Proactive Indoor Navigation using Commercial Smart-phones

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Chet Gnegy, Evan Glasgow and Piotr Yordanov

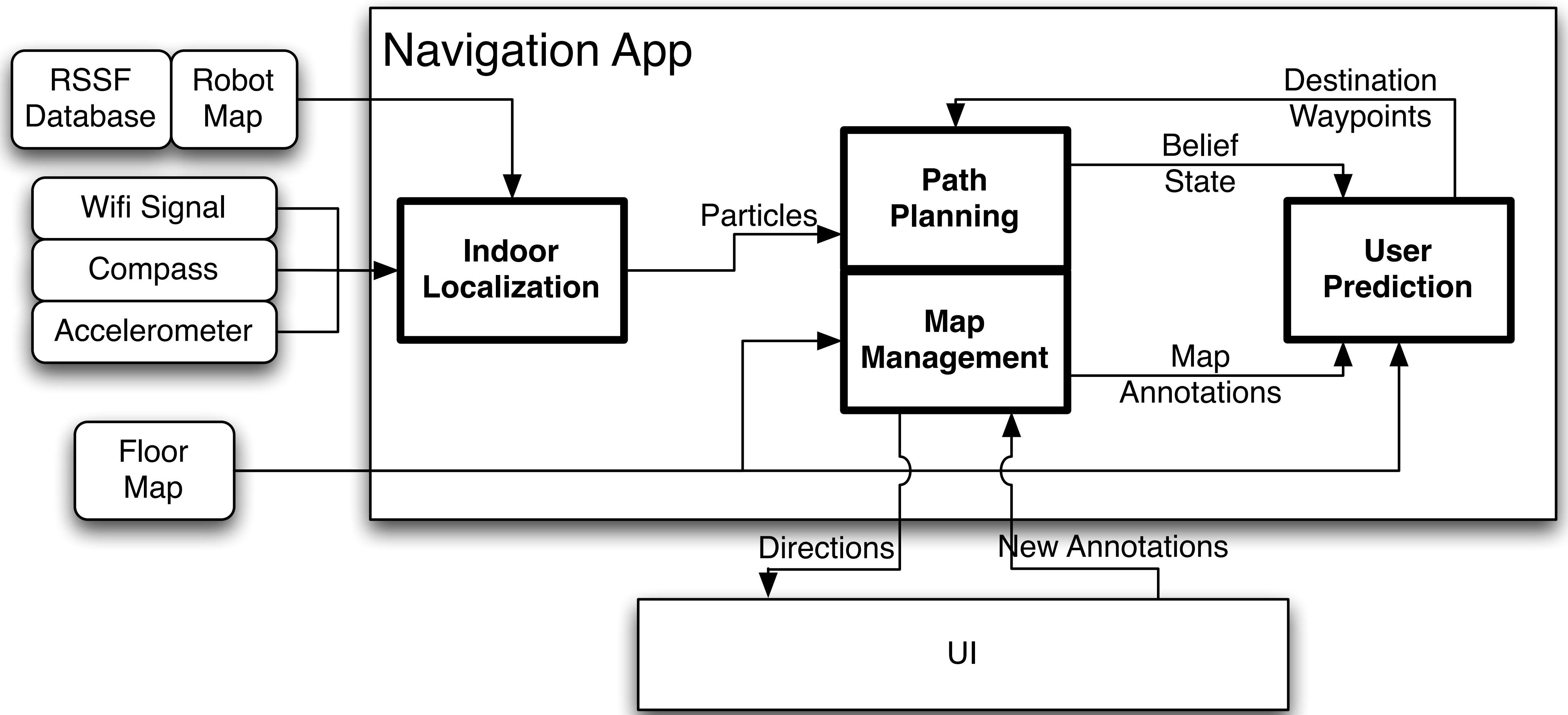
Background and Outline

- Why did we build that app? “Google Core AI”@CMU
  - Challenge to create **usable** AI components for an App library
  - Involving **producers** and **consumers** to motivate application
- Two components produced for a Proactive Indoor Navigation App
  - Indoor Localization
  - User Prediction

Core AI Components

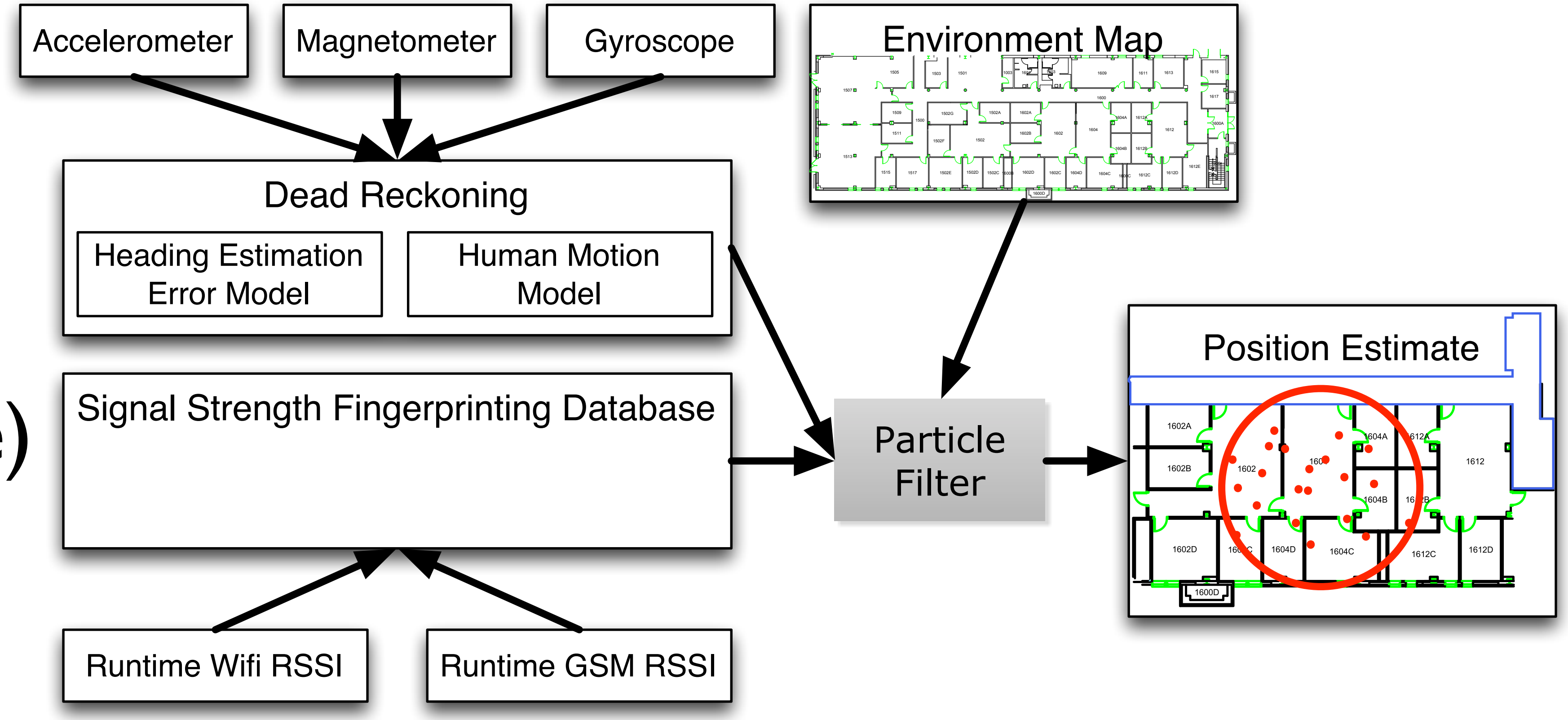
- User Prediction (Producer Team)
  - Felipe, Katia and Piotr
  - Decision theoretical intention recognizer
- Indoor Navigation (Consumer Team)
  - Balajee, Bernardine and Evan
- App Team
  - Felipe, Balajee and Chet

