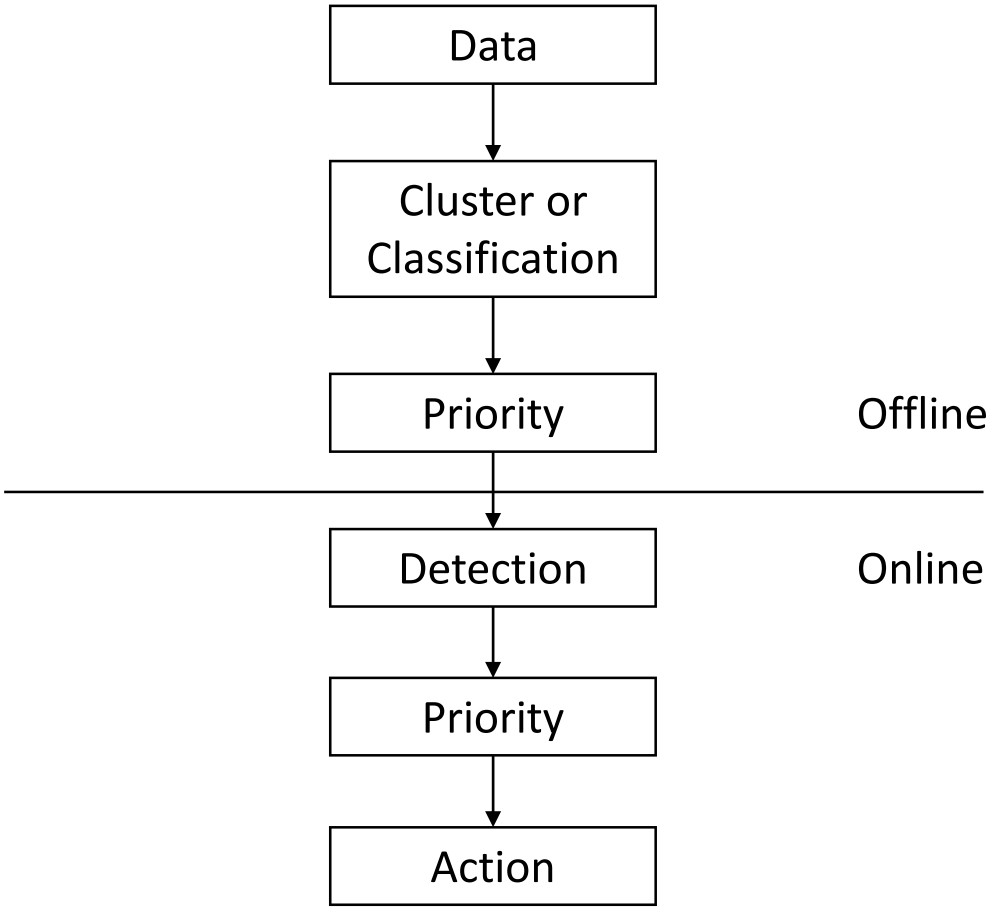
Pipeline for Active Perception



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