Robotics

Chapter 25-a
Robots

- Robots are becoming more and more used in various applications:
  - space exploration
  - manufacturing
  - reconnaissance and aerial inspection
Robot Types

- **Manipulators** - robot arms
  - Manufacturing, automobile assembly
  - Surgeon assistants
  - Space station / space shuttle

- **Mobile robots**
  - Unmanned Land Vehicles (ULV)
  - Unmanned Air Vehicles (UAV)
  - Autonomous Underwater Vehicles (AUV)
  - Planetary Rovers

- **Humanoid robots**
  - Mimics a full human or human torso
Robot Sensors

Example: Laser range finder
Robot Sensors

- Passive sensors - simply observe environment
  - Cameras
  - Microphones
  - Whiskers
  - Tactile sensors
  - GPS receivers

- Active sensors - send out energy into environment
  - Sonar
  - Radar
  - Laser range finders / Lidar

- Proprioceptive sensors - sense robot state
  - Shaft decoders - count motor revolutions
  - Odometers - count wheel turns
  - Inertial sensors (gyroscopes, accelerometers)
  - Force and torque sensors
Robot State

• Effectors
  - “The means by which robots move and change [body shape]”
  - Examples: revolute joints, prismatic joints

• Degrees of Freedom (DOF)
  - 1 DOF for each direction that the robot (or its effectors) can move
  - Example: A UAV has 6 degrees of freedom, \((x, y, z)\) plus \((pitch, roll, yaw)\)

• Kinematic state (pose)
  - Position and orientation, but not speed

• Dynamic state
  - Includes pose plus velocity for each pose dimension.
Configuration of robot specified by 6 numbers

\[ \Rightarrow 6 \text{ degrees of freedom (DOF)} \]

6 is the minimum number required to position end-effector arbitrarily.

For dynamical systems, add velocity for each DOF.

(Q) Why 6 degrees of freedom for arbitrary positioning?
Holonomic vs. Non-Holonomic Robots

- Holonomic robot - as many controllable degrees of freedom as effective degrees of freedom.
- A car has more DOF (3) than controls (2), so it is non-holonomic. It cannot transition between all adjacent configurations.

(Q) Give an example of how a car is not holonomic.

(Q) What operations does this make difficult?
Robot Perception

- Localization - Compute current state, including position, orientation, and pose, given a sequence of observations and actions:

\[ X_{t+1} = X_t + A_t - Z_t - Z_{t-1} \]

- \( X_t \) = environment and robot state at time \( t \)
- \( Z_t \) = observation at time \( t \)
- \( A_t \) = action taken at time \( t \), leading to state \( X_{t+1} \)

- \( P(X_t|z_{1:t}, a_{1:t-1}) = \) belief state at time \( t \)
  - based on all previous observations \((z_{1:t})\) and actions \((a_{1:t-1})\)

(Q) Why are we including all of the observations and actions? How do they help us?
Filtering

Filtering computes a new belief state for time $t + 1$ from a belief state at time $t$ and a new (possibly empty) action $a_t$ and a new observation $z_{t+1}$:

$$P(X_{t+1}|z_{1:t+1}, a_{1:t}) = f(a_t, z_{t+1}, P(X_t|z_{1:t}, a_{1:t-1}))$$

Note that $X_t$ is not a single state. Conceptually, it is a probability distribution over many states.

(Q) In practice, how should the belief state $(X_t)$ be represented?
Filtering

- $f(\cdot)$ computes $X_{t+1}$ by integrating over the belief-action-percept space:

$$P(X_{t+1}|z_{1:t+1}, a_{1:t}) = \int_{X_t} f(a_t, z_{t+1}, P(X_t|z_{1:t}, a_{1:t-1}))$$

$$P(X_{t+1}|z_{1:t+1}, a_{1:t}) = \alpha P(z_{t+1}|X_{t+1}) \int_{X_{t}} P(X_{t+1}|x_t, a_t)P(x_t|z_{1:t}, a_{1:t-1})dx_t$$

- $P(X_{t+1}|z_{1:t+1}, a_{1:t}) =$ belief state at time $t+1$
- $\alpha =$ a normalization factor
- $z_{t+1} =$ percept at time $t+1$
- $X_{t+1} =$ state at time $t+1$
- $P(z_{t+1}|X_{t+1}) =$ prob. of observing $z_{t+1}$ given $X_{t+1}$
- $a_t =$ action taken at time $t$
- $x_t =$ possible state at time $t$
- $P(X_{t+1}|x_t, a_t) =$ prob. of being in state $X_{t+1}$ given $x_t$ and $a_t$
- $P(x_t|z_{1:t}, a_{1:t-1}) =$ prob of being in state $x_t$ at time $t$

- Notice how the equation is essentially based on Bayes’ rule.
Kalman Filter

• A Kalman filter represents the belief state as a Gaussian with a particular mean and covariance.

• The Gaussian moves over time based on actions and observations.

(Q) Why use a Gaussian representation?
• Suppose we are tracking something moving at velocity $v_t$ in direction $\theta$, but that the position $x_t$, velocity $v_t$ and direction $\theta$ are uncertain.

\[
\hat{X}_{t+1} = X_t + \begin{pmatrix}
v_t \Delta t \cos \theta_t \\
v_t \Delta t \sin \theta_t \\
\omega_t \Delta t
\end{pmatrix}
\]
Tracking with a Kalman Filter

- Assume Gaussian noise in motion prediction, sensor range measurements

\[
P(X_{t+1}|X_t, v_t, w_t) = N(\hat{X}_{t+1}, \Sigma_x)
\]

- \(N(\hat{X}_{t+1}, \Sigma_x)\) = gaussian distribution with mean \(\hat{X}_{t+1}\) and covariance \(\Sigma_x\).

- Since \(v_t\) and \(w_t\) are assumed to vary in a gaussian fashion, the result is another gaussian with updated covariance.

- Even if the result is not an exact Gaussian, we can approximate the result by a Gaussian, preserving the representation (called an extended Kalman filter).

(Q) Why would it be okay to use a Gaussian if the transition model does not actually produce Gaussians?
Sensor Model With Landmarks

- If the robot senses a landmark with known position, we can estimate the robot position based on the landmark.
- If the estimate based on the landmark is better than the current belief state (has smaller covariance), we can replace the belief state by it.