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Particle Filter

- Particle Filter is an implementation of Bayesian Filters
- State space is approximated by a set of N weighted particles

- S_t : set of N weighted particles at time t. $S^i_t=(s^i_t,w^i_t)$ the i[th] particle and its weight
- O_t : observation at time t
- A_t : action at time t

- Hypothesis :
  - Order 1 Markov model
    - $P(S_t \mid S_{t-1},A_t)$: dynamic model
  - Sensor model
    - $P(O_t \mid S_t)$: sensor model

- Goal : compute *prior* distribution $P(S_T \mid O_{0:T},A_{1:T})$

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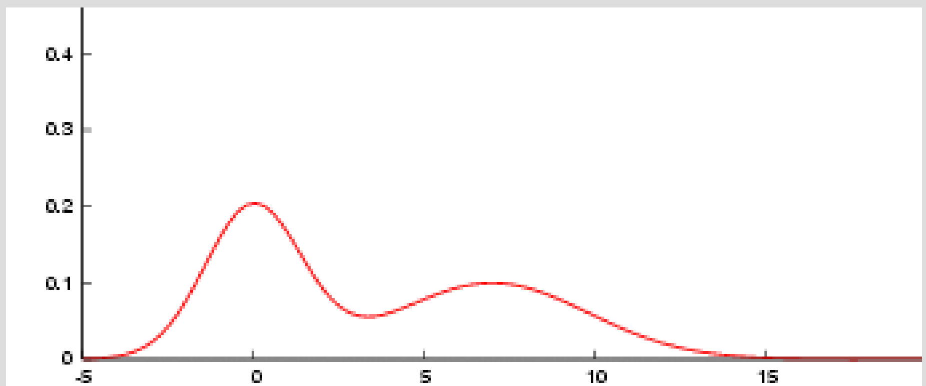
Particle filtering

- Particle and weight representation of posterior pdf

$P(S_T \mid A_{1:T}, O_{0:T})$



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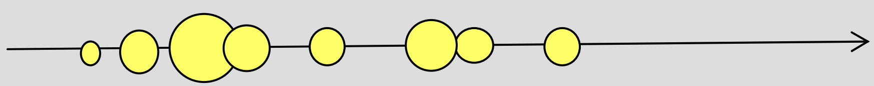

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Particle filter

- Numerical method to solve nonlinear and/or non-Gaussian Bayesian filtering problems
- Known variously as: bootstrap filtering, condensation algorithm, interacting particle approximation, survival of the fittest, etc.

- S. Arulampalam et al. A Tutorial on Particle Filters for On-Line Non-linear/Non-Gaussion Bayesian Tracking. *IEEE Transactions on Signal Processing*, 50(2), 2002.

Particle filter algorithm

- Input: $S_t = (s_t^i, w_t^i)$, $1<=i<=N$
  - $S_{t+1} = Ø$
  - For i = 1 to N
    - Sample s_{t+1}^i from $P(s_{t+1}^i|s_t^i, A_{t+1})$
    - $W_{t+1}^i = P(O_{t+1}|s_{t+1}^i)$
    - $S_{t+1} = S_{t+1} + (s_t^i, w_t^i)$
  - EndFor
  - Return (S'_{t+1})

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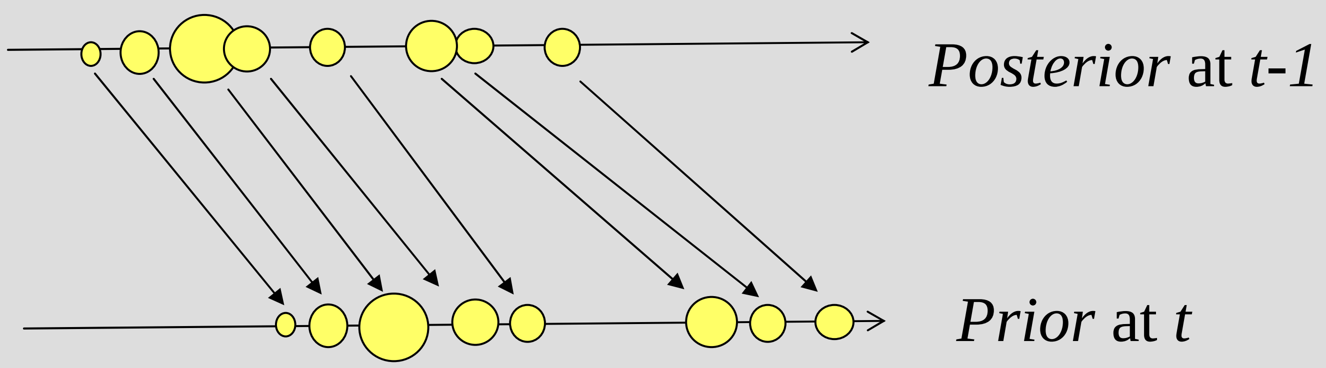
Prediction step

