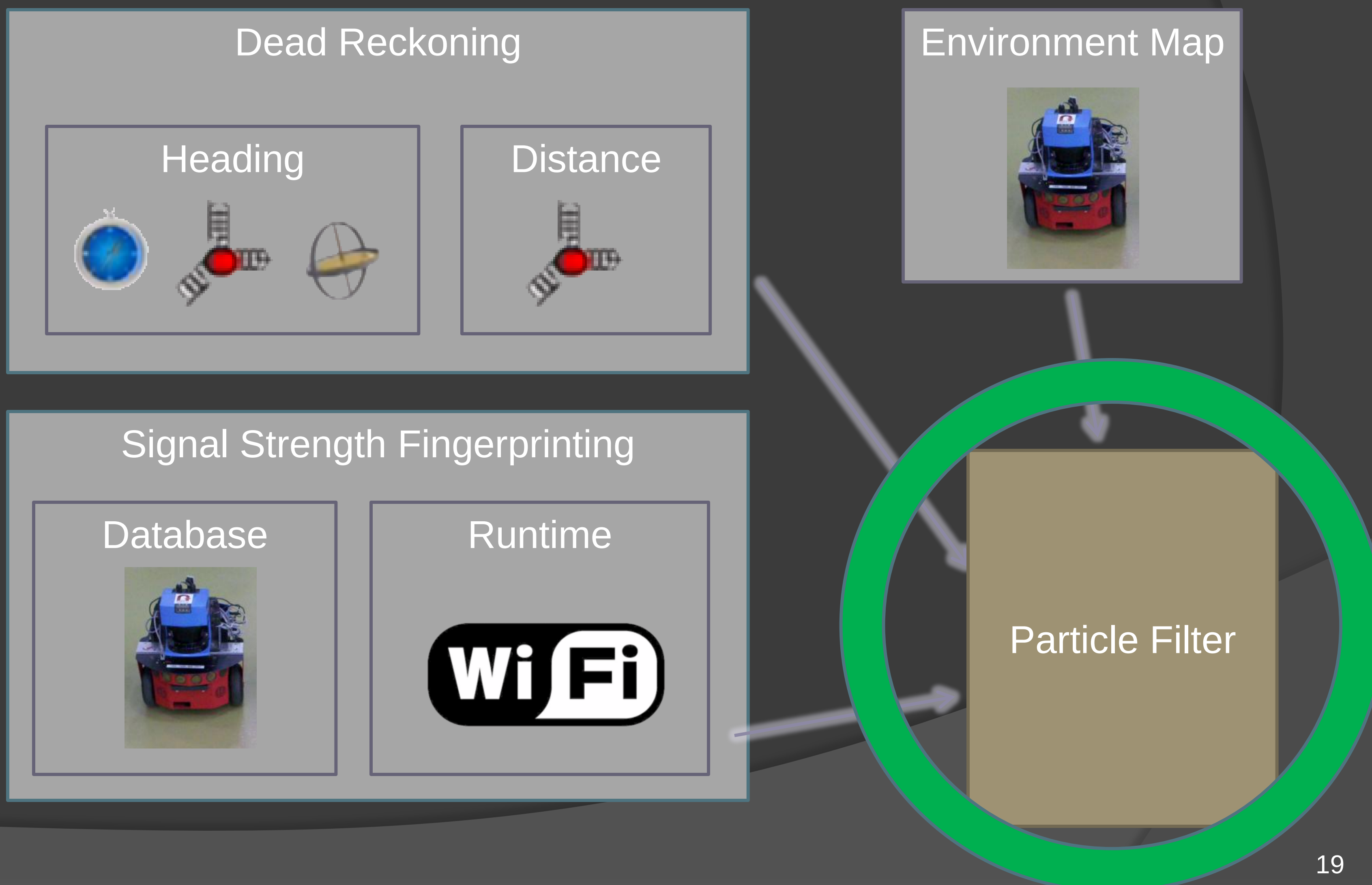
Signal Strength Database



In practice, the distance is calculated as a weighted average of the nearby calibration points to reduce noise.

AP = Wifi Access Point

System Architecture



Particle Filter

- Integrate sources of knowledge in a principled, Bayesian framework
  - Dead reckoning for short term updates
  - Signal strength algorithm to correct for drift
- Enforce map constraints

Particle Filter Algorithm

Initial Distribution: Uniformly random over entire environment

1. 30Hz - Use dead reckoning model to update particles.

