CSE-P590a
Robotics

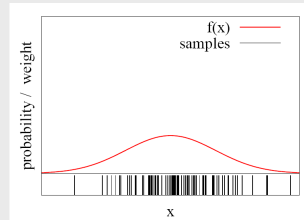
Bayes Filter Implementations

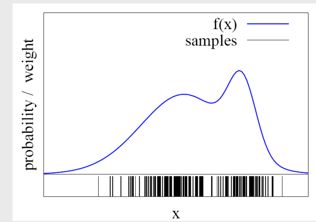
Particle filters

1

Density Approximation

- Particle sets can be used to approximate densities





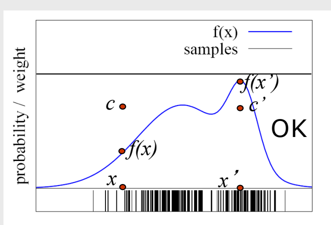
- The more particles fall into an interval, the higher the probability of that interval
- How to draw samples form a function/distribution?

2

2

Rejection Sampling

- Let us assume that $f(x)<=1$ for all x
- Sample x from a uniform distribution
- Sample c from [0,1]
- if $f(x) > c$ keep the sample
  otherwise reject the sampe



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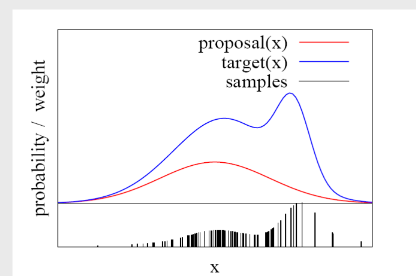
Importance Sampling Principle

- We can even use a different distribution g to generate samples from f
- By introducing an importance weight w, we can account for the "differences between g and f"
- $w = f / g$
- f is often called target
- g is often called proposal



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Resampling

- **Given**: Set S of weighted samples.
- **Wanted** : Random sample, where the probability of drawing x_i is given by w_i.
- Typically done n times with replacement to generate new sample set S'.

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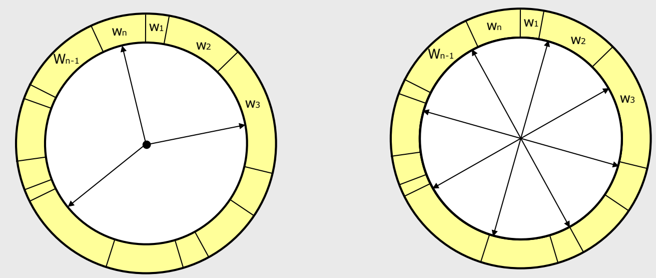
Resampling



- Roulette wheel
- Binary search, n log n

- Stochastic universal sampling
- Systematic resampling
- Linear time complexity
- Easy to implement, low variance

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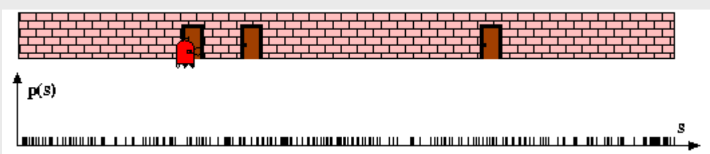
Particle Filters



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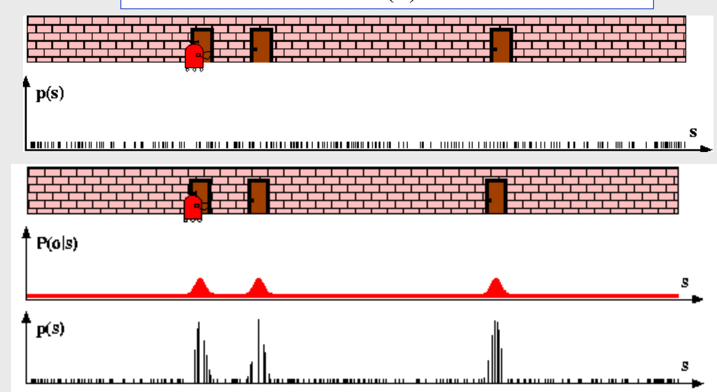
Sensor Information: Importance Sampling

$$Bel(x) \leftarrow \alpha\ p(z\,|\,x)\, Bel^{-}(x)$$

$$w \leftarrow \frac{\alpha\ p(z\,|\,x)\, Bel^{-}(x)}{Bel^{-}(x)} = \alpha\ p(z\,|\,x)$$



