# Motion and Measurement Models And Some Things About It

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November 25, 2022

#### Outline

1 Motion Models

2 Measurement Models

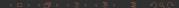
### Motion Models



Robot kinematic models are deterministic. We assume, that controls are definite and update the state exactly.

In reality, that's not the case. Control inputs are exposed to noise, and unmodeled external factors can affect robot state.

Probabilistic Motion Models are designed to cater for these uncertainties Which is how the world works in reality



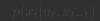
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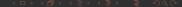
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$$p(x_t|u_t, x_{t-1})$$

### Model Types

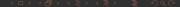
There are two basic model types

- Velocity Motion Model
- Odometry Motion Model



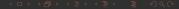
### Velocity Motion Model

Assumes that the robot is actuated by independent translational (v) and rotational velocities  $(\omega)$ 



### Velocity Motion Model

$$\begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} -\frac{v}{\omega}sin\theta + \frac{v}{\omega}sin(\theta + \omega\delta t) \\ \frac{v}{\omega}cos\theta - \frac{v}{\omega}cos(\theta + \omega\delta t) \\ \omega\delta t + \gamma\delta t \end{bmatrix}$$



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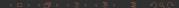
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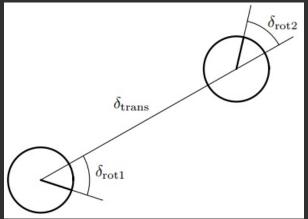
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We can get to any pose by executing 3 operations (rotate, translate and rotate, like the basic steps of the dubins path)



The odometry reports back to us a related advance from  $\bar{x}_{t-1}=(\bar{x}\bar{y}\bar{\theta})$  to  $\bar{x}_t=(\bar{x}'\bar{y}'\bar{\theta}')$ 

The bars indicate that these are odometry measurements embedded in the robot-internal coordinate whose relation to the world coordinate is unknown.

The key concept for utilizing this information in state estimation is the fact that the relative difference between  $\bar{x}_{t-1}$  and  $\bar{x}_t$ , under a specific definition of the term "difference," is a good estimator for the difference of the true poses  $x_{t-1}$  and  $x_t$ 

The motion information  $u_t$  is then given by the pair as shown below

$$u_t = \begin{pmatrix} \bar{x}_{t-1} \\ \bar{x}_t \end{pmatrix}$$

Relative odometry can then be extracted by transforming this information in a sequence of three steps (rotation, translation and rotation)

Thus there exist a unique set of three parameters to construct the relative motion between any pair of poses  $\bar{s}$  and  $\bar{s}'$ 

$$\begin{pmatrix} \delta_{rot1} \\ \delta_{trans} \\ \delta_{rot2} \end{pmatrix}$$

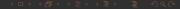
The motion model assumes that these parameters are corrupted by noise.

Given odometry reading  $u_t=(\bar{x}_{t-1}\bar{x}_t)^T$  and prior  $x_{t-1}$ , We calculate the predicted next state as follows

$$\delta_{rot1} = atan2(\bar{y}' - \bar{y}, \bar{x}' - \bar{x}) - \bar{\theta}$$

$$\delta_{trans} = \sqrt{(\bar{x}' - \bar{x})^2 + (\bar{y}' - \bar{y})^2}$$

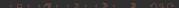
$$\delta_{rot2} = \bar{\theta}' - \bar{\theta} - \delta_{rot1}$$



#### Finally we have the motion model

$$\begin{bmatrix} x' \\ y' \\ \theta' \end{bmatrix} = \begin{bmatrix} x \\ y \\ \theta \end{bmatrix} + \begin{bmatrix} \delta_{trans}cos(\theta + \delta_{rot1}) \\ \delta_{trans}sin(\theta + \delta_{rot1}) \\ \theta + \delta_{rot1} + \delta_{rot2} \end{bmatrix}$$

Note that these parameters are affected by noise and the true values have the noise subtracted.



Measurement models describe the formation process by which sensor measurements are generated in the physical world.

Measurement models (in the realm of Probabilistic Robots) account for the inherent uncertainty in the robot's sensors. The measurement model is defined as a conditional probability distributio  $p(z_t|x_t,m)$ , where  $x_t$  is the robot pose,  $z_t$  is the measurement at time t,

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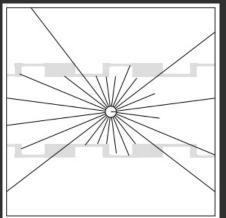
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The principle can be applied to any kind of sensor



Try to obtain a probability  $p(z_t|x_t)$  rather than using a deterministic  $z_t=f(x_t)$ 

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Some sensor models utilize raw sensor measurements while an alternative approach is to extract features from the measurements. Feature extractors extract a small number of features from high dimensional sensor measurements thereby enormously reduction of computational complexity. In robotics, it is also common to define places as features, such as hallways, vertical columns, intersections, etc.

In many robotics applications, features correspond to distinct objects in the physical world such as door posts or window stills in indoor environments; outdoors they may correspond to tree trunks or corners of buildings. It is common to call those physical objects landmarks, to indicate that they are being used for robot navigation.

It is assumed that the sensor can measure the range and bearing of the landmark relative to the robot's local coordinate frame. In addition, the feature extractor may generate a *signature* which could have a numerical value indicating colour, landmark type, height, etc.

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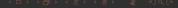
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$$f(z_t) = \{f_t^1, f_t^2, \dots\} = \{ \begin{pmatrix} r_t^1 \\ \phi_t^1 \\ s_t^1 \end{pmatrix}, \begin{pmatrix} r_t^2 \\ \phi_t^2 \\ s_t^2 \end{pmatrix}, \dots \}$$



Given the location of the  $j^{th}$  landmark corresponding to the  $i^{th}$  feature, denoted as  $m_{j,x}$  and  $m_{j,y}$  which is it's coordinate in the global coordinate frame of the map and the robot pose  $x_t = (x,y,\theta)^T$ ,

$$\begin{pmatrix} r_t^i \\ \phi_t^i \\ s_t^i \end{pmatrix} = \begin{pmatrix} \sqrt{(m_{j,x} - x)^2 + (m_{j,y} - y)^2} \\ atan2((m_{j,y} - y), (m_{j,x} - x)) - \theta \\ s_j \end{pmatrix}$$

## Known Correspondence

To implement this measurement model, we need to define a variable that establishes correspondence between the feature  $f_t^i$  and the (known) landmark  $m_i$  in the map.

It is denoted as  $c_t^i$ . Correspondences can be generated however you want.

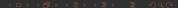
### Acknowledgments

Appreciation goes to Dr. Geesara and all my noble colleagues.



#### References

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- Wikipedia. Odometry. https://en.wikipedia.org/wiki/Odometry.



# The End