   Update Step

2. Remove particles that intersect walls.
   1Hz - When a Wifi reading is received, update particle weights.

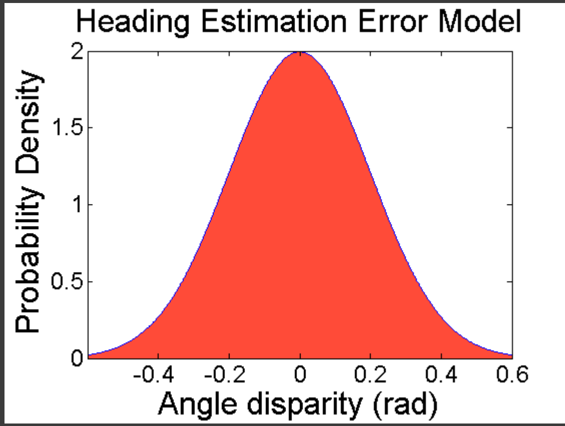
   Importance Estimation

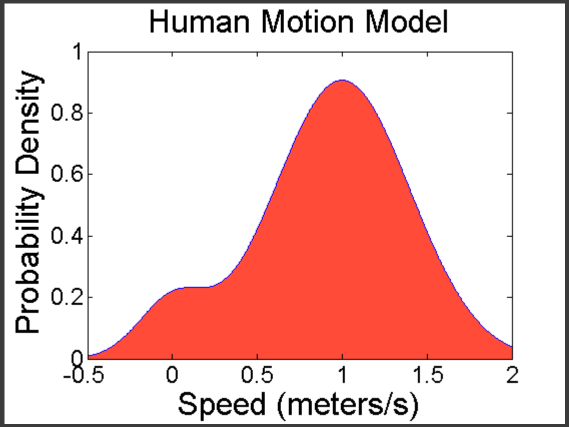
3. 1Hz - Draw, with replacement, a new set of N particles from the old set where the chance of drawing a particle is proportional to its weight.