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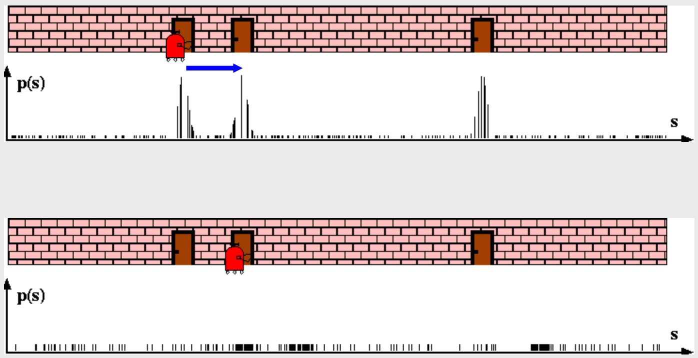
Robot Motion

$$Bel^-(x) \leftarrow \int p(x \mid u, x')\, Bel(x')\, \mathrm{d}x'$$



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Sensor Information: Importance Sampling

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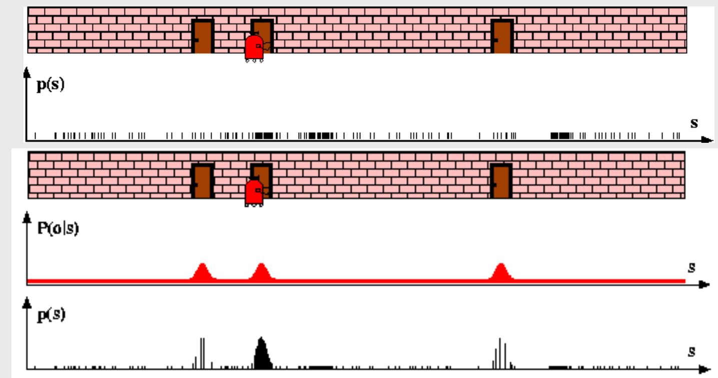

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Robot Motion

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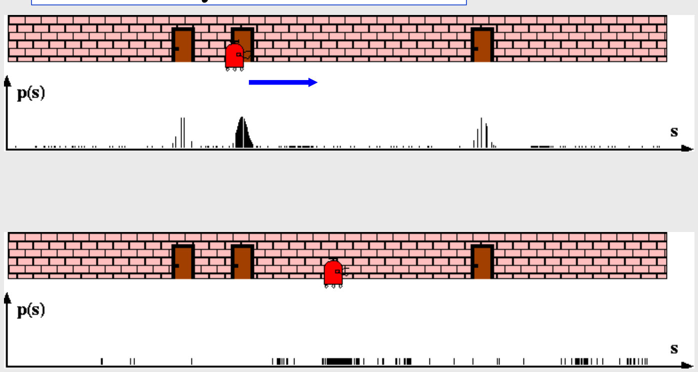

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Particle Filter Algorithm

$$Bel(x_t) = \eta\, p(z_t \mid x_t) \int p(x_t \mid x_{t-1}, u_{t-1})\, Bel(x_{t-1})\, dx_{t-1}$$

- draw x^i_{t-1} from $Bel(x_{t-1})$
- draw x^i_t from $p(x_t \mid x^i_{t-1}, u_{t-1})$
- Importance factor for x^i_t:

$$w^i_t = \frac{\text{target distribution}}{\text{proposal distribution}} = \frac{\eta\, p(z_t \mid x_t)\, p(x_t \mid x_{t-1}, u_{t-1})\, Bel(x_{t-1})}{p(x_t \mid x_{t-1}, u_{t-1})\, Bel(x_{t-1})} \propto p(z_t \mid x_t)$$