Architecture Overview



Indoor Localization

- Indoor localization performed with sensors in the mobile phone
  - Signal strength fingerprinting (precise, high CPU usage)
  - Dead reckoning (low CPU usage, error prone)

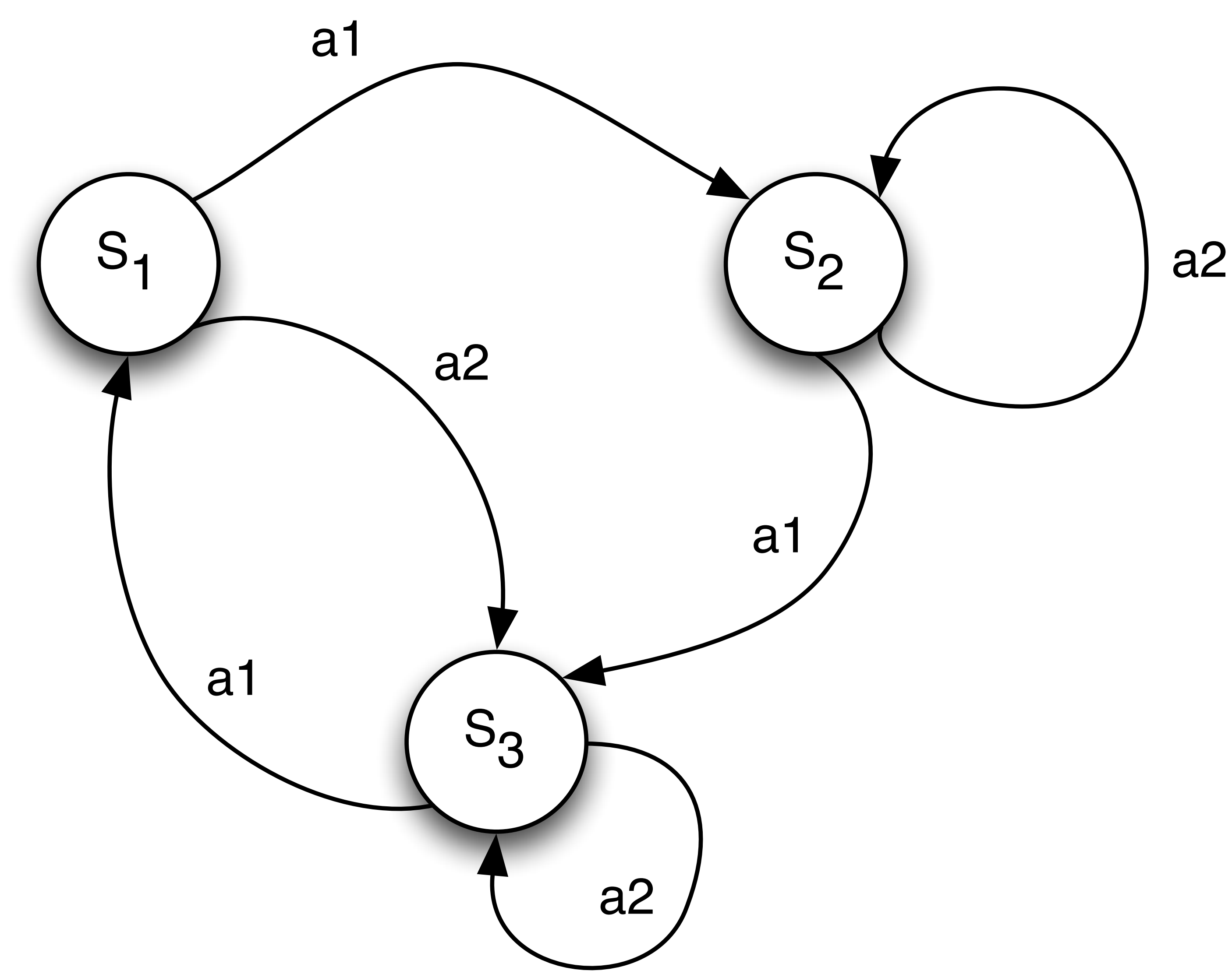


RSSI Database Construction

- Requires a map correlating APs signal in a building with precise locations
- Built using a robot equipped with accurate sensors
  (Rangefinder and Gyroscope)
  - Tele-operated in each floor of a building
  - Creates a map of empty space
- Map is shared with all mobile phones entering the building

Intention Prediction

- Based on a decision-theoretical model behaviour
  Markov Decision Process (MDP)
- An MDP is defined in terms of
  - An initial state S0
  - A transition model T(s,a,s′) — P(s′|a,s) (Markovian)
  - A reward function R(s) — sometimes expressed as R(a,s)
- A solution to a MDP must specify what the agent should do for any state. Such a solution is called a **policy**