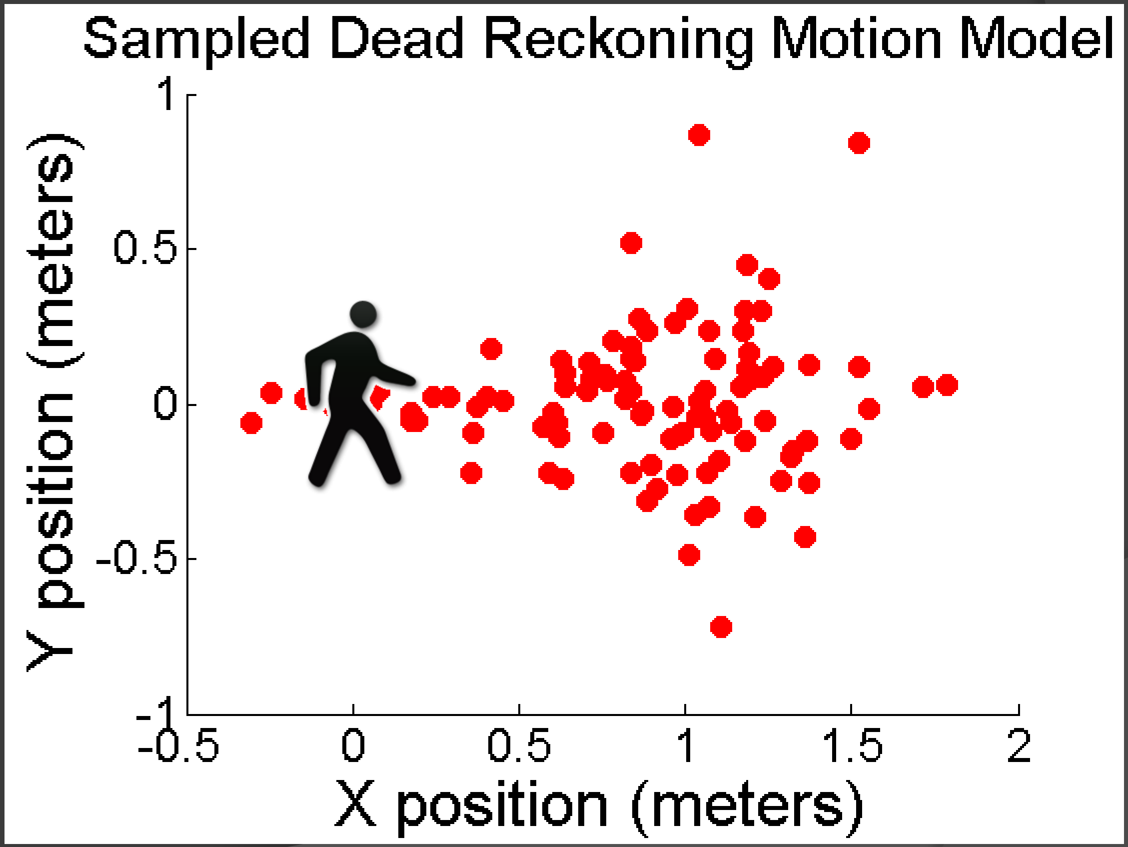
   Resampling

Update Step

Replace each particle with a single new particle drawn from this distribution.