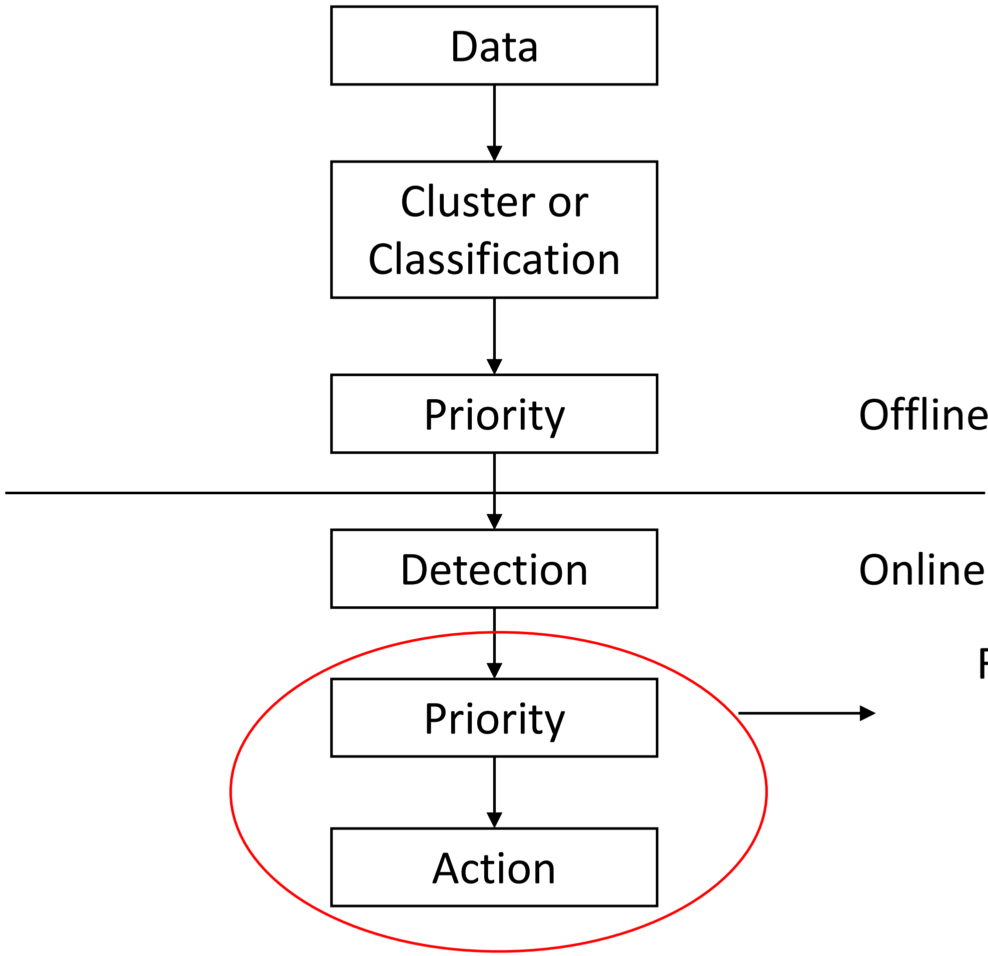
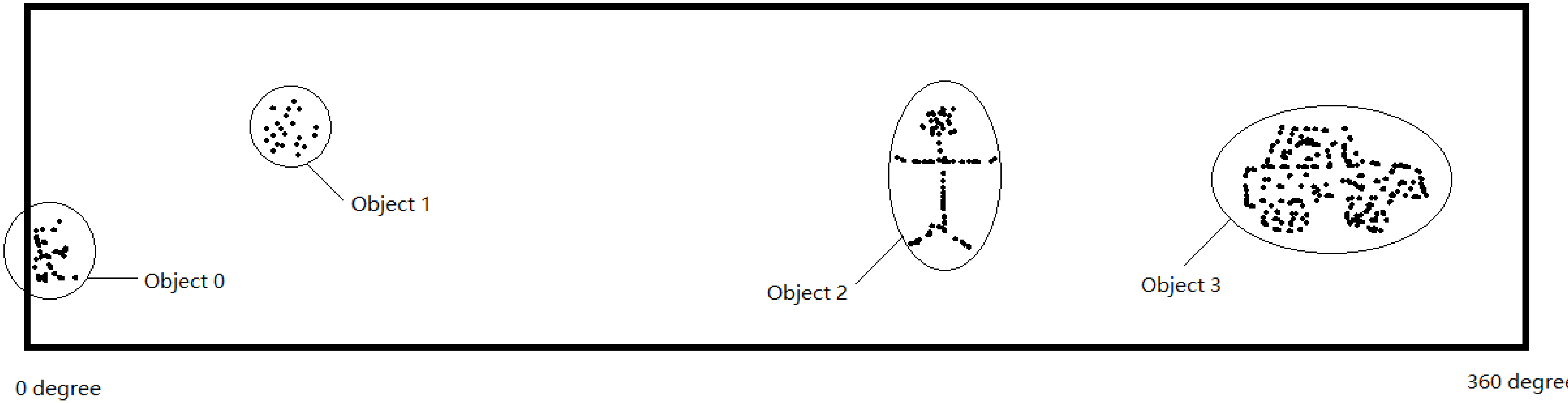


Requirements:

1. Scan more frequently in places with high priority
2. Also have chance to scan other areas with low priority
3. Cannot go beyond the physical constraints of sensors

LiDAR Data and Classification



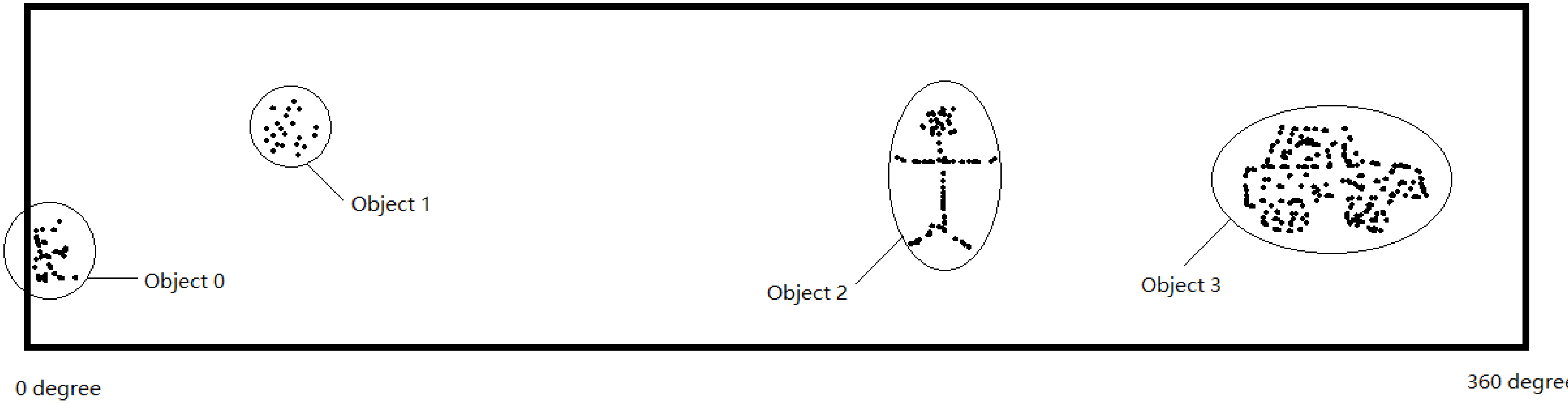
Object i at time t has following properties :

$$\{r_t^i, \theta_t^i, \overrightarrow{\Delta V_t^i}\}$$

Both these properties decide the priority p_t^i of Object i :

$$p_t^i = f_p(r_t^i, \theta_t^i, \overrightarrow{\Delta V_t^i})$$

POMDP Model



Let s_t denote the state at time t, and let s_t^i denote the distribution of p_t^i, so $b(s_t)$ will be :

$$b(s_t) = P\{s_t^i | i = 0,1,2 \ldots\}$$

Assume $s_t^i \sim N(\mu_t^i, \sigma_t^i)$, and μ_t^i, σ_t^i fulfill :