- Apply the dynamic model $P(S_t|S_{t-1},A_t)$ to all particles: each particle s^i_{t-1} is replaced by a point drawn from $P(S_t|s^i_{t-1},A_t)$



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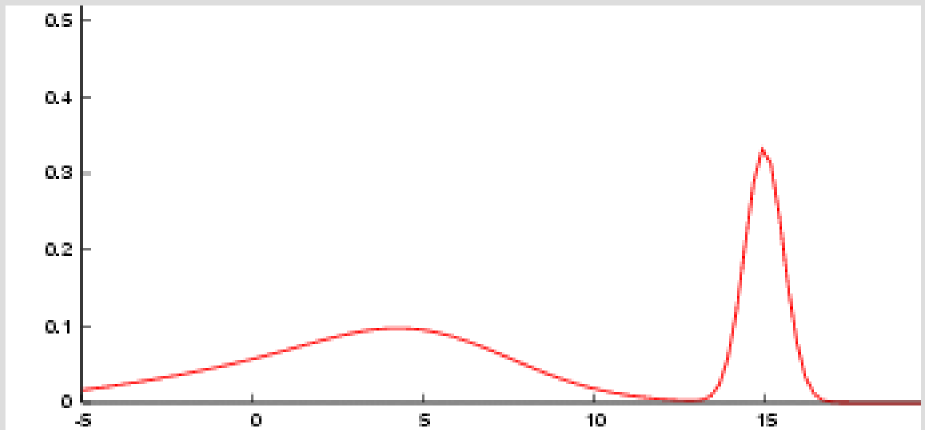
Estimation step

- Update and renormalize the weights *w.r.t* $P(O_t|S_t)$



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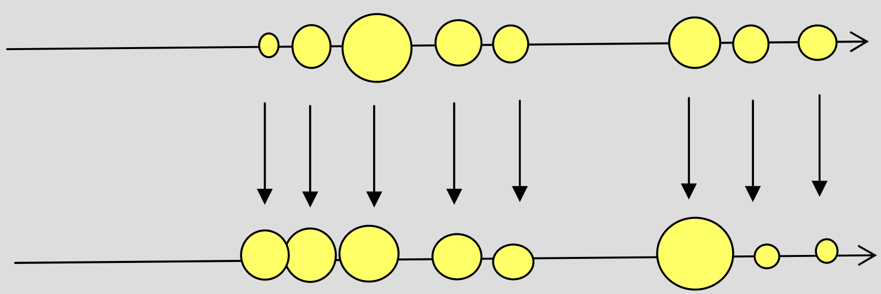
Sensor model



Posterior at t

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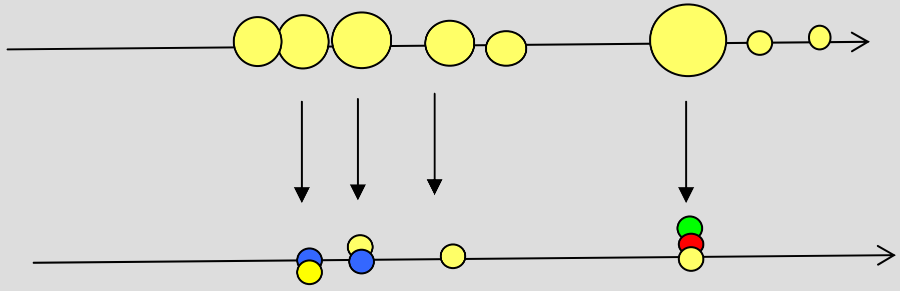
Resampling