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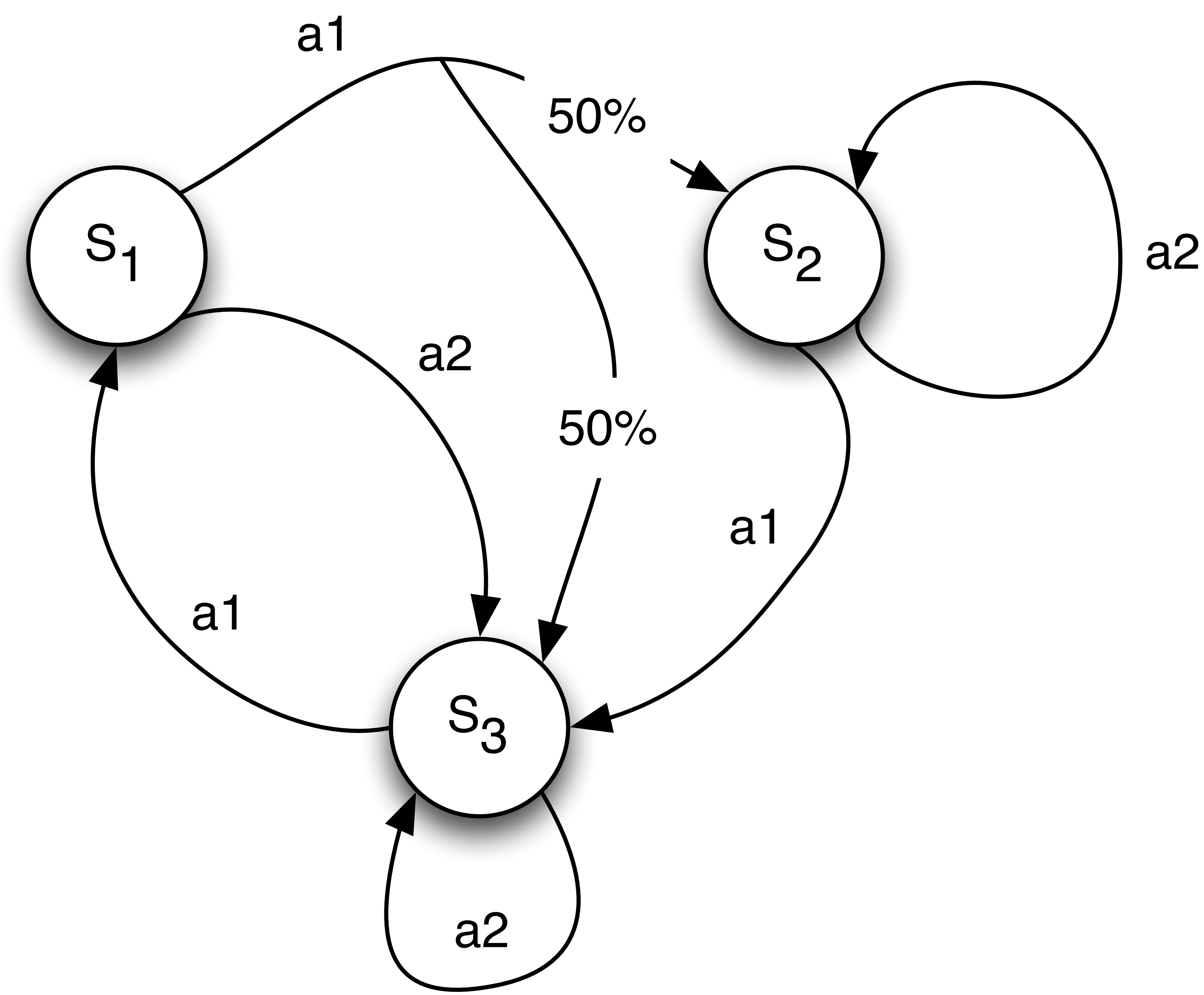


Intention Prediction

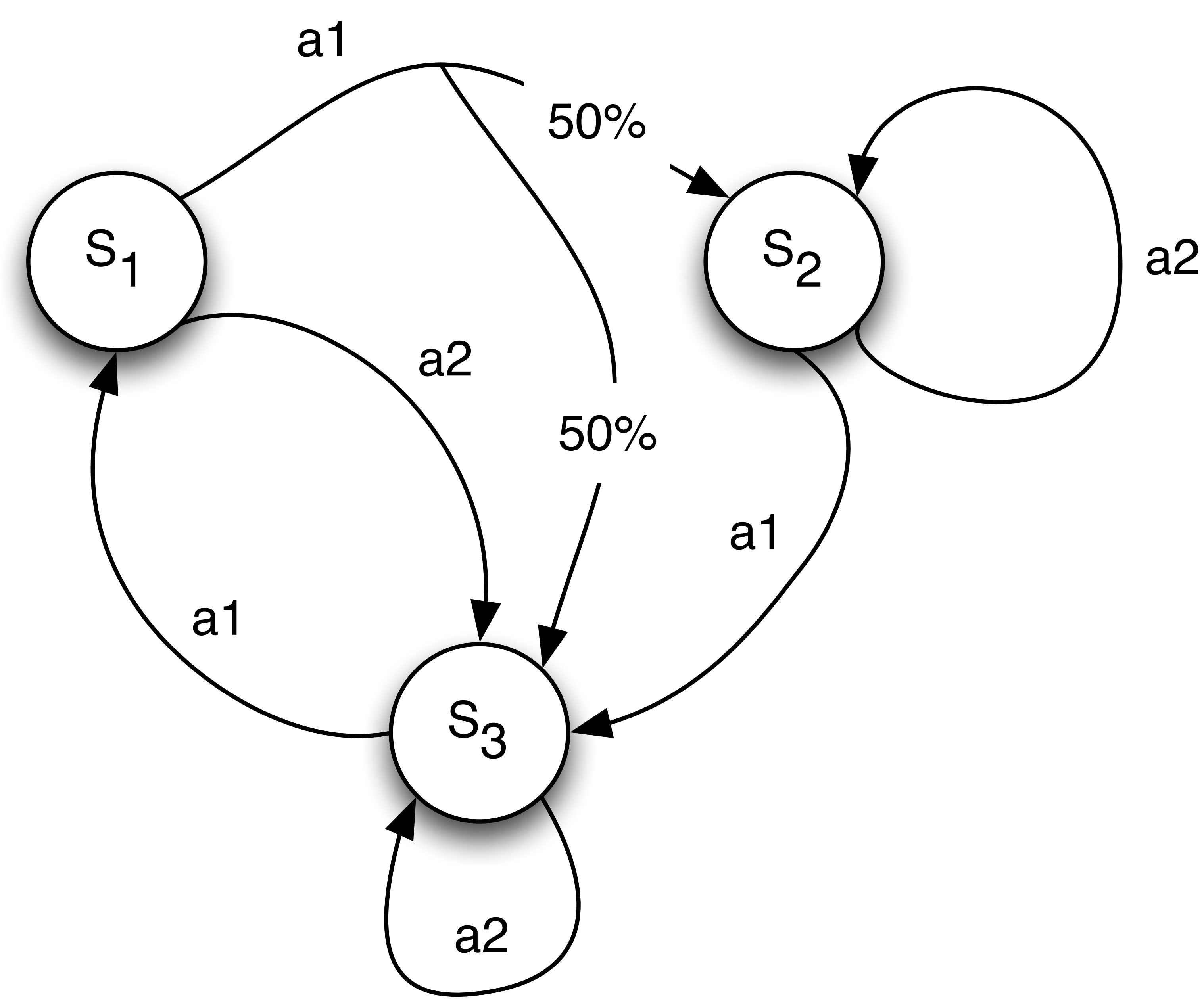
- Based on a decision-theoretical model behaviour
  Markov Decision Process (MDP)
- While, the solution to MDPs usually assumes a **perfect** decision-maker to generate a policy