$$\mu_t^i = \theta_t^i$$

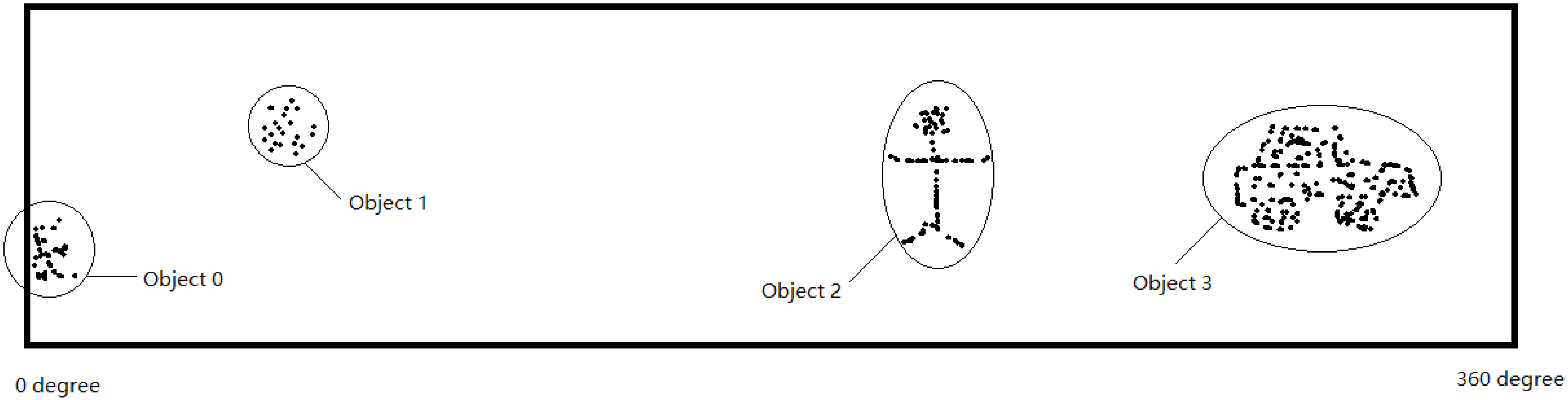
$$\sigma_t^i \propto \frac{1}{r_t^i}$$

Properties of Object i at time t

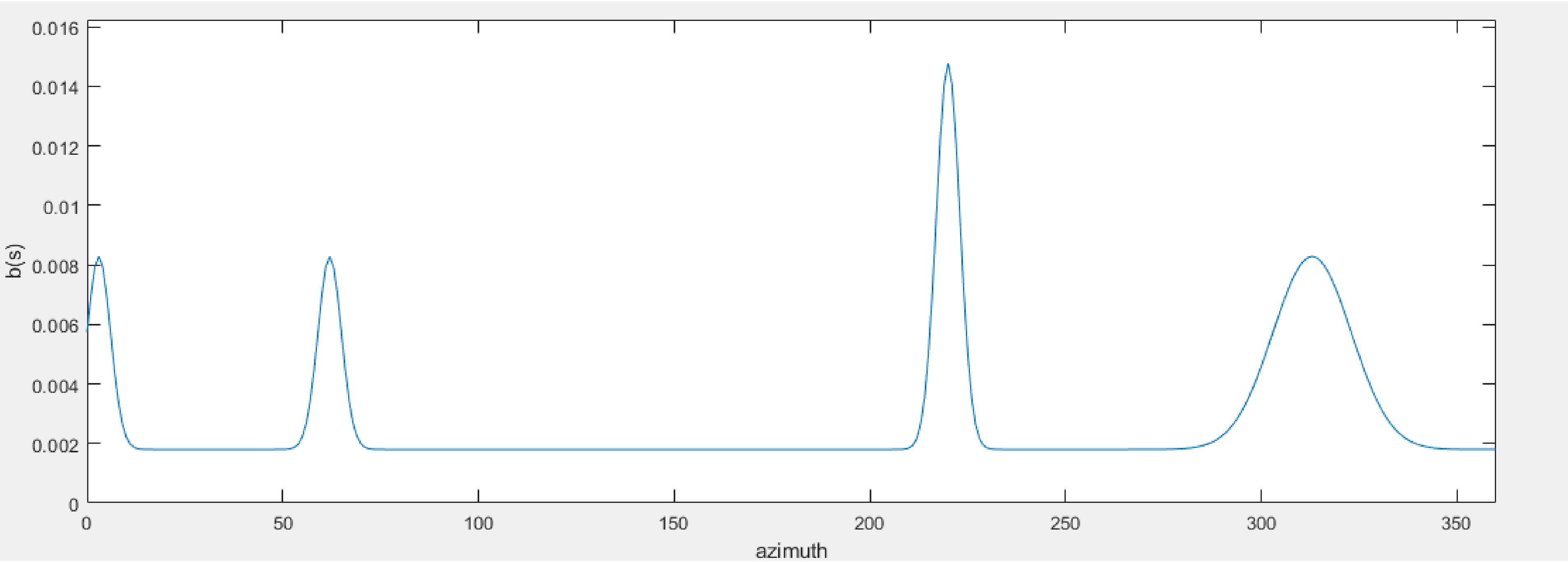
$$\{r_t^i, \theta_t^i, \Delta\overrightarrow{V_t^i}\}$$