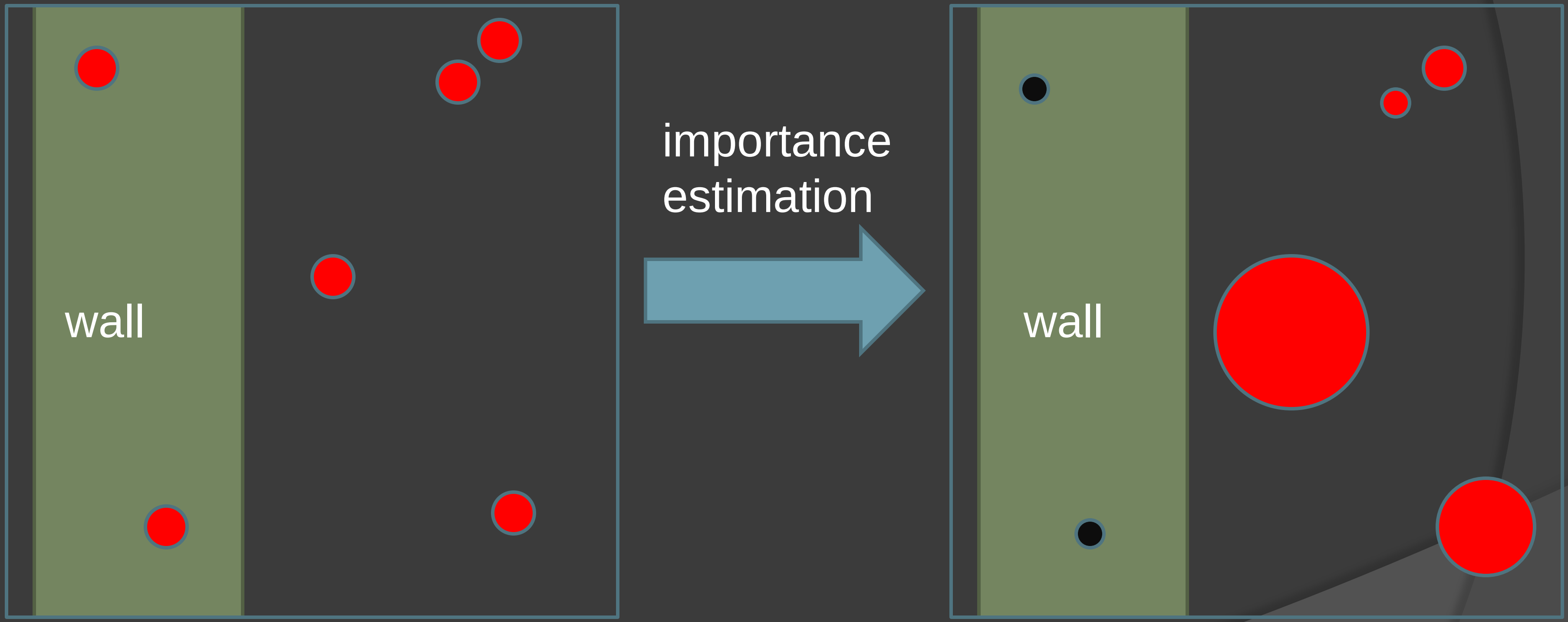






Importance Estimation

1. Remove particles in walls
2. Re-weight particles based on signal strength readings

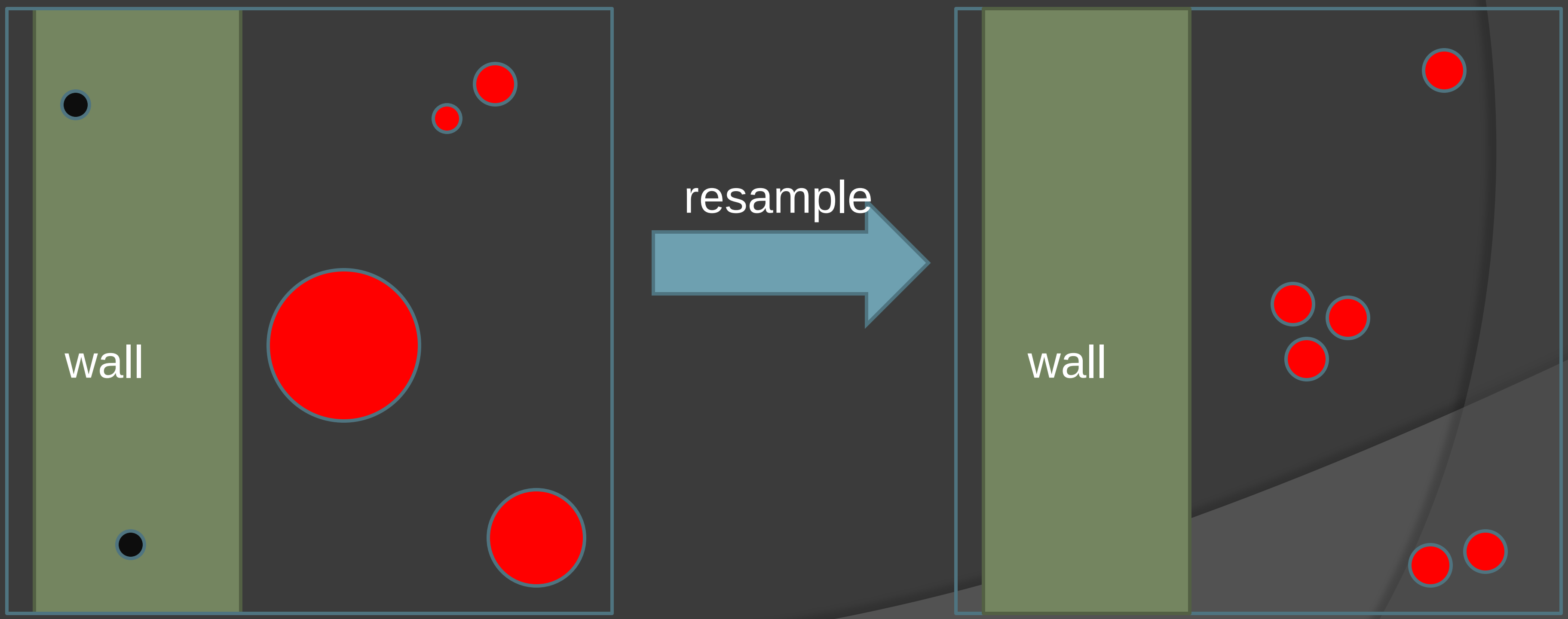


Before importance estimation step

After importance estimation step

Resampling

- Draw, with replacement, a new set of particles where the chance of drawing a particle is proportional to its weight.



