Robot Mapping

Extended Kalman Filter

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SLAM is a State Estimation Problem

- Estimate the map and robot’s pose
- Bayes filter is one tool for state estimation

**Prediction**

$$\overline{bel}(x_t) = \int p(x_t \mid u_t, x_{t-1}) \, bel(x_{t-1}) \, dx_{t-1}$$

**Correction**

$$bel(x_t) = \eta \, p(z_t \mid x_t) \, \overline{bel}(x_t)$$
Kalman Filter

- It is a Bayes filter
- Estimator for the linear Gaussian case
- Optimal solution for linear models and Gaussian distributions
Kalman Filter Distribution

- Everything is Gaussian

\[ p(x) = \frac{1}{\sqrt{\det(2\pi \Sigma)}} \exp \left( -\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right) \]
Properties: Marginalization and Conditioning

- Given
  
  \[ x = \begin{pmatrix} x_a \\ x_b \end{pmatrix} \quad p(x) = \mathcal{N} \]

- The marginals are Gaussians
  
  \[ p(x_a) = \mathcal{N} \quad p(x_b) = \mathcal{N} \]

- as well as the conditionals
  
  \[ p(x_a \mid x_b) = \mathcal{N} \quad p(x_b \mid x_a) = \mathcal{N} \]
Marginalization

- Given \( p(x) = p(x_a, x_b) = \mathcal{N}(\mu, \Sigma) \)

  with \( \mu = \begin{pmatrix} \mu_a \\ \mu_b \end{pmatrix} \) \( \Sigma = \begin{pmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{pmatrix} \)

- The marginal distribution is

  \( p(x_a) = \int p(x_a, x_b) \, dx_b = \mathcal{N}(\mu, \Sigma) \)

  with \( \mu = \mu_a \) \( \Sigma = \Sigma_{aa} \)
Conditioning

- Given \( p(x) = p(x_a, x_b) = \mathcal{N}(\mu, \Sigma) \)

  with \( \mu = \begin{pmatrix} \mu_a \\ \mu_b \end{pmatrix} \) \( \Sigma = \begin{pmatrix} \Sigma_{aa} & \Sigma_{ab} \\ \Sigma_{ba} & \Sigma_{bb} \end{pmatrix} \)

- The conditional distribution is

  \[
p(x_a \mid x_b) = \frac{p(x_a, x_b)}{p(x_b)} = \mathcal{N}(\mu, \Sigma)
  \]

  with \( \mu = \mu_a + \Sigma_{ab} \Sigma_{bb}^{-1} (b - \mu_b) \)

  \[\Sigma = \Sigma_{aa} - \Sigma_{ab} \Sigma_{bb}^{-1} \Sigma_{ba}\]
Linear Model

- The Kalman filter assumes a linear transition and observation model
- Zero mean Gaussian noise

\[ x_t = A_t x_{t-1} + B_t u_t + \epsilon_t \]

\[ z_t = C_t x_t + \delta_t \]
Components of a Kalman Filter

$A_t$ Matrix $(n \times n)$ that describes how the state evolves from $t - 1$ to $t$ without controls or noise.

$B_t$ Matrix $(n \times l)$ that describes how the control $u_t$ changes the state from $t - 1$ to $t$.

$C_t$ Matrix $(k \times n)$ that describes how to map the state $x_t$ to an observation $z_t$.

$\epsilon_t$ Random variables representing the process and measurement noise that are assumed to be independent and normally distributed with covariance $R_t$ and $Q_t$ respectively.
Linear Motion Model

Motion under Gaussian noise leads to

\[ p(x_t \mid u_t, x_{t-1}) = ? \]
Linear Motion Model

- Motion under Gaussian noise leads to

\[ p(x_t \mid u_t, x_{t-1}) = \text{det}(2\pi R_t)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} (x_t - A_t x_{t-1} - B_t u_t)^T R_t^{-1} (x_t - A_t x_{t-1} - B_t u_t) \right) \]

- \( R_t \) describes the noise of the motion
Linear Observation Model

- Measuring under Gaussian noise leads to

\[ p(z_t \mid x_t) =? \]
Linear Observation Model

- Measuring under Gaussian noise leads to

\[ p(z_t \mid x_t) = \det(2\pi Q_t)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} (z_t - C_t x_t)^T Q_t^{-1} (z_t - C_t x_t) \right) \]

- \( Q_t \) describes the measurement noise
Everything stays Gaussian

- Given an initial Gaussian belief, the belief is always Gaussian

\[
\overline{\text{bel}}(x_t) = \int p(x_t \mid u_t, x_{t-1}) \ \underline{\text{bel}}(x_{t-1}) \ dx_{t-1}
\]

\[
\text{bel}(x_t) = \eta \ p(z_t \mid x_t) \ \underline{\text{bel}}(x_t)
\]

- Proof is non-trivial
(see Probabilistic Robotics, Sec. 3.2.4)
Kalman Filter Algorithm

1:  \