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Particle Filter Algorithm

1. Algorithm **particle_filter**(S_{t-1}, u_{t-1} z_t):
2. $S_t = \emptyset, \quad \eta = 0$
3. **For** $i = 1 \ldots n$ ***Generate new samples***
4. Sample index $j(i)$ from the discrete distribution given by w_{t-1}
5. Sample x_t^i from $p(x_t \mid x_{t-1}, u_{t-1})$ using $x_{t-1}^{j(i)}$ and u_{t-1}
6. $w_t^i = p(z_t \mid x_t^i)$ ***Compute importance weight***
7. $\eta = \eta + w_t^i$ ***Update normalization factor***
8. $S_t = S_t \cup \{< x_t^i, w_t^i >\}$ ***Insert***
9. **For** $i = 1 \ldots n$
10. $w_t^i = w_t^i / \eta$ ***Normalize weights***

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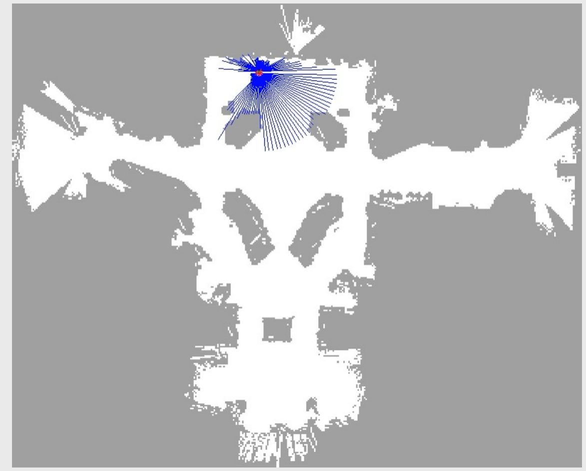
Recovery from Failure



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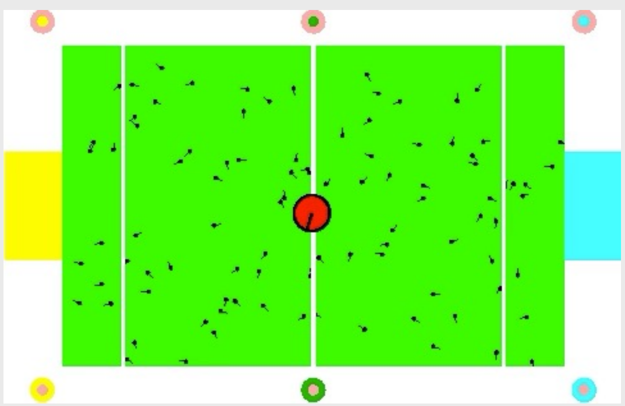
Localization for AIBO robots



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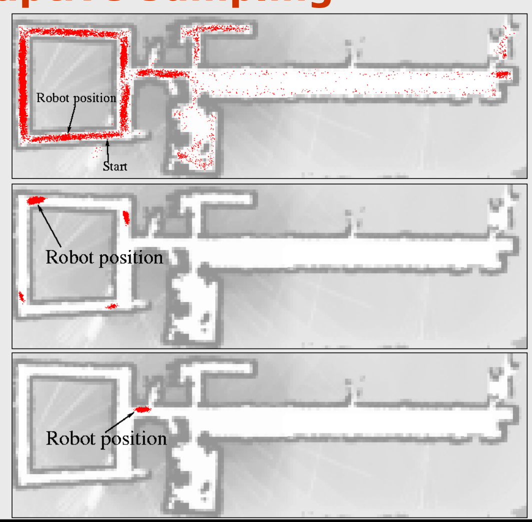
Adaptive Sampling



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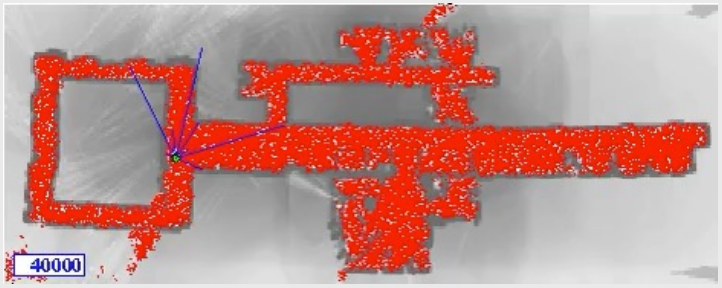
KLD-Sampling Sonar