- Avoid the degeneracy problem: *after few iterations, all but one particle will have negligible weight*



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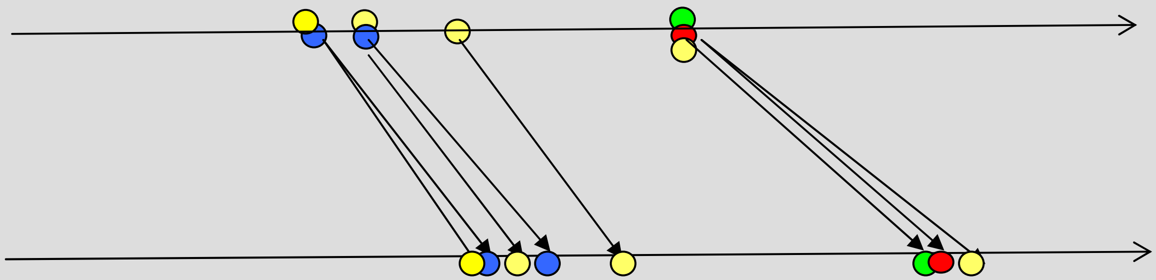
Prediction step

- Apply the dynamic model $P(S_t|S_{t-1},A_t)$ to all particles: each particle s^i_{t-1} is replaced by a point drawn from $P(S_t|s^i_{t-1},A_t)$



Particle filter algorithm with resampling

- Input: $S_t = (s_t^i, w_t^i)$, $1 <= i <= N$
  - $S_{t+1} = Ø$
  - For i = 1 to N do
    - Sample s_{t+1}^i from $P(s_{t+1}^i | s_t^i, A_{t+1})$
    - $W_{t+1}^i = P(O_{t+1} | s_{t+1}^i)$
    - $S_{t+1} = S_{t+1} + (s_{t+1}^i, w_{t+1}^i)$
  - EndFor
  - $S'_{t+1} = Ø$
  - For i = 1 to N do
    - Sample a particle s_{t+1}^i from W_t
    - $S'_{t+1} = S'_{t+1} + \{s_{t+1}^i, 1/N\}$
  - EndFor
  - Return (S'_{t+1})