POMDP Model

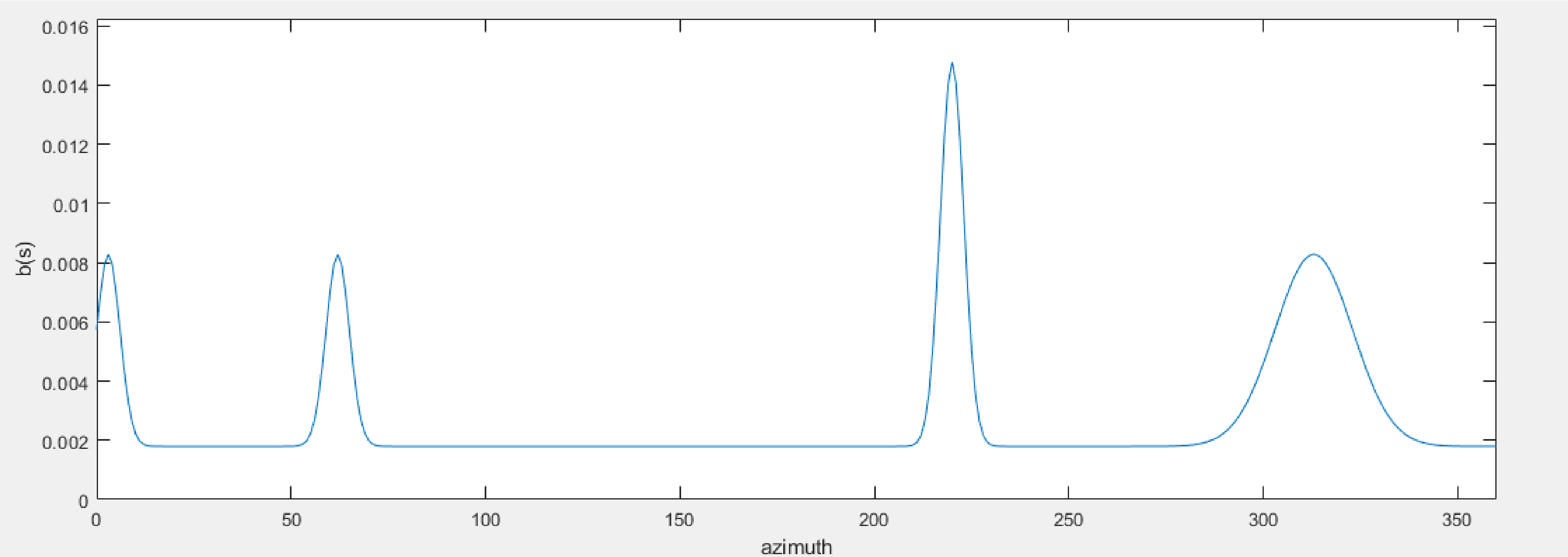
Properties of Object i at time t
$\{r_t^i, \theta_t^i, \Delta V_t^i\}$



Then $b(s_t)$ will be like :



POMDP Model



Mathematical representation for $b(s_t)$:

$$b(s_t) = \frac{\sum \pi_t^i N(\mu_t^i, \sigma_t^i) + U(0, 2\pi)}{N_t}$$

Properties of Object i at time t

$$\{r_t^i, \theta_t^i, \Delta\overrightarrow{V_t^i}\}$$

$$\pi_t^i \propto \frac{1}{r_t^i}$$

$$N_t = \int (\sum \pi_t^i N(\mu_t^i, \sigma_t^i) + U(0, 2\pi)) ds_t$$ - Normalization Factor

POMDP Model

Mathematical representation for POMDP model :

$$b(s_t{}') = P(s_t{}'|s_t, a_t)b(s_t)$$

$$b(s_{t+1}) = \beta P(O_t|s_t{}', a_t)b(s_t{}')$$

First, what is $b(s_t{}')$?

POMDP Model

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First, what is $b({s_t}')$?

$b({s_t}')$ means the $belief$ of s_t after action a_t but before O_t

So what makes the change of $b({s_t}')$ from $b(s_t)$?

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Action a_t and time lapse !