$$\pi^*(s) = \arg\max_a Q^*(s,a)$$

- We define a **stochastic policy**

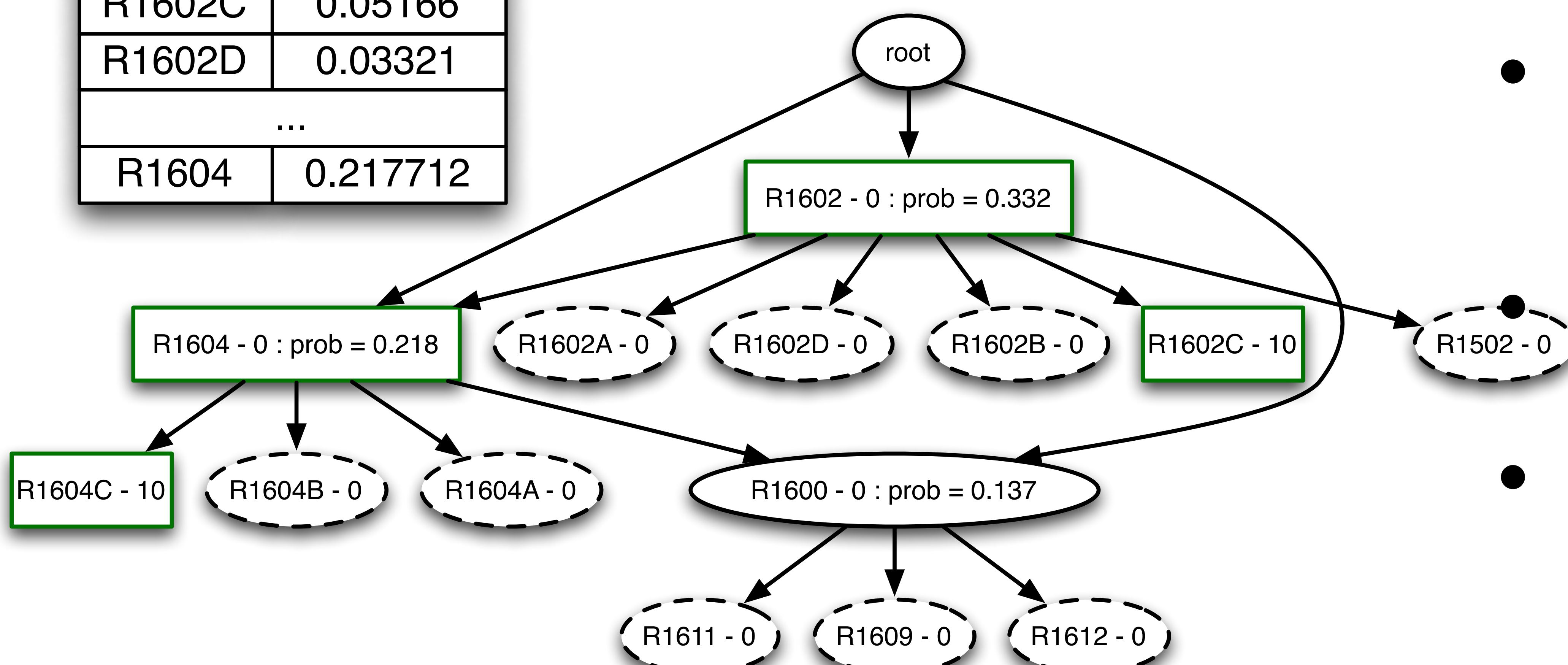
$$\pi^{\approx}(a|s) = \frac{Q^*(s,a)}{\sum_{a' \in A} Q^*(s,a')}$$

- That yields the probability of an action being chosen, proportionally to its optimality



Generating a prediction

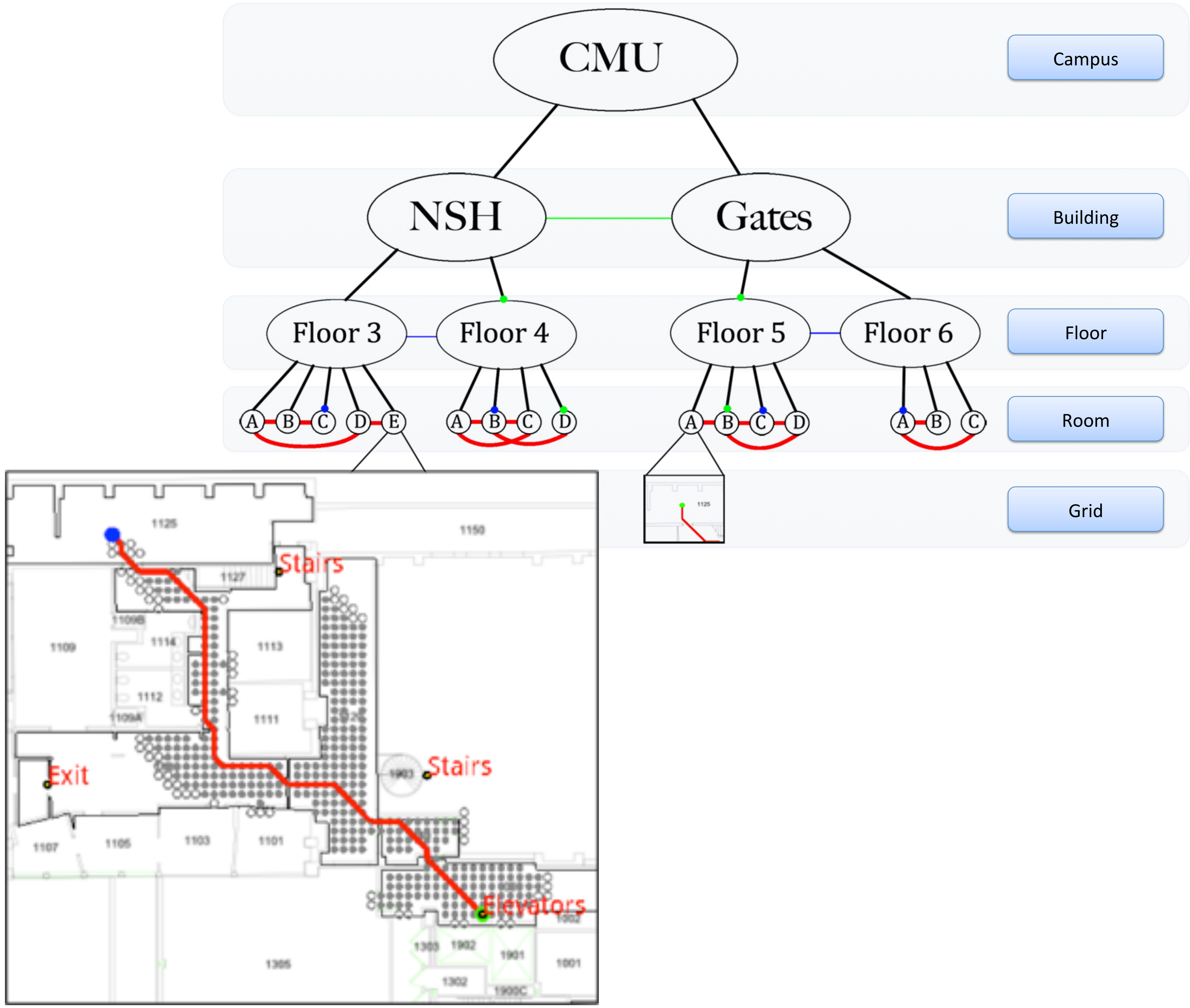
...	
R1600	0.136531
...	
R1602	0.332103
R1602A	0.00369
R1602B	0.03321
R1602C	0.05166
R1602D	0.03321
...	
R1604	0.217712