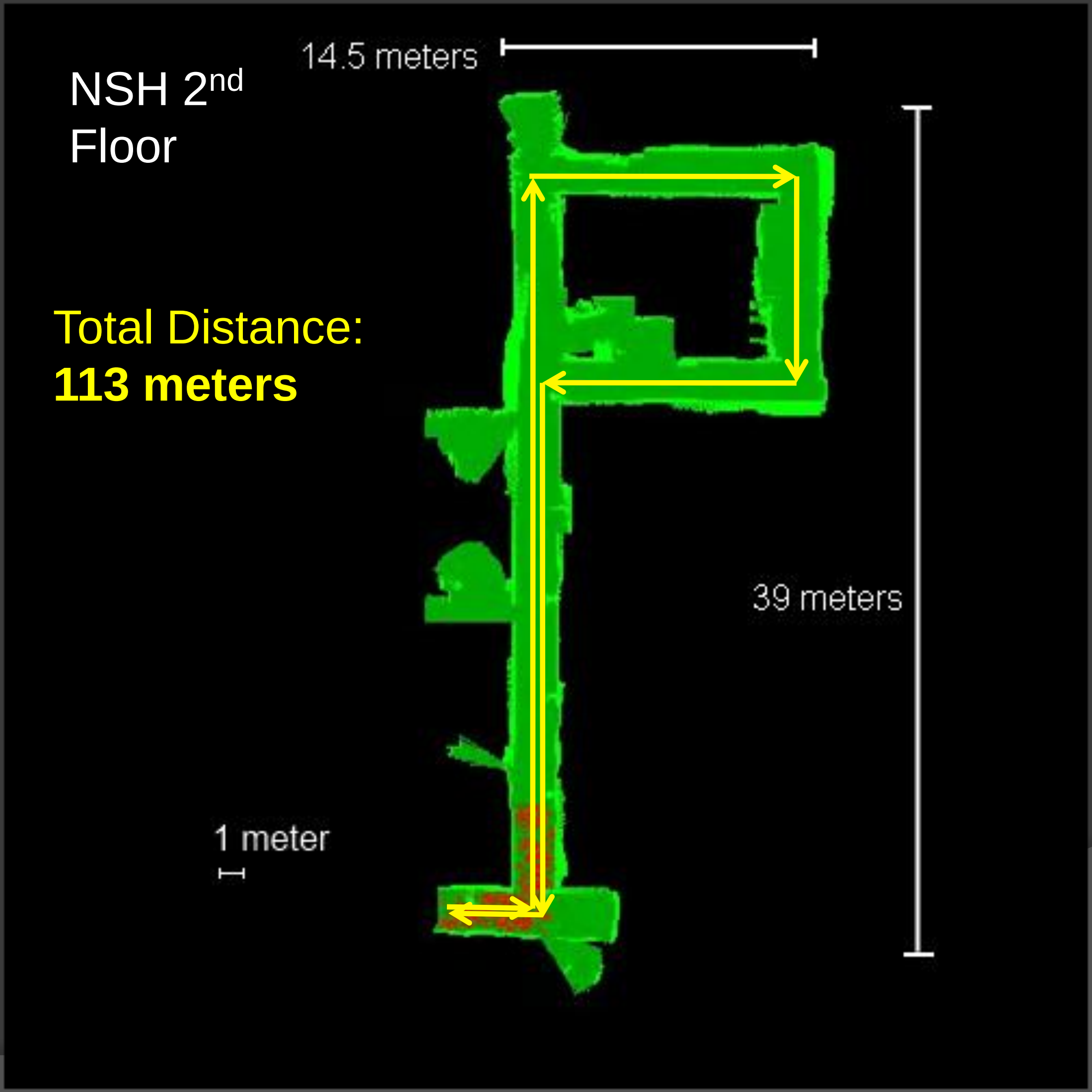
Before resampling step

After resampling step

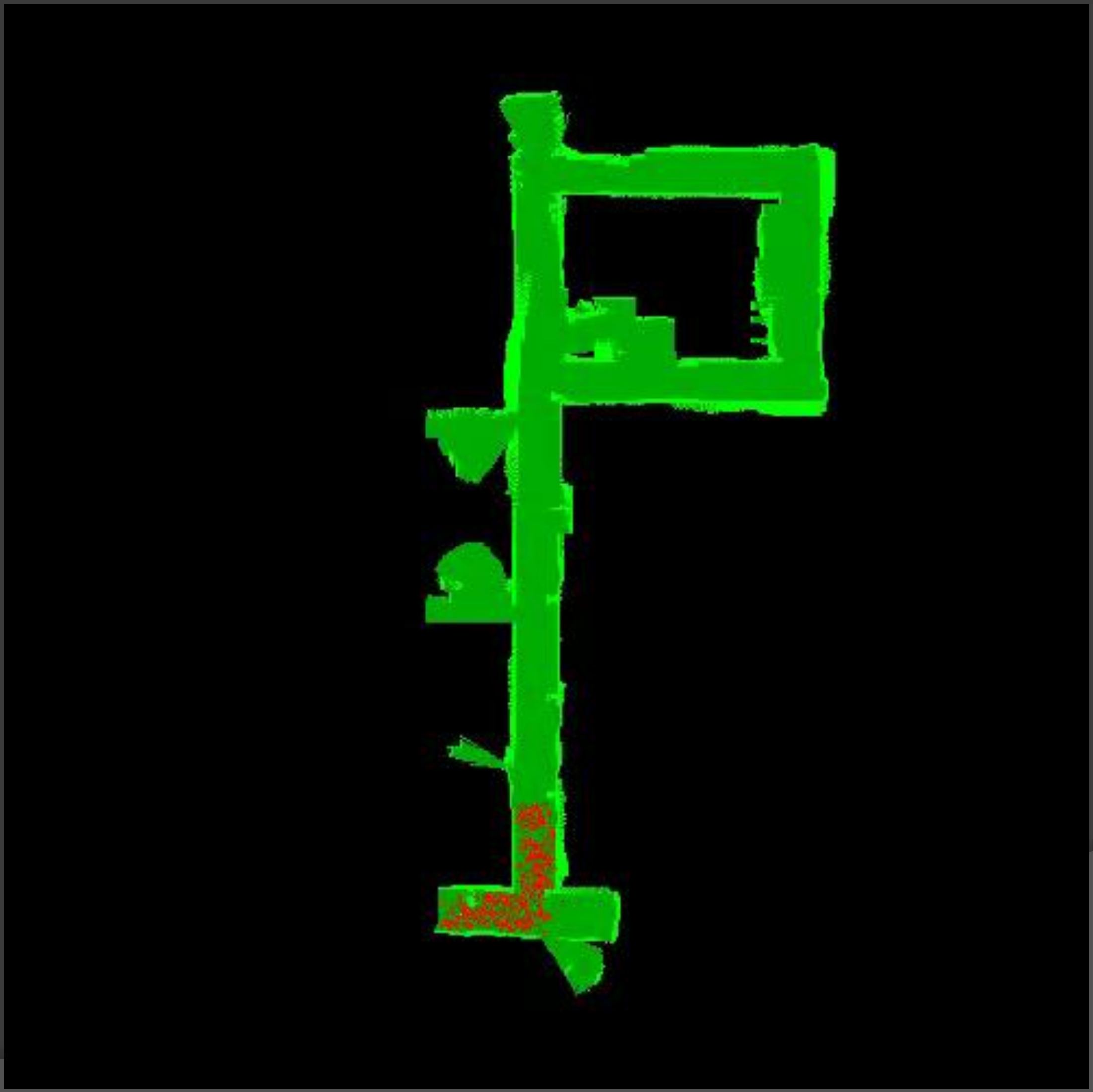
Experimental Design

- 2 indoor environments (Gates 6th floor and NSH 2nd floor)
- A pre-selected closed loop for each environment
- 5 participants, 3 runs / participant
- Ground truth estimated using the known path and a constant speed assumption