So $b(s_t{}')$ should be like:

$$b(s_t{}') = \frac{\sum \pi_t^{i\prime} N(\mu_t^{i\prime}, \sigma_t^{i\prime}) + U(0, 2\pi)}{N_t{}'}$$

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$$\pi_t^{i'} = f_\pi(\pi_t^i, r_t^i, \theta_t^i, \Delta\overrightarrow{V_t^i}, a_t)$$
$$\mu_t^{i\prime} = f_\mu(\mu_t^i, r_t^i, \theta_t^i, \Delta\overrightarrow{V_t^i}, a_t)$$
$$\sigma_t^{i\prime} = f_\sigma(\sigma_t^i, r_t^i, \theta_t^i, \Delta\overrightarrow{V_t^i}, a_t)$$

Properties of Object i at time t

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Then, how to calculate $b(s_{t+1})$ or how to get $P(O_t|s_t{}', a_t)$?

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O_t denotes the state that we can observe because of action a_t

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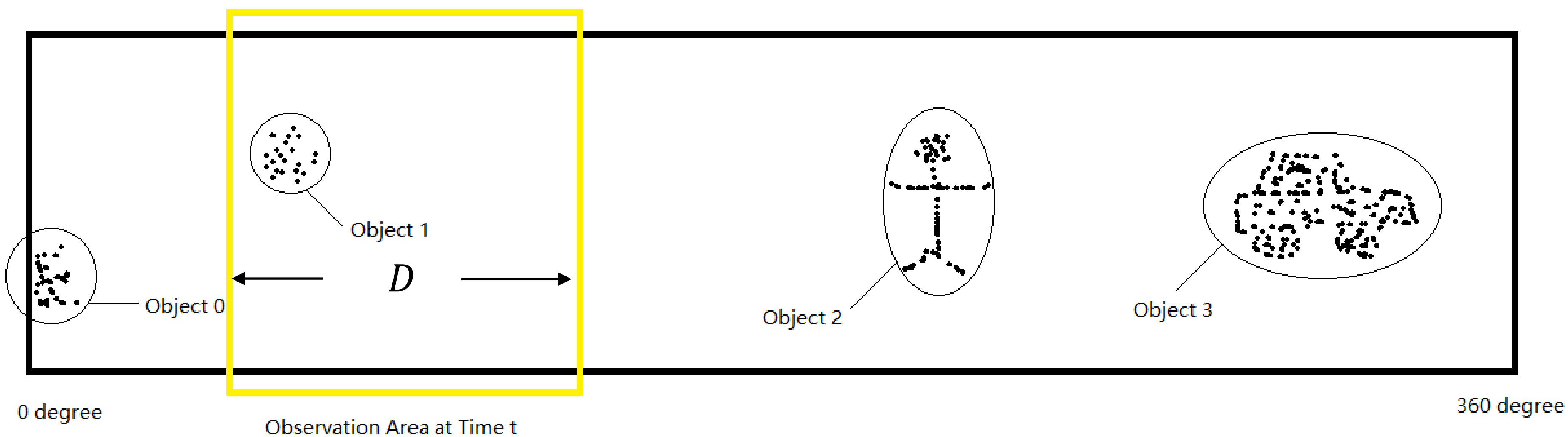

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So $p(O_t|s_t{}', a_t)$ should be like that:

$$P(O_t|s_t{}', a_t) = \sum_{\mu_{o,t}^j \in [a_t - \frac{D}{2}, a_t + \frac{D}{2}]} \pi_{o,t}^j N(\mu_{o,t}^j, \sigma_{o,t}^j)$$

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So how to calculate $b(s_{t+1})$?

KL-divergence !

POMDP Model

Recall :

$$b(s_t{}') = \frac{\sum \pi_t^{i\prime} N(\mu_t^{i\prime}, \sigma_t^{i\prime}) + U(0, 2\pi)}{N_t{}'}$$

$$P(O_t | s_t{}', a_t) = \sum_{\mu_{o,t}^j \in [a_t - \frac{D}{2}, a_t + \frac{D}{2}]} \pi_{o,t}^j N(\mu_{o,t}^j, \sigma_{o,t}^j)$$

Calculate $b(s_{t+1})$ *(* $p(O_t | s_t{}', a_t)$, $b(s_t{}')$ *):*

for gaussian distribution $N(\mu_{o,t}^j, \sigma_{o,t}^j)$ *in* $P(O_t | s_t{}', a_t)$ *:*

find gaussian distribution $N(\mu_t^{i\prime}, \sigma_t^{i\prime})$ *which fulfills :*