- Given a probability estimate of the current user-position (Belief state)
- Generate a tree of future paths using the stochastic MDP policy, such that:
  - Actions used to create successor states have a minimum probability
    $$\pi^{\approx}(a|s) \geq thr$$
  - All possible successor states to such actions are added to the tree
  - Only states along an increasing gradient towards target states are followed

Hierarchical Path Planning

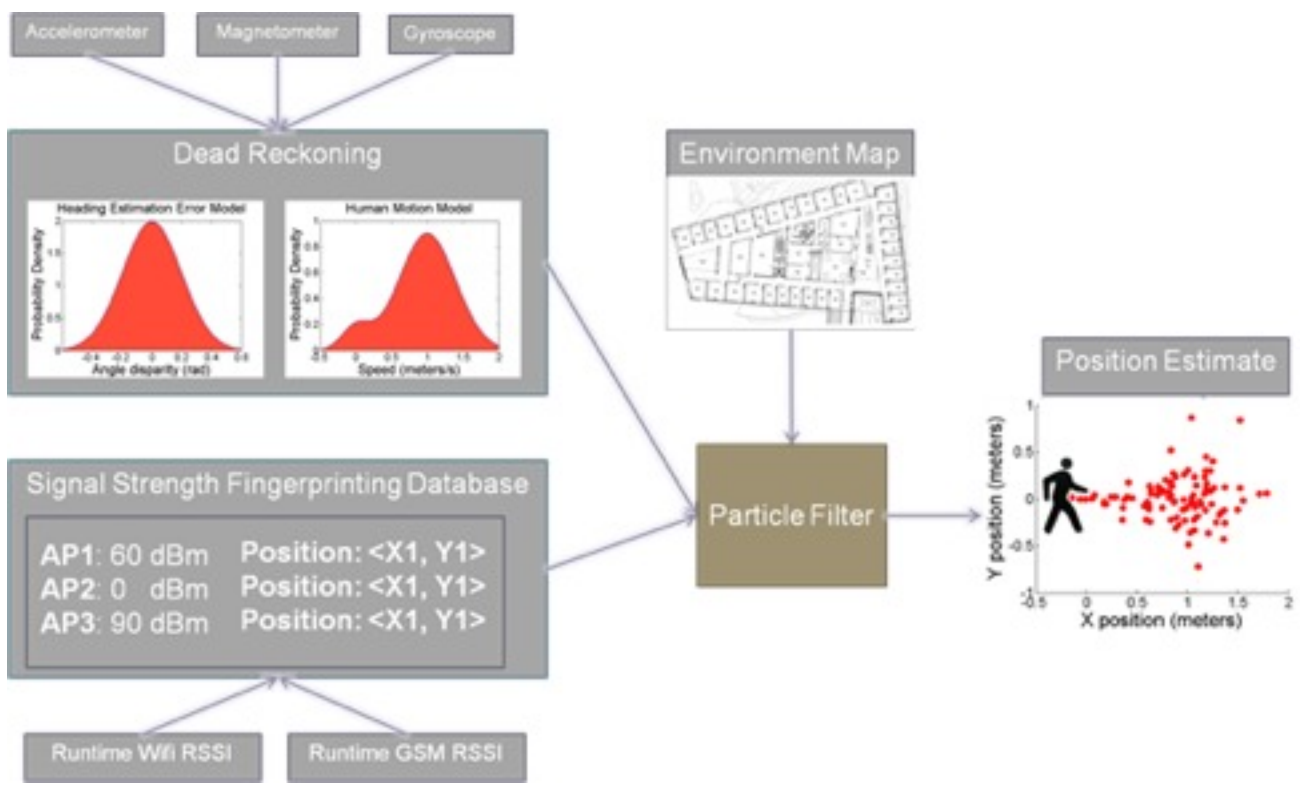
- Algorithm based *D*-lite*
- Hierarchical map representation in two levels of granularity
  - Higher-level structural graph (multiple rooms, floors, buildings)
  - Low-level grid of the free space (single floor)

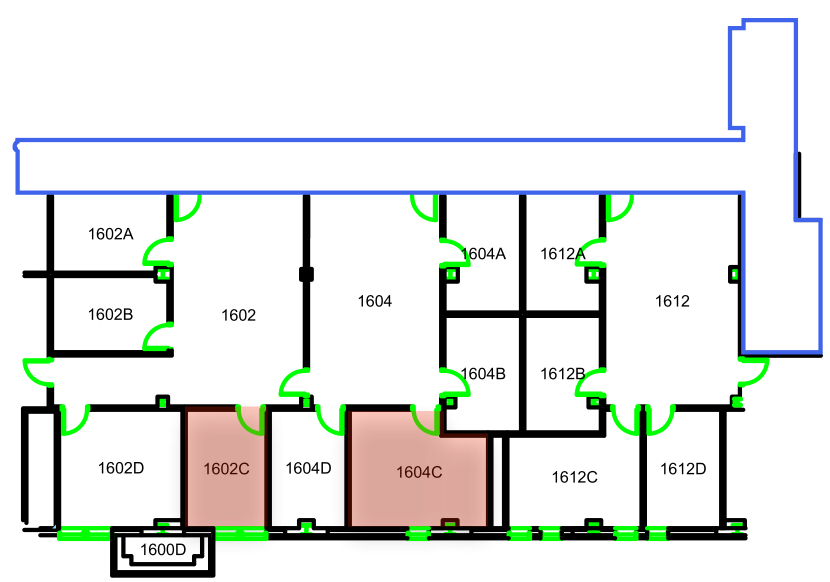


Putting it all together

- Navigation App was built using three separate Android services controlled by the main App
    - Communication via Android messaging
    - Profiling of each component led to substantial design changes