Adapt number of particles on the fly based on statistical approximation measure

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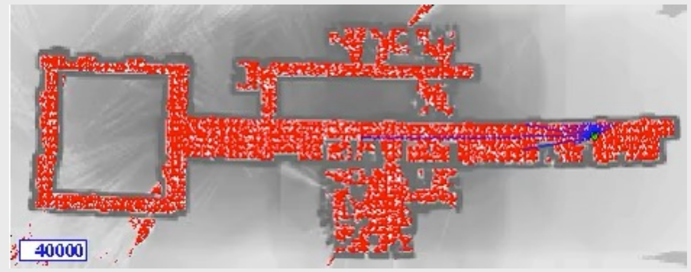
KLD-Sampling Laser



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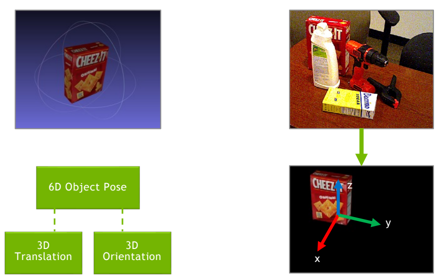
6D OBJECT POSE ESTIMATION



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ORIENTATION UNCERTAINTY

Depends on context, shape, sensor

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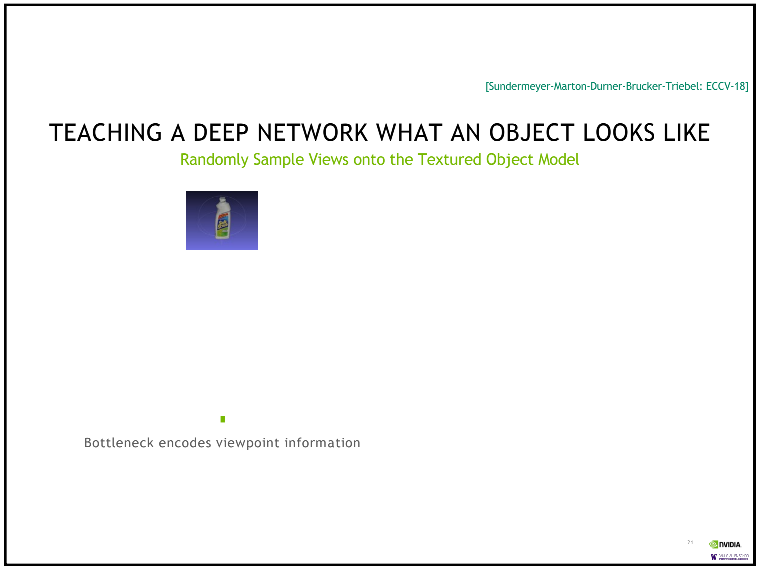
[Sundermeyer-Marton-Durner-Brucker-Triebel: ECCV-18]
TEACHING A DEEP NETWORK WHAT AN OBJECT LOOKS LIKE
Randomly Sample Views onto the Textured Object Model
Bottleneck encodes viewpoint information
NVIDIA

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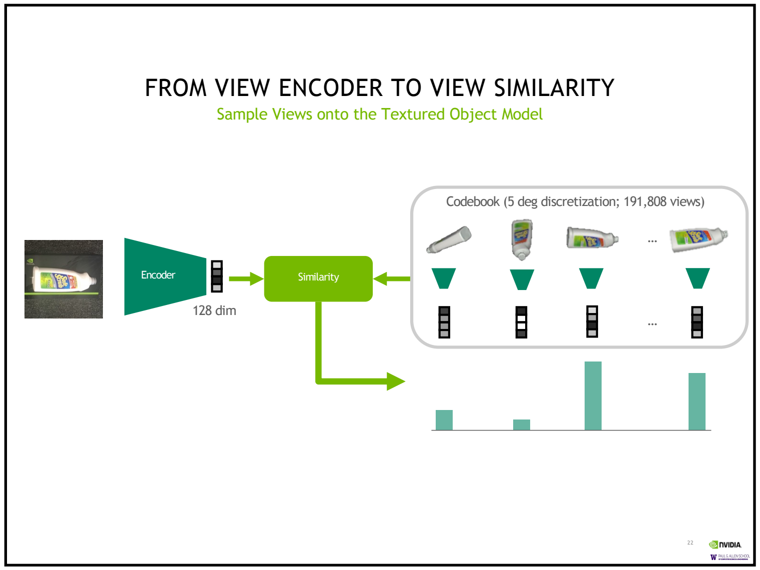
FROM VIEW ENCODER TO VIEW SIMILARITY
Sample Views onto the Textured Object Model
Codebook (5 deg discretization; 191,808 views)
Encoder
128 dim
Similarity
NVIDIA