Results – Dead Reckoning Only



Results – Dead Reckoning Only



Results– Dead Reckoning and Wifi

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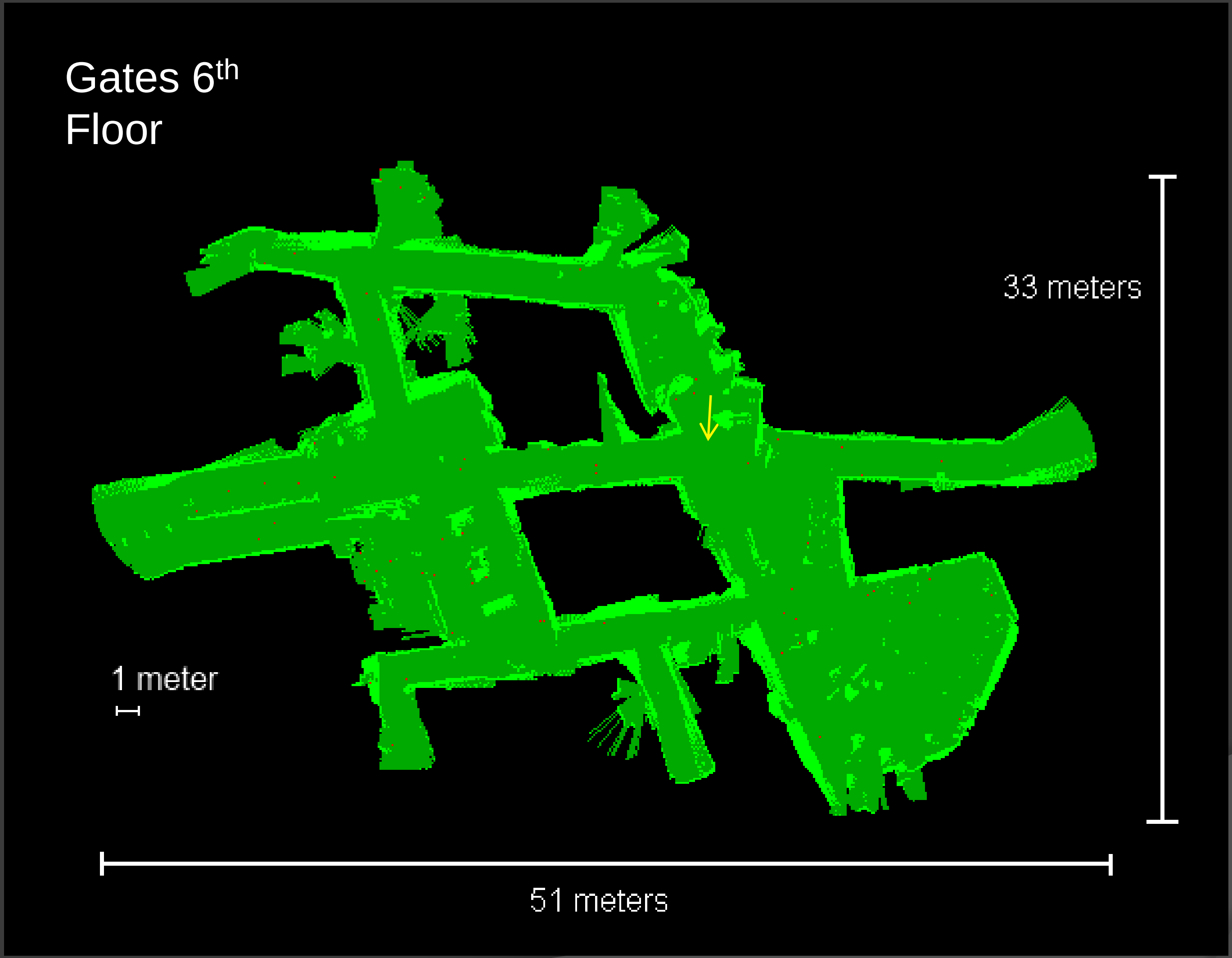

Results – Data

	Mean Error of Most Probable Location*		***Additional Features***	
	Newell-Simon 2nd Floor	Gates 6th Floor	*Automatically initializes position*	*Error bounded over time*
Dead Reckoning only	7m	6m	No	No
Wifi only	12m	10m	Yes (<5 sec)	Yes
Dead Reckoning with Wifi	7m	7m	Yes (<5 sec)	Yes

*Determined by finding the point with the most particles within a 1m radius
*First 5 seconds excluded to give the filter time to converge

Scenarios

Capability	System Requirements
1. Tell a lost person where he or she is	Automatic initialization
2. Guide a person to within sight of a target	Room-level, ~10 meter accuracy

Conclusion

- Useful indoor localization is possible on a cell phone.
- Achieving reliability requires multiple, redundant sensors.

Future Work

- Incorporate other sensors
  - Camera [Se, Lowe, Little 2001]
  - RFID / Near-field Communication
  - GSM [Otsason et al. 2005]
- Extended Kalman Filter for heading estimation
- Test over longer periods and multiple floors
- Build complete applications using localization capability

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Questions?

References

- Ross Stirling, Jussi Collin, Ken Fyfe, and Gérard Lachapelle. “An Innovative Shoe-Mounted Pedestrian Navigation System” *Proc. European Navigation Conf. GNSS,* 2003, pp. 22-25.
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