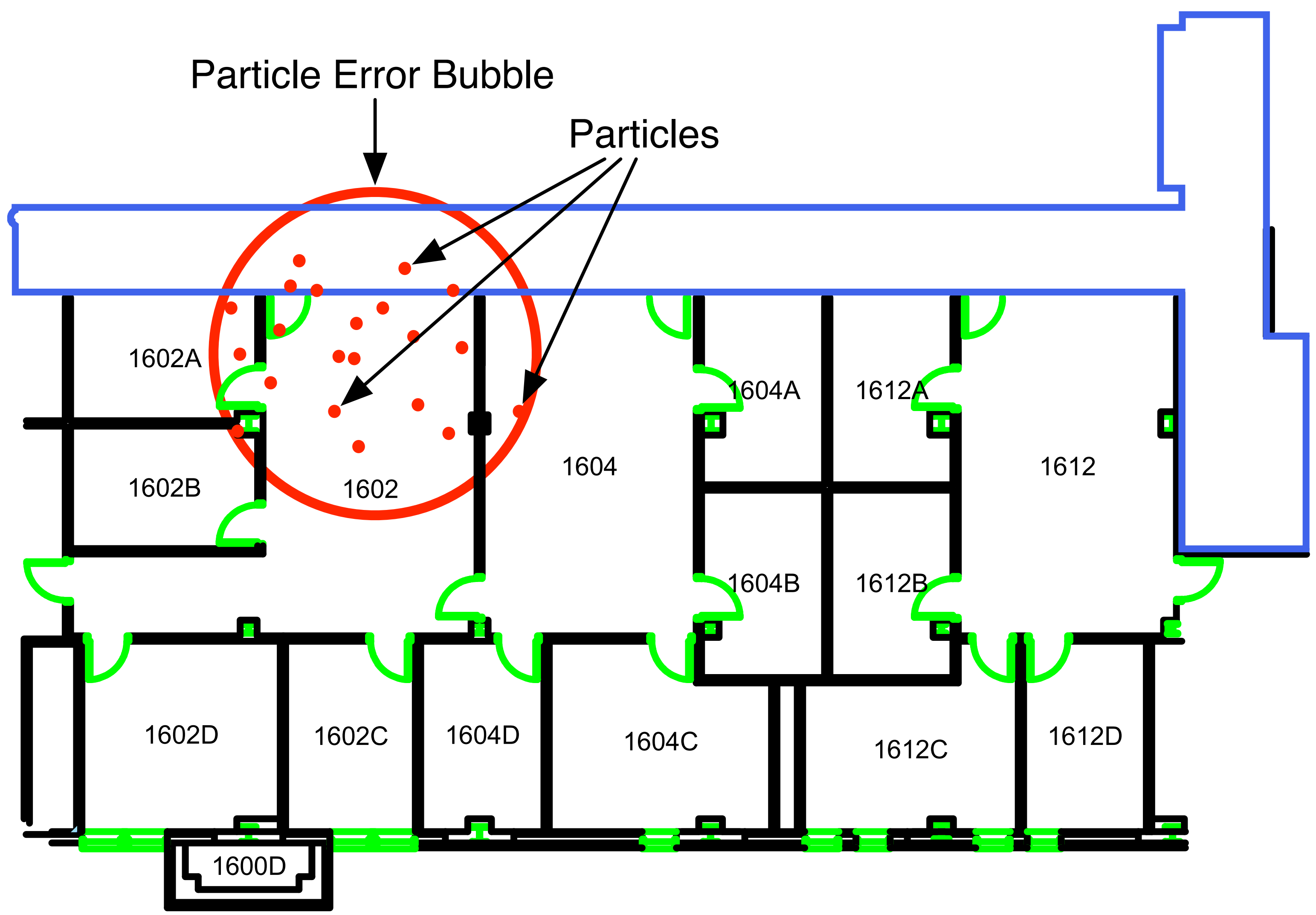
Navigation Step-by-step





- Step 1 - Inputs
  - RSSI database
  - Floor plans for target building
  - User annotations or learned habits