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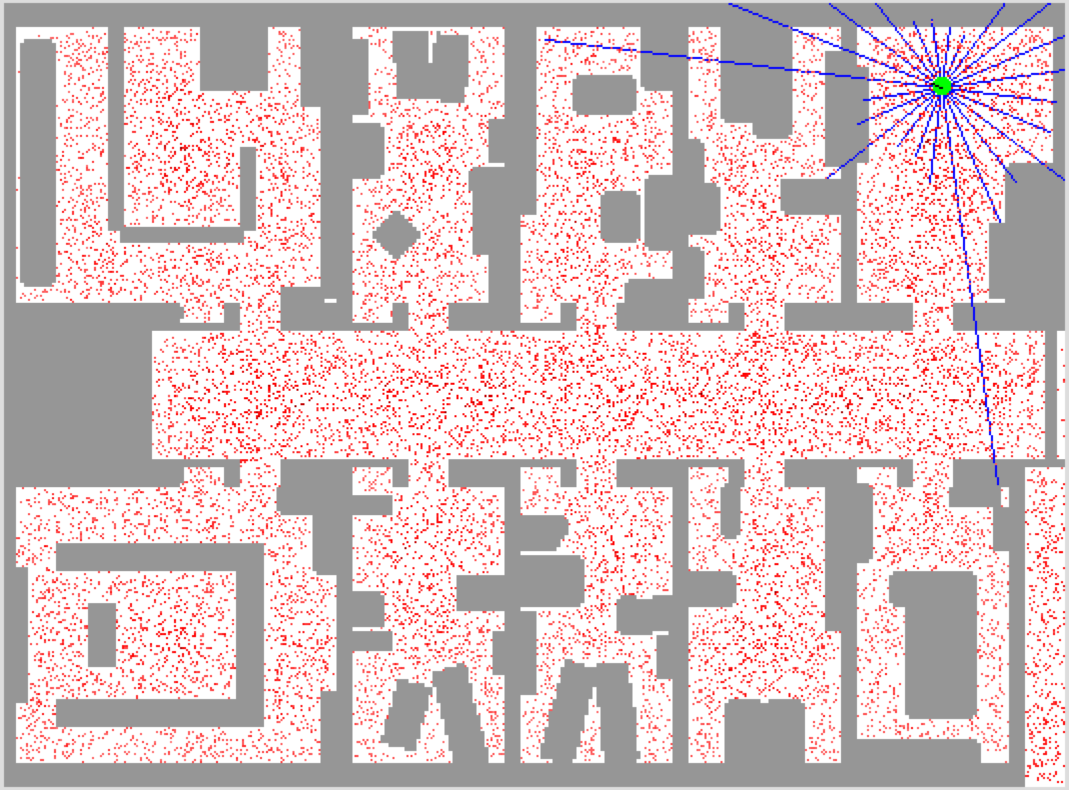
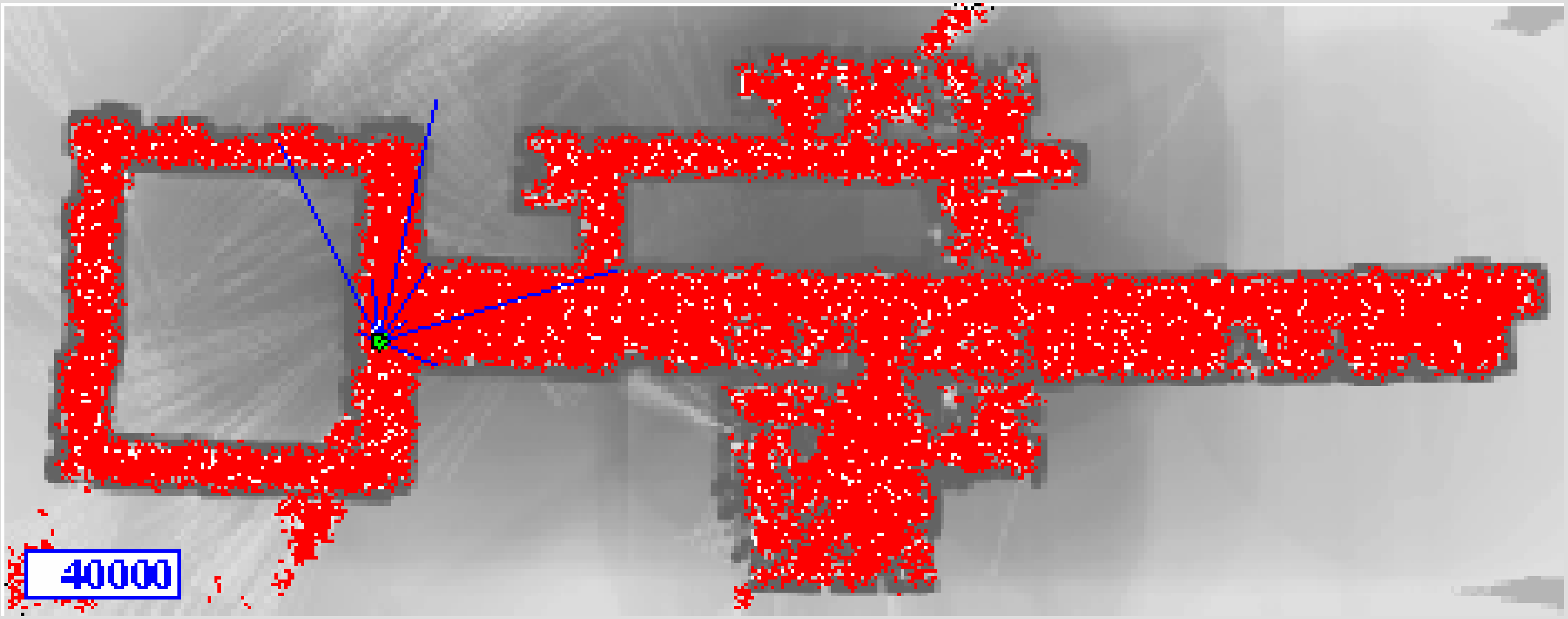
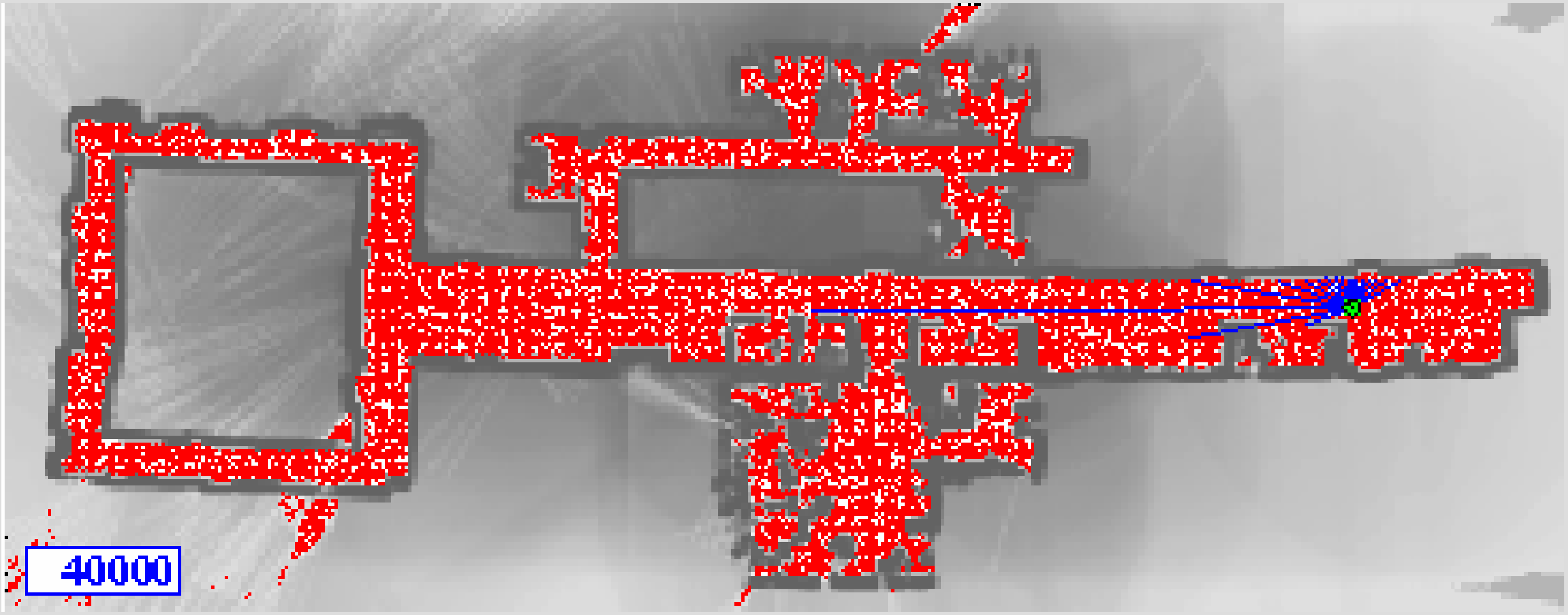
Initial position unknown: ultrasonic sensor[Fox'98]



