A Comparison between EKF and Sequential Monte Carlo Techniques for Simultaneous Localisation and Map-building

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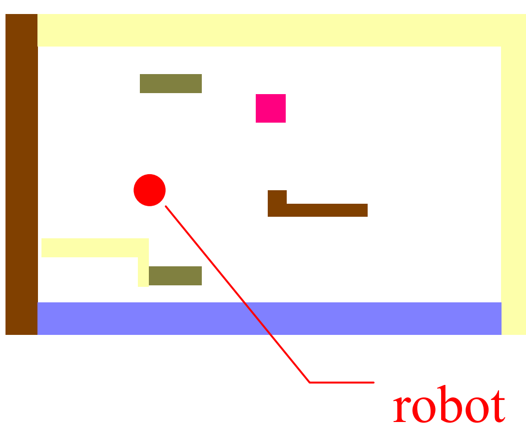
Overview

- Introduction
- Goal: Extend SMC SLAM to work under continuous state-space
- Our Sequential Monte Carlo (SMC) implementation
- Extension to Simultaneous Localisation and Map-building (SLAM)
- Results
- Conclusions

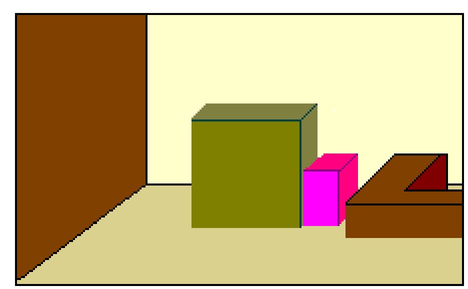
Localisation

- Identify the observer's own position
- Simplest method: dead reckoning
  - Unreliable due to error accumulation.
- Use egocentric sensor data

Global View



Egocentric View

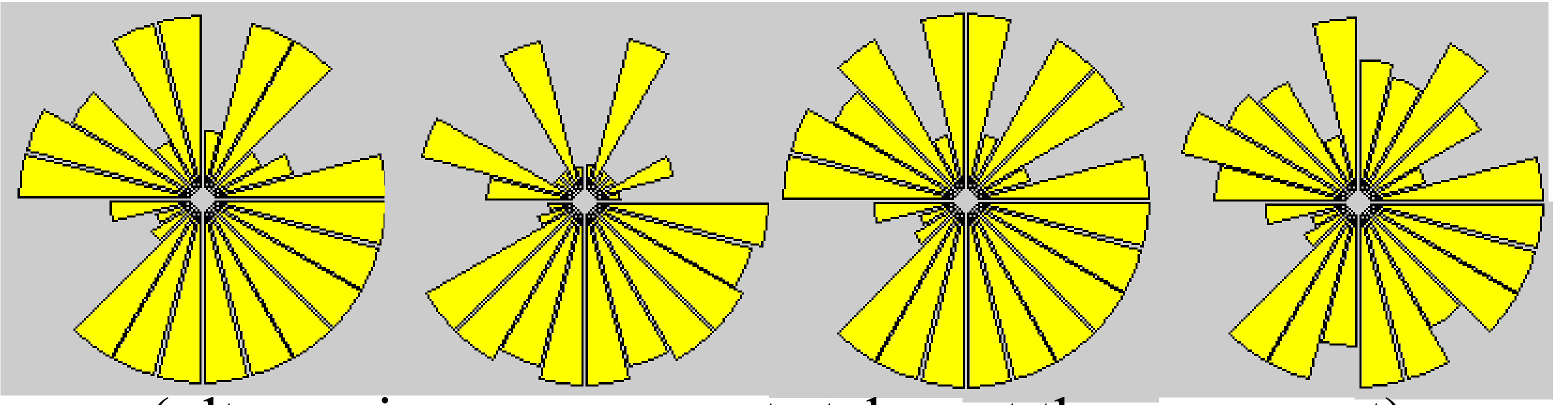


Problem nature

- Localisation is an estimation problem
- Related to a few classes of problems
  1. Position estimation
  2. Tracking
     - known previous robot position
     - need to be fast
  3. SLAM
     - evaluate both the robot and obstacle positions

Difficulties

- Model uncertainty
- Sensor noise
  - image: illumination changes, reflection, etc.
  - sonar: cross talk, multiple path, air turbulence, specular reflection etc.