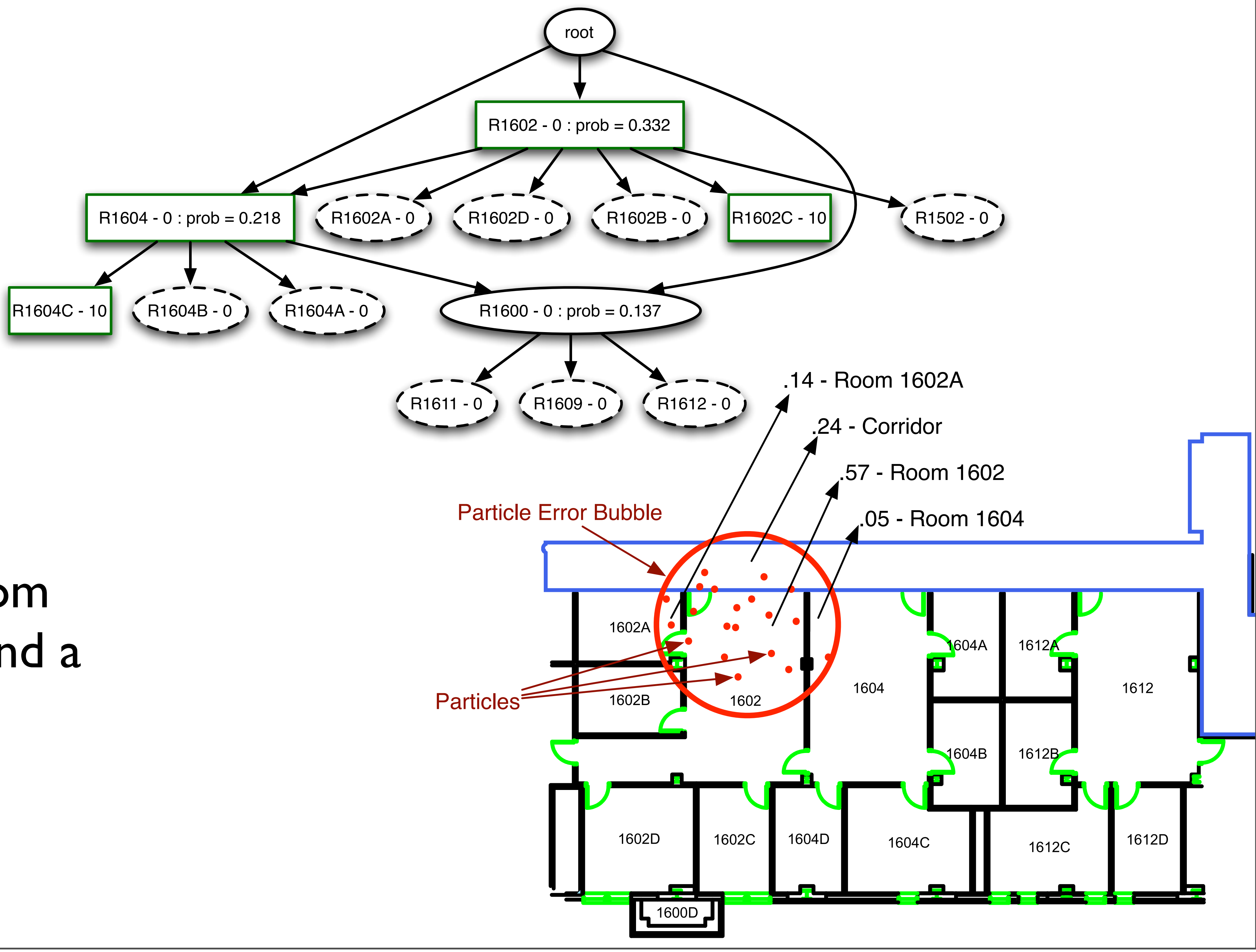
Navigation Step-by-step



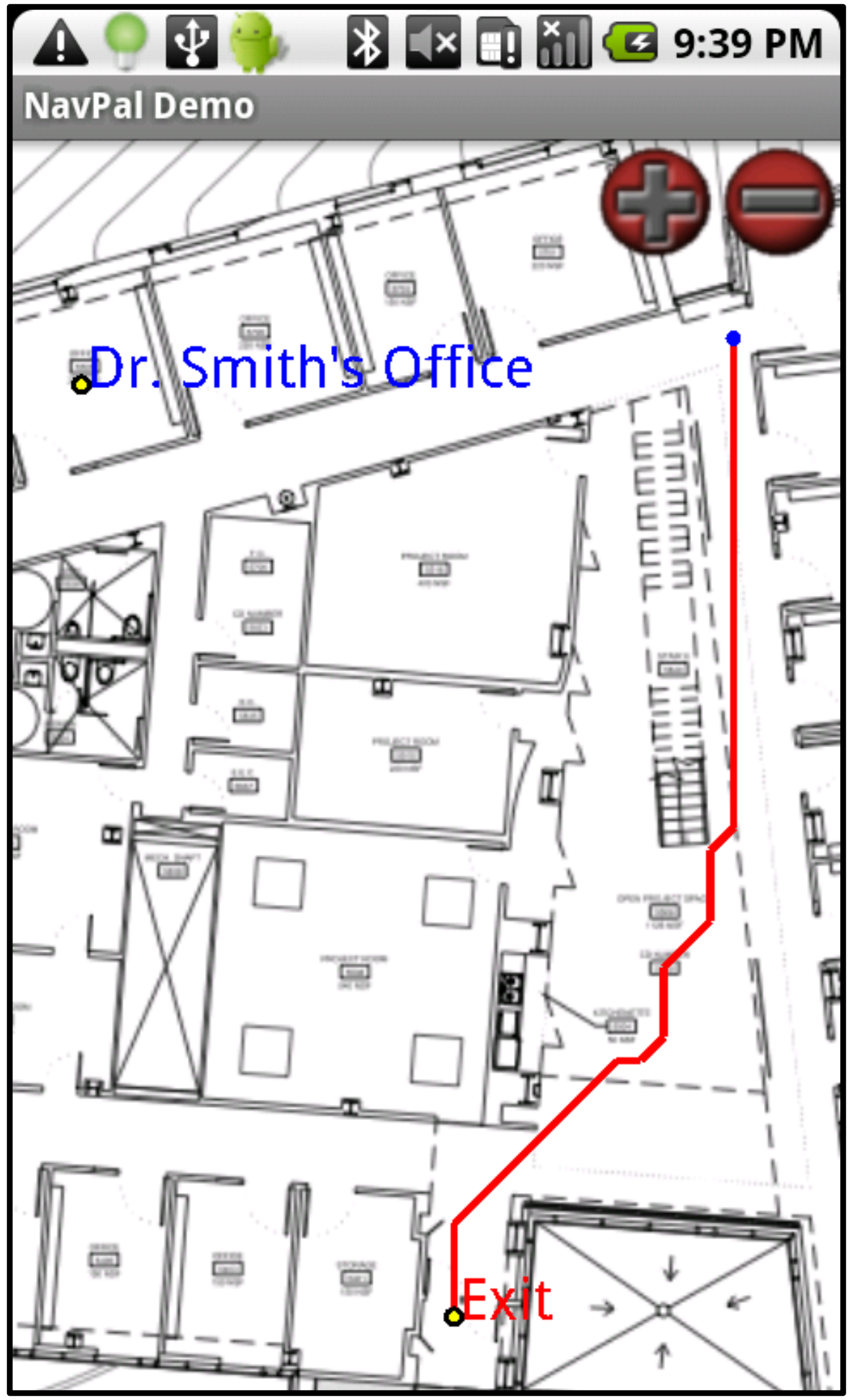
- Step 2 - Particle filter update
  - Particles generated by the PF using the WiFi data (1 Hz)
  - Particles updated by the dead-reckoning system (30 Hz)
  - Particles outside known space discarded

Navigation Step-by-step

- Step 3 - Prediction update
  - Particles from the Indoor Localization component are converted to a Belief-State
  - Prediction tree is generated from most likely current state (beyond a certain threshold)



Navigation Step-by-step



- Step 4 - Path planning
  - Most likely destination is extracted from the prediction tree
  - Optimal path is generated taking into consideration obstacles along the way
  - Path-planning performed for the same floor and between floors

Key Insights and Results

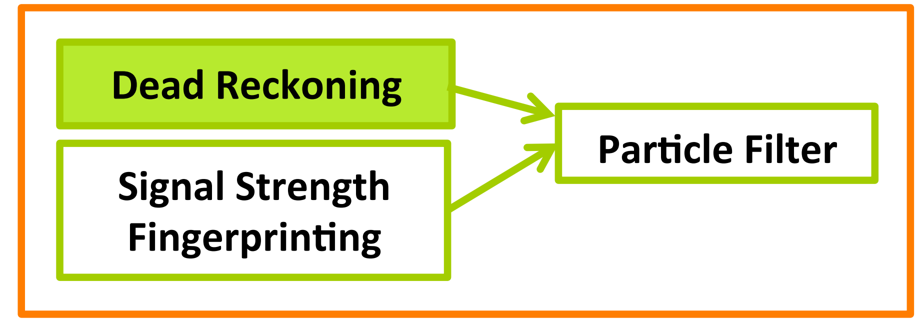
- Producer/consumer model for AI components interesting motivator
- Major bottlenecks
  - WiFi based localization - required adjustments on update frequency
  - MDP Policy recalculation - whenever possible done via external service
- Accuracy and runtime results
  - Variance in destination prediction when in long corridors
  - Magnetic disturbances in the building have large effect on localization

Potential for Future Work

- RSSI database acquisition
  - Implement autonomous robot scanning
  - Use crowd sourcing for RSSI database updates
- MDP learning and solver algorithm
  - Generate a stochastic policy using policy iteration (anytime algo)
  - Online learning of user habits

Questions?