Initial position unknown: ultrasonic sensor[Fox'98]



Initial position unknown: laser sensor[Fox'98]



Conclusion

- Particle filtering allows approximated inferences whatever the dynamic and sensor models
- Able to deal with multiple hypothesis
- Number of particles is constant
- Resampling problem
  - Numerous resampling methods exist in the literature
  - Numerous techniques to compute the weight of each particle
  - Automatic criteria to detect the degeneracy problem
    - Resampling only when necessary

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Summary about Bayesian filters (1/2)

- Goal : tracking a single object as a set of observations and actions become available on-line
- Only a conceptual solution
  - Integrals are seldom intractable
- Based on:
  - Sensor model
  - Dynamic model

Summary about Bayesian filters(2/2)

- Practical solutions are only possible under some hypothesis:
  - Discretization of state-space:
    - Markov chain, Hidden Markov models, Markov localization or discrete bayesian filters
  - Representation of state space by a gaussian
    - Kalman filters, Extended Kalman filters
  - Representation of state-space by particles:
    - Particle filters;
- Different type of filters:
  - Markov chain: no actions, no observations;
  - Hidden Markov models: no actions;
  - Markov localization, Kalman filters, particle filters;
- IMM filters
  - Able to deal with complex motions;
  - Several filters in parallel;
  - Fusion of filters to estimate the position of the object.

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