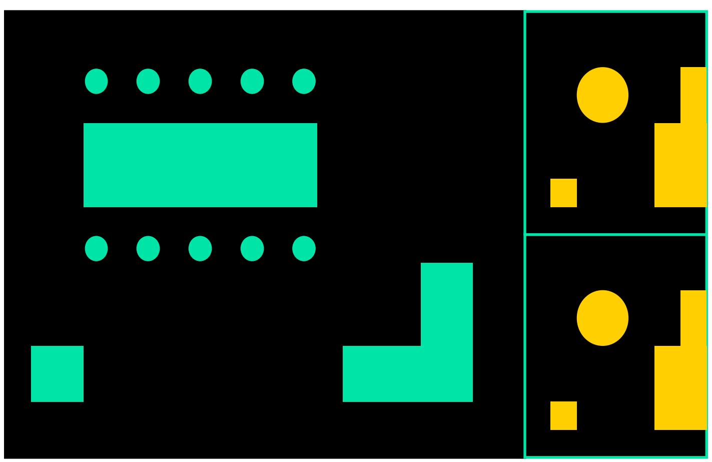


(ultrasonic measurements taken at the same spot)

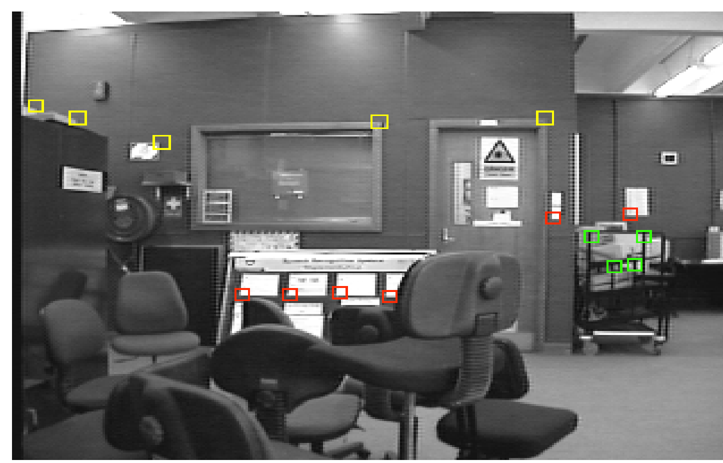
Difficulties

- Similarity problems
  - macroscopic (e.g. symmetric rooms)
  - microscopic (e.g. non-unique features)

Symmetric rooms



Non-unique features



Bayesian statistics

Bayes Theorem: estimate the posterior distribution

$$P(B_j \mid A) = \frac{P(B_j)P(A|B_j)}{\sum_{i=1,2,\ldots,k} P(B_1)\cdot P(A|B_1)+P(B_2)\cdot P(A|B_2)+\ldots+P(B_i)\cdot P(A|B_i)}$$

- Recursively update using current measurements
- Often relies on the approximate forms
  - Extended Kalman Filtering (EKF)
  - Sequential Monte Carlo (SMC) methods

Approximated by EKF

- Prevalent solution
- Especially for SLAM (Dissanayake et al., 2001,)
- Fast, but
- Liable to outliers
- Relies on the first order Taylor approximation
- Limited by the Gaussian error assumption

Approximated by SMC

- Also called particle filtering (PF)
- Particle = state estimate + importance factor
- Advantage:
  - not restricted by Gaussian error assumption
  - can handle nonlinear systems
  - easy to implement
- Disadvantage:
  - need more computation