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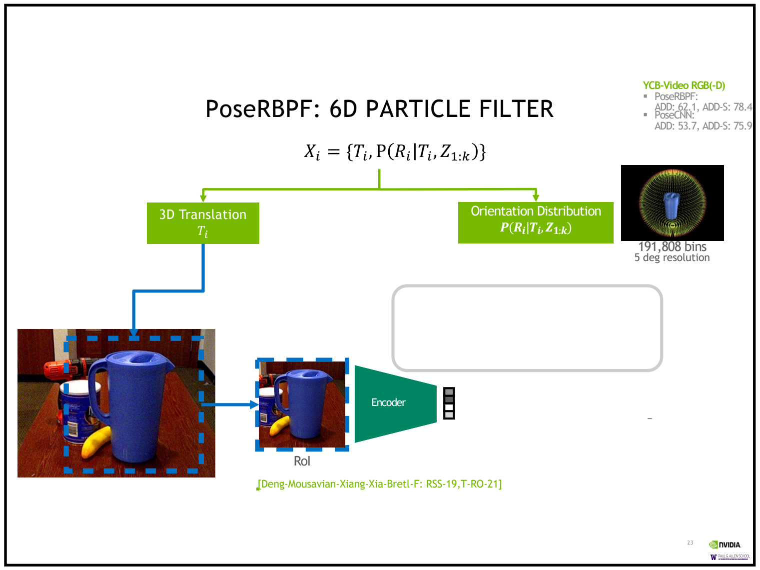
PoseRBPF: 6D PARTICLE FILTER
YCB-Video RGB(-D)
PoseRBPF: ADD: 62.1, ADD-S: 78.4
PoseCNN: ADD: 53.7, ADD-S: 75.9
$X_i = \{T_i, P(R_i|T_i, Z_{1:k})\}$
3D Translation T_i
Orientation Distribution $P(R_i|T_i, Z_{1:k})$
191,808 bins
5 deg resolution
Encoder
RoI
[Deng-Mousavian-Xiang-Xia-Bretl-F: RSS-19,T-RO-21]
NVIDIA

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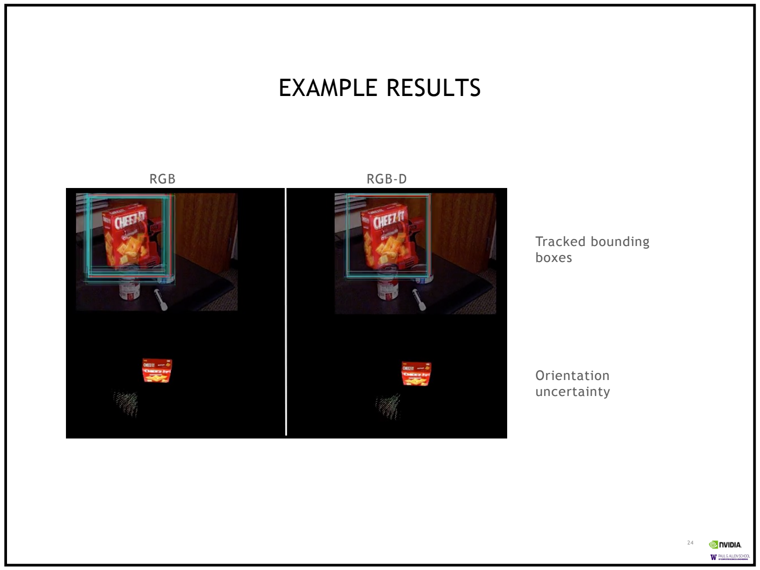
EXAMPLE RESULTS
RGB
RGB-D
Tracked bounding boxes
Orientation uncertainty
NVIDIA

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GLOBAL LOCALIZATION EXAMPLE

Sample Uniformly in Translation Space

1st frame: 5,000 particles, then 500 particles until strong match, then 50 particles
500 particles: 2.6 fps; 50 particles: 20 fps