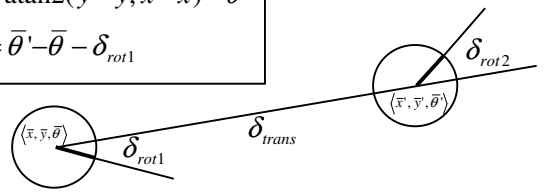
# CSE-571
# AI-based Mobile Robotics

**Probabilistic Motion Models**

## Probabilistic Kinematics

- Robot moves from $\langle \bar{x}, \bar{y}, \bar{\theta} \rangle$ to $\langle \bar{x}', \bar{y}', \bar{\theta}' \rangle$.
- Odometry information $u = \langle \delta_{rot1}, \delta_{rot2}, \delta_{trans} \rangle$.

$$\delta_{trans} = \sqrt{(\bar{x}'-\bar{x})^2 + (\bar{y}'-\bar{y})^2}$$
$$\delta_{rot1} = \text{atan2}(\bar{y}'-\bar{y}, \bar{x}'-\bar{x}) - \bar{\theta}$$
$$\delta_{rot2} = \bar{\theta}'-\bar{\theta} - \delta_{rot1}$$



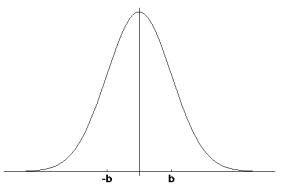

## Noise Model for Motion

- The measured motion is given by the true motion corrupted with noise.

$$\hat{\delta}_{rot1} = \delta_{rot1} + \varepsilon_{\alpha_1 |\delta_{rot1}| + \alpha_2 |\delta_{trans}|}$$
$$\hat{\delta}_{trans} = \delta_{trans} + \varepsilon_{\alpha_3 |\delta_{trans}| + \alpha_4 |\delta_{rot1} + \delta_{rot2}|}$$
$$\hat{\delta}_{rot2} = \delta_{rot2} + \varepsilon_{\alpha_1 |\delta_{rot2}| + \alpha_2 |\delta_{trans}|}$$

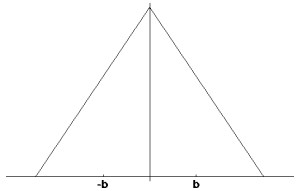
## Noise Models

Normal distribution




$$\varepsilon_b(x) = \frac{1}{\sqrt{2\pi b}} e^{-\frac{1}{2}\frac{x^2}{b}}$$

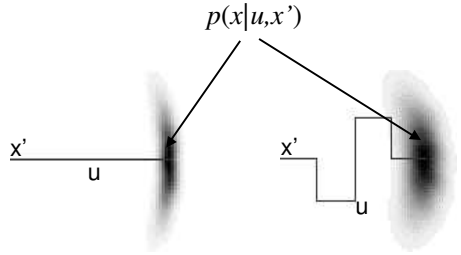
Triangular distribution



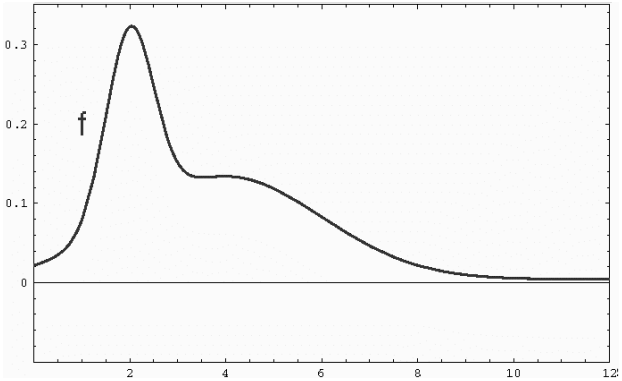

$$\varepsilon_b(x) = \begin{cases} 0 \text{ if } |x| > \sqrt{6b} \\ \frac{\sqrt{6b} - |x|}{6b} \end{cases}$$

## Probabilistic Kinematics

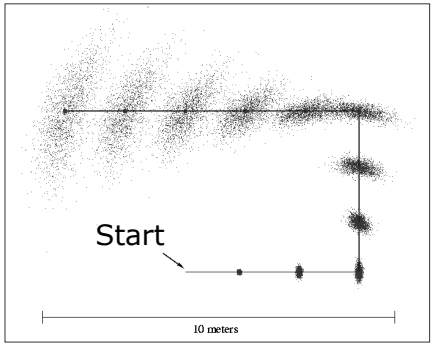
- Odometry information is inherently noisy.
- How can we model this uncertainty?