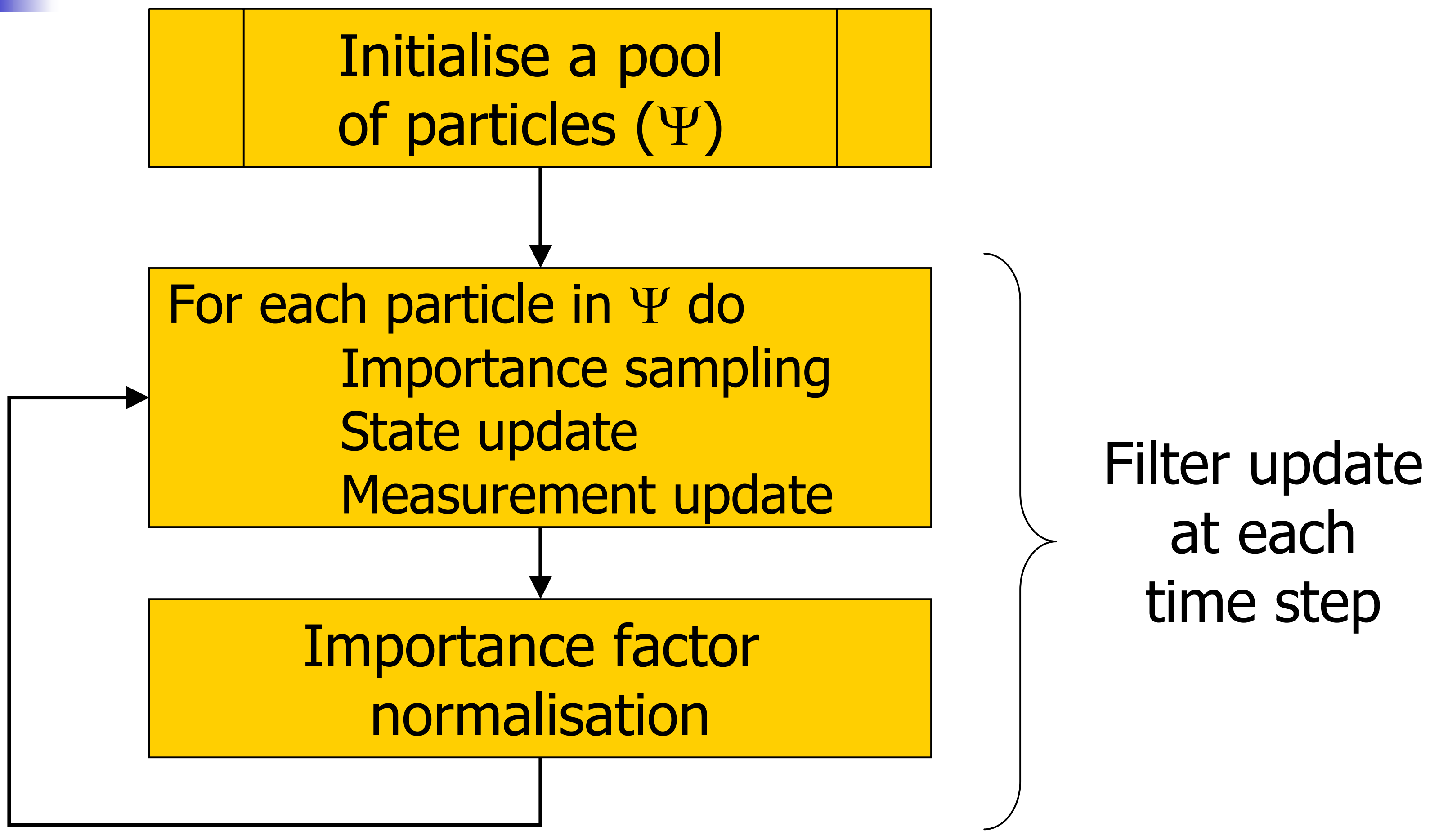
Robotics & SMC method

- Very robust
- Demonstrated to work for (Fox et. al. 2000)
  - robot position estimation
  - tracking
  - kidnapped robot problem
- Solved SLAM problem in 10 x 10 grid world (Murphy, 2000)

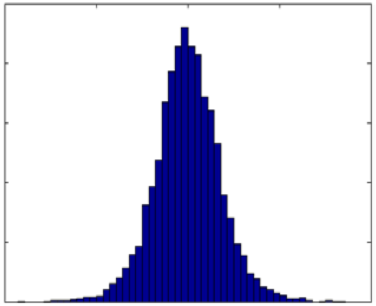
Our goal:

Extend SMC SLAM to work under continuous state-space

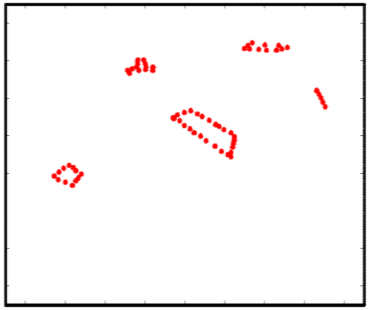
Our SMC implementation



Assumptions

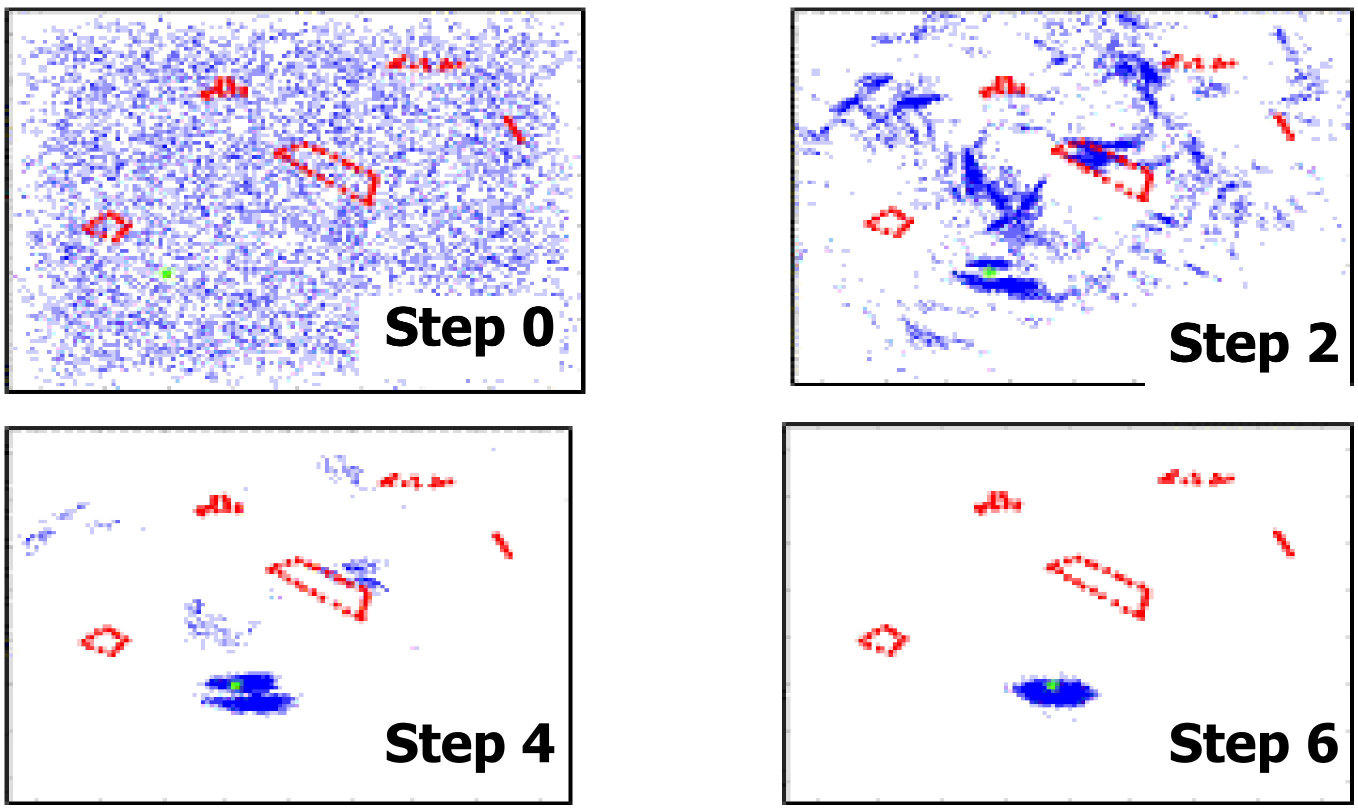


- The robot
  - can move forward/backward
  - can "turn-on-the-spot"
  - has a ring of 24 ultrasonic range finder
  - corrupted by Gaussian and exponential noises