Dead Reckoning



Heading

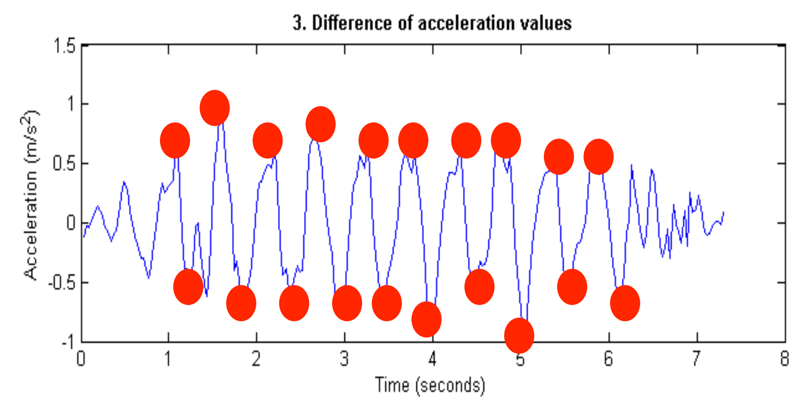
- Accelerometer + Magnetometer

  Externally referenced –

  - ✚ Bounded error
  - ▬ Magnetic interference indoors
- Gyroscope
  - ✚ Low noise and high accuracy
  - ✚ Not susceptible to interference
  - ▬ Error growth is unbounded over time

Distance Measurement

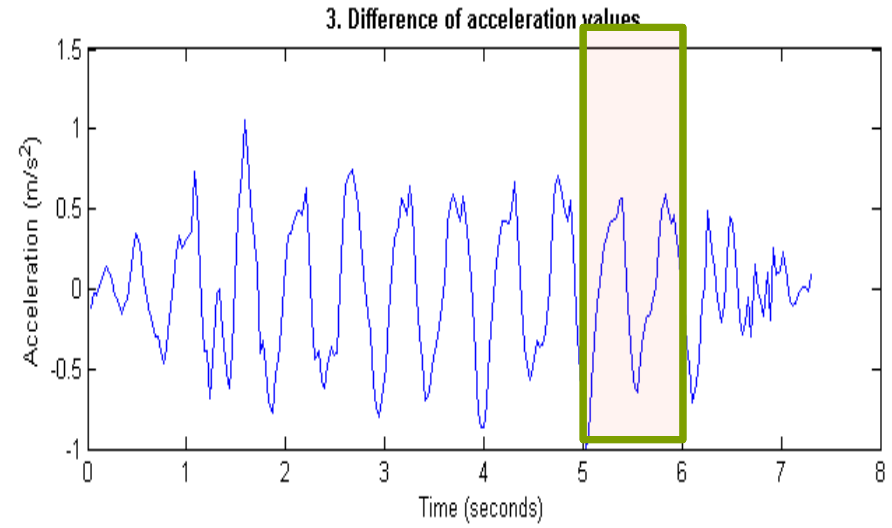
- Peak Detection Filter



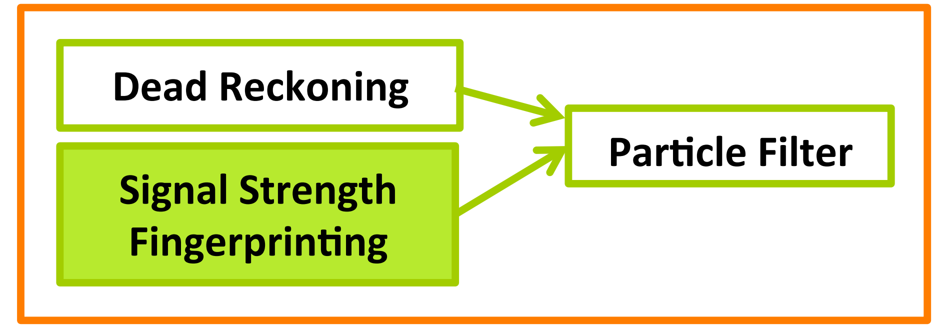
Each pair corresponds to a step

- Variance Threshold

  Calculate running standard deviation



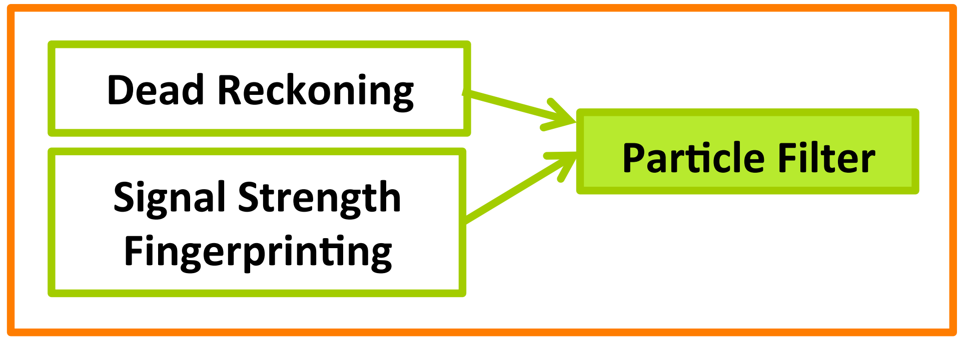
Signal Strength Fingerprinting



- Automated WiFi signal strength database generation using a pioneer robot
- 2-D dynamic robot map of the environment
- At runtime, the distance is calculated as a weighted average of the nearby calibration points to reduce noise

- **Accurate, high density signal strength database in a short time**
- **Shape and structure of the laser map allows us to speed up our pose estimation and reduce computation**

Particle Filter



Initial Distribution: Uniformly random over entire environment

- Step: Use dead reckoning model to update particles

If there are new observations, update the probability of each particle

- Step a: Use robot map to identify and remove particles that lie on walls

  Step b: When a Wifi reading is received, update particle weights

Re-arrange the samples to be concentrated in the most important areas

- Step: Re-sample using importance resampling: a new set of *n* particles from the old set proportional to its weight