## Sample-based Density Representation




## Sample-based Motion




## Sample-based Motion Model

1. Algorithm **sample_motion_model**(u, x):

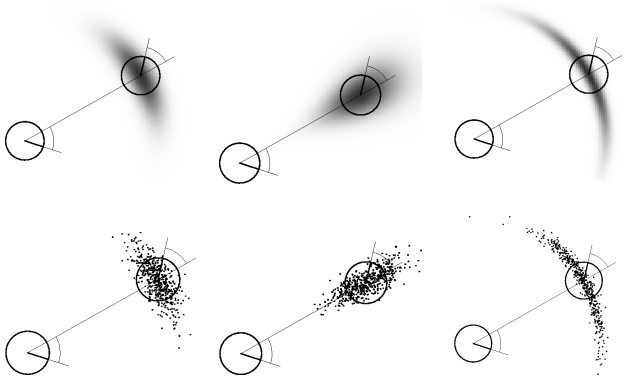
   $u = \langle \delta_{rot1}, \delta_{rot2}, \delta_{trans} \rangle, x = \langle x, y, \theta \rangle$

1. $\hat{\delta}_{rot1} = \delta_{rot1} + \text{sample}(\alpha_1 \mid \delta_{rot1} \mid + \alpha_2 \ \delta_{trans})$
2. $\hat{\delta}_{trans} = \delta_{trans} + \text{sample}(\alpha_3 \ \delta_{trans} + \alpha_4 \ (\mid \delta_{rot1} \mid + \mid \delta_{rot2} \mid))$
3. $\hat{\delta}_{rot2} = \delta_{rot2} + \text{sample}(\alpha_1 \mid \delta_{rot2} \mid + \alpha_2 \ \delta_{trans})$

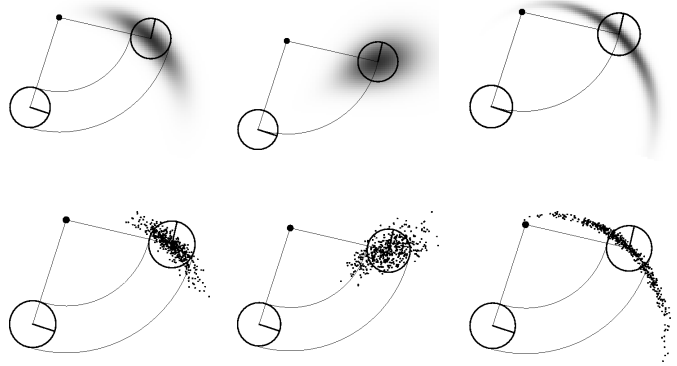
4. $x' = x + \hat{\delta}_{trans} \cos(\theta + \hat{\delta}_{rot1})$
5. $y' = y + \hat{\delta}_{trans} \sin(\theta + \hat{\delta}_{rot1})$
6. $\theta' = \theta + \hat{\delta}_{rot1} + \hat{\delta}_{rot2}$

7. Return $\langle x', y', \theta' \rangle$

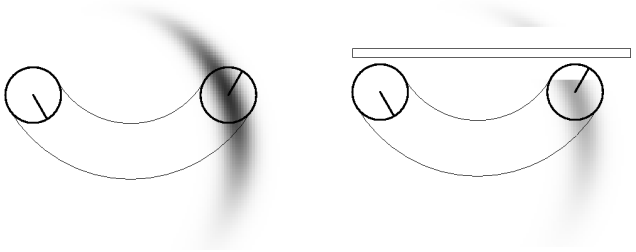
## Examples (odometry based)



## Examples (velocity based)



## Motion Model with Map



$P(x \mid u, x')$



$P(x \mid u, x', m) = \eta\, P(x \mid m)\, P(x \mid u, x')$

- When does this approximation fail?