1. $\mu_t^{i\prime} \in [a_t - \frac{D}{2}, a_t + \frac{D}{2}]$

2. KL($N(\mu_{o,t}^j, \sigma_{o,t}^j)$, $N(\mu_t^{i\prime}, \sigma_t^{i\prime})$*) is the smallest*

$$N\left(\mu_{t+1}^i, \sigma_{t+1}^i\right) = \beta N\left(\mu_t^{i\prime}, \sigma_t^{i\prime}\right) N\left(\mu_{o,t}^j, \sigma_{o,t}^j\right)$$

for gaussian distribution $N(\mu_t^{i\prime}, \sigma_t^{i\prime})$ *in* $b(s_t{}')$ *that has not been calculated:*

$N\left(\mu_{t+1}^i, \sigma_{t+1}^i\right) = N\left(\mu_t^{i\prime}, \sigma_t^{i\prime}\right)$ ***// TODO: This equation is ugly and needs change***

$$b(s_{t+1}) = \frac{\sum \pi_{t+1}^i N(\mu_{t+1}^i, \sigma_{t+1}^i) + U\ (0{,}2\pi)}{N_{t+1}}$$

return $b(s_{t+1})$

Decision

Mathematical representation for POMDP model :

$$b({s_t}') = P({s_t}'|s_t, a_t)b(s_t)$$

$$b(s_{t+1}) = \beta P(O_t|{s_t}', a_t)b({s_t}')$$

So next step is to choose action a_t based on present $b(s_t)$.

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$$b(s_{t+1}) = \beta P(O_t|s_t', a_t)b(s_t')$$

So next step is to choose action a_t based on present $b(s_t)$.

Recall the requirements for active perception:

1. Scan more frequently in places with high priority
2. Also have chance to scan other areas with low priority
3. Cannot go beyond the physical constraints of sensors

Traditional way for POMDP model to choose action is based on the reward function:

$$R(a_t) = f(a_t)$$

$$a_t = \underset{a_t}{\operatorname{argmax}} R(a_t)$$

Decision

Requirements for active perception:

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Traditional way for POMDP model to choose action is based on the reward function:

$$R(a_t) = f(a_t)$$

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This is useful but it cannot fulfill the second requirement. So we need to sample a_t from the distribution of a_t instead of directly choose a a_t.

Also, to fulfill the third requirement, the a_t should be like :

$$a_t = \{a_t^p, a_t^g\}$$

Decision

Requirements for active perception:

1. Scan more frequently in places with high priority
2. Also have chance to scan other areas with low priority
3. Cannot go beyond the physical constraints of sensors

To fulfill the third requirement, a_t should be like :

$$a_t = \{a_t^p, a_t^g\}$$

a_t^p denotes the present angle of sensor and a_t^g denotes the present goal of sensor.

a_t^p should increase or decrease toward a_t^g and both of them should fulfill the requirements below :

1. The difference between a_{t-1}^g and a_t^g should be small, which is:
$$\left|a_t^g - a_{t-1}^g\right| < \varepsilon_g$$
2. The difference between a_t^p and a_{t-1}^p should be in the physical constraint of sensor.
3. If a_t^p and a_t^g is very close, then a_{t+1}^g should not be close to a_t^g any more.

Decision

a_t^p and a_t^g should fulfill the requirements below :

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2. The difference between a_t^p and a_{t-1}^p should be in the physical constraint of sensor.
3. If a_t^p and a_t^g is very close, then a_{t+1}^g should not be close to a_t^g any more.

So the distribution of a_t^g should be like:

$$R\left(a_t^g\right) = \frac{\left|a_t^g - a_t^p\right|^m}{\left|a_t^g - a_{t-1}^g\right|^n} \int_{a_t^g - \frac{D}{2}}^{a_t^g + \frac{D}{2}} b(s_t)\,ds_t$$

$$P\left(a_t^g \middle| s_t\right) = \frac{R\left(a_t^g\right)}{\int R\left(a_t^g\right)da_t^g}$$

Sample a_t^g from its distribution and choose a_t^p which fulfills the requirements.