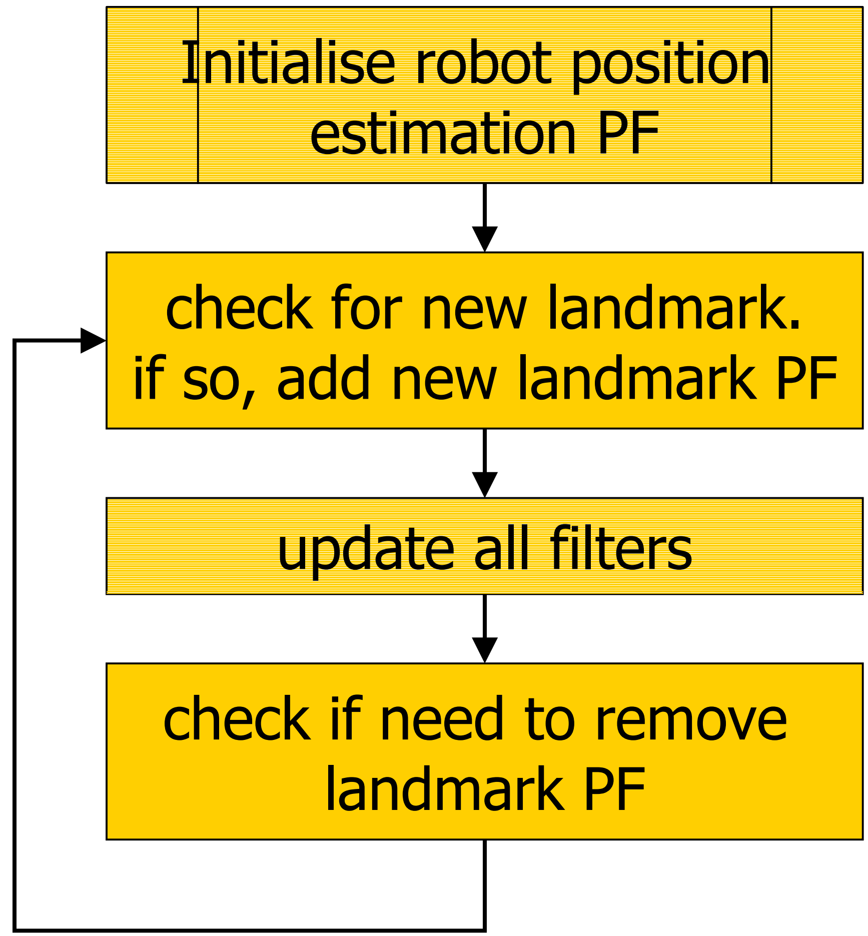
- The environment
  - consists of only point objects
  - work space > max detection range

Localisation results



Extending to SLAM

