Localization 3: Histogram filters and particle filters

Probabilistic localization

Probabilistic models

Recall the state transition function:

$$x_{k+1} = f(x_k, u_k, \theta_k)$$

and the observation function

$$y_k = h(x_k, \psi_k).$$

If errors are random, we can express the same information using conditional probabilities:

- Transition model: $P(x_k \mid x_{k-1}, u_{k-1})$
- Observation model: $P(y_k \mid x_k)$

Posterior distribution

Recall that the goal of probabilistic localization is to keep track of a probability distribution over the state space, given the history:

$$P(x_k \mid u_1, \ldots, u_{k-1}, y_1, \ldots, y_k)$$

This is sometimes called the **posterior distribution**.

Posterior updates

We can get an update equation for the posterior distribution using **Bayes rule**, along with **marginalization**:

$$
\begin{aligned}
&P(x_k|u_1, \ldots, u_{k-1}, y_1, \ldots, y_k) \\
&\qquad = \alpha_k P(y_k \mid x_k) \sum_{x_{k-1} \in X} [P(x_k|x_{k-1}, u_{k-1}) P(x_{k-1} \mid u_1, \ldots, u_{k-2}, y_1, \ldots, y_{k-1})]
\end{aligned}
$$

Missing parts

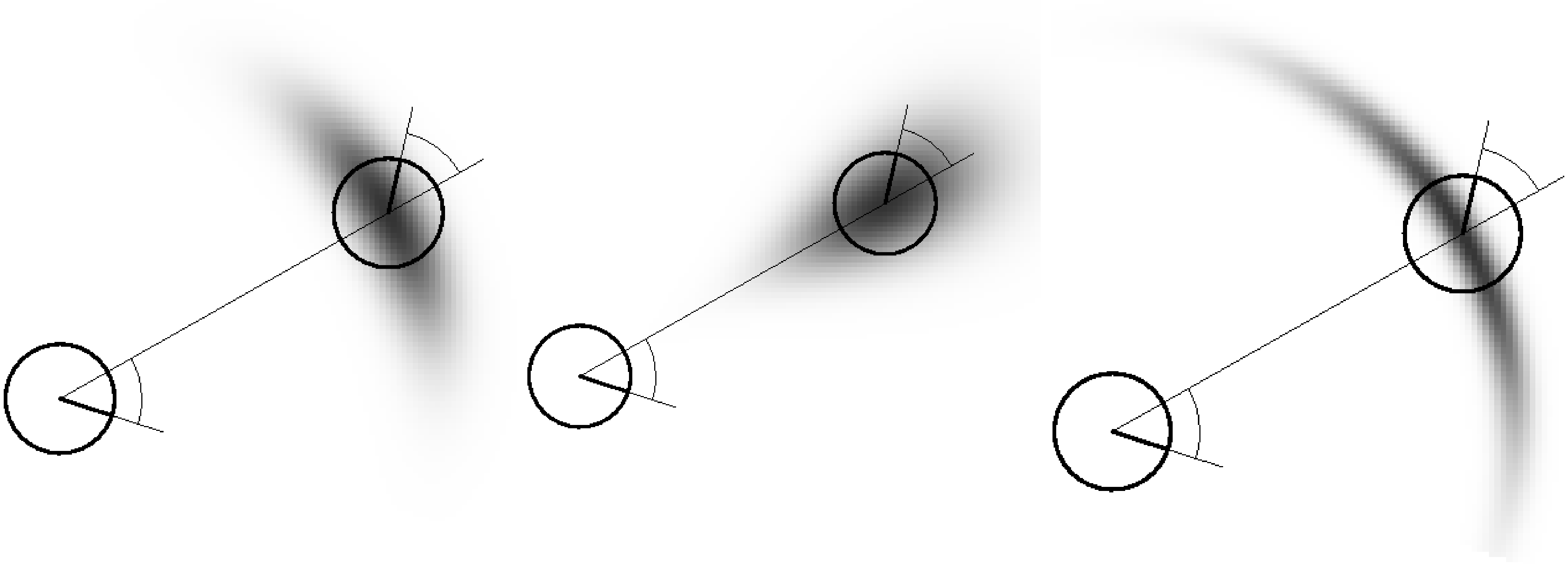
The previous page doesn't tell us about:

- the transition distribution
- the observation distribution
- the posterior distribution

We need to fill these details to get a complete algorithm.

Transition distributions

Example: Assume errors occur in rotation and translation separately.



Observation distributions

Example: Range sensor. Sources of error: noise, crosstalk, reflections, dynamic obstacles (e.g. people), maximum range, etc.