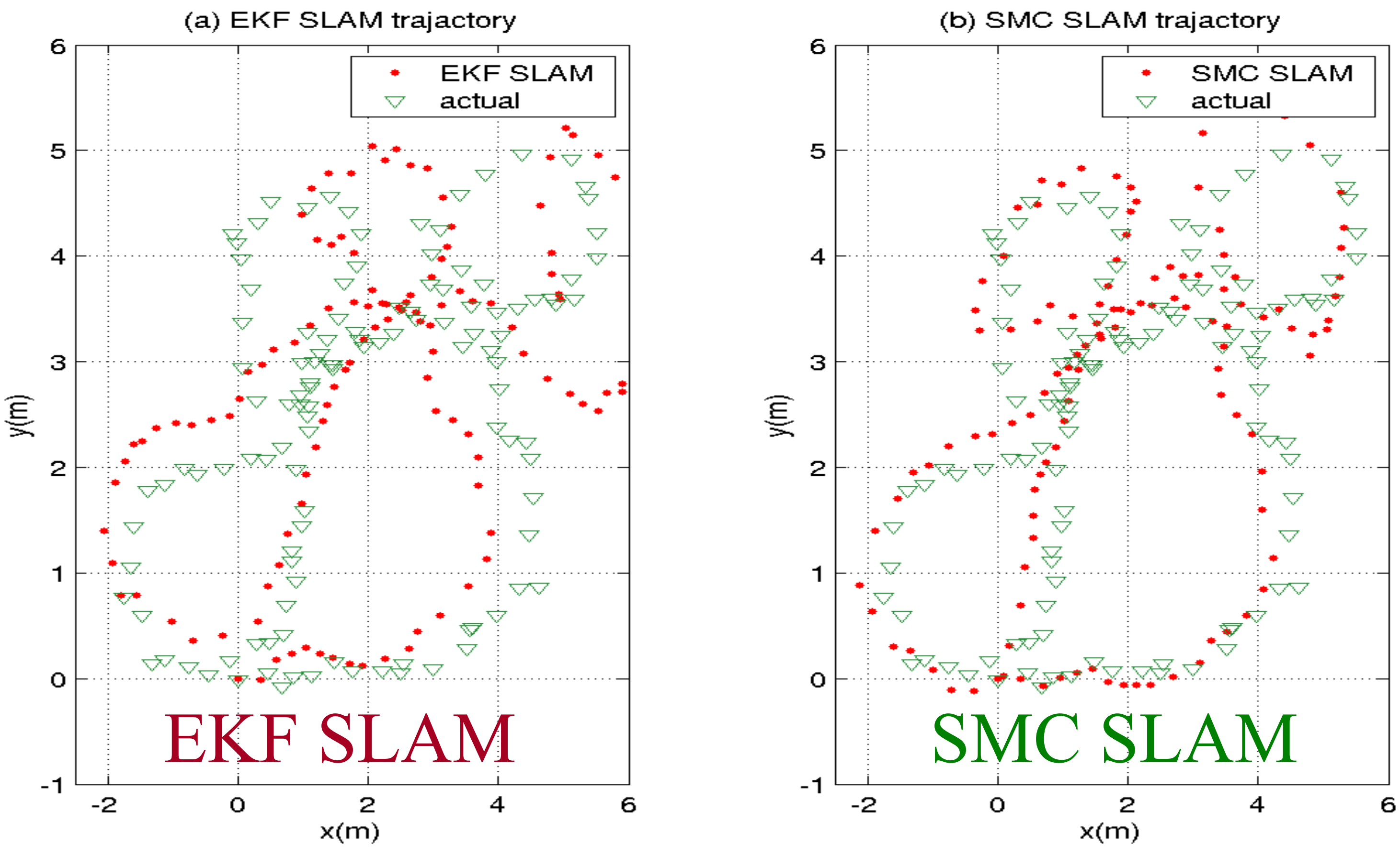
- Run multiple particle filters (PF)
- Separated PF for each new landmark
- Filter update can be in parallel
- Need landmark detection and removal rules



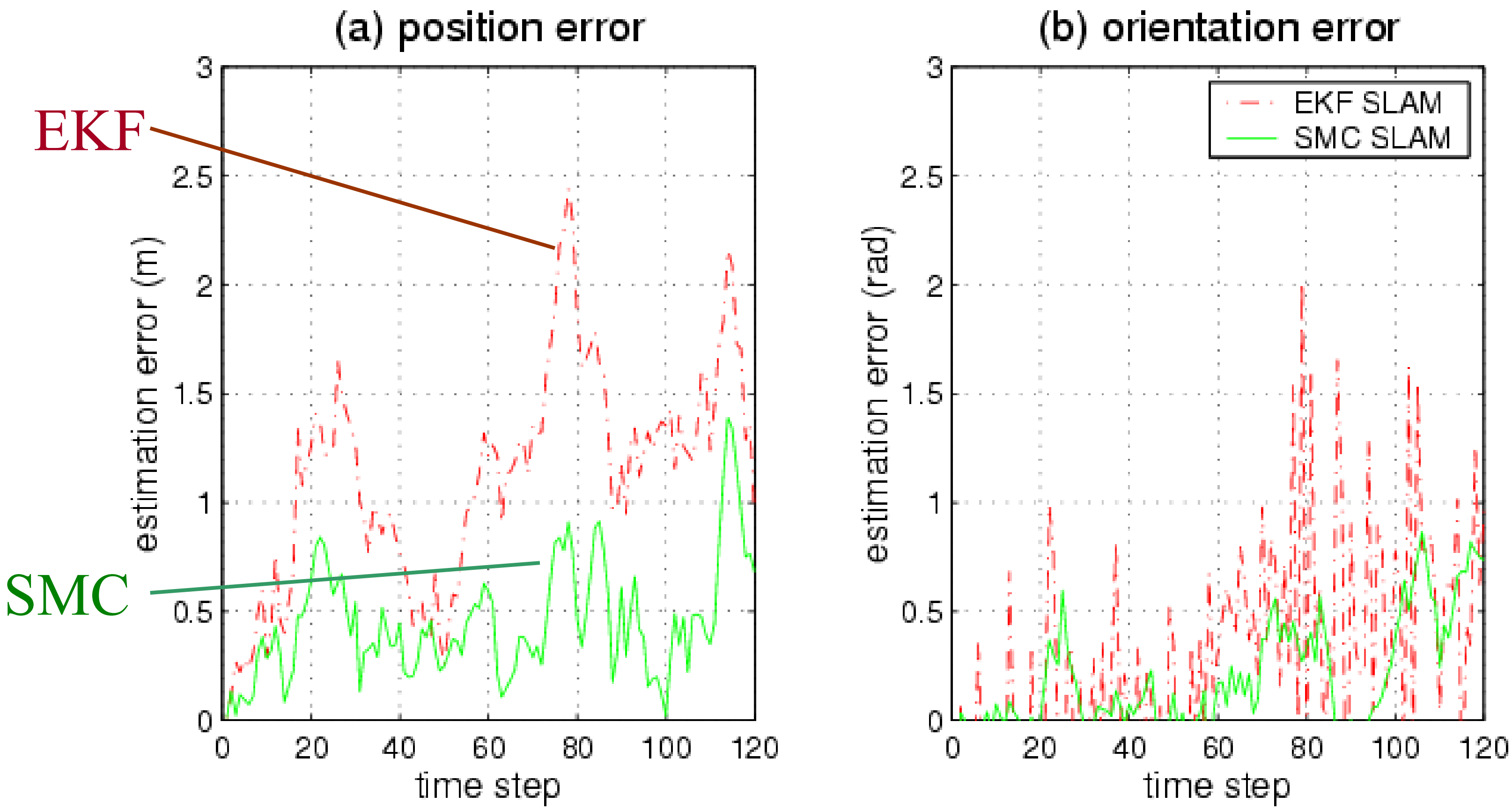
Landmark management

- Addition rule:
  - compare observations with estimates
  - create separated PF to detect new landmark when the difference is substantial.
- Acceptance rule:
  - check consistency in state distribution in the particles of landmark PFs
  - sufficiently consistent: identified new landmark
  - store the position before removal of the PF

SLAM results



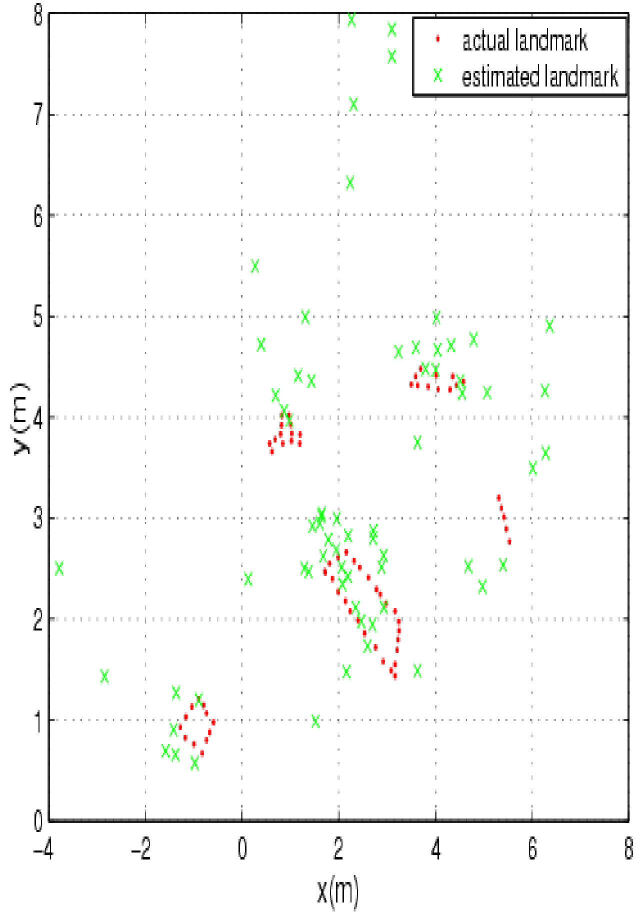
SLAM results



SLAM results

SMC SLAM

- a promising solution
- self-localisation
  - better than EKF
- map-building
  - mediocre
  - sometimes fails to recognise already identified landmarks.



Conclusions

- The modeling uncertainty, the senor noise and similarity problems associated with the typical robot environment complicates the robot localisation task.
- The performance between EKF and SMC based SLAM implementations are compared.
- The proposed SMC algorithm shows promising results, especially for the self localisation of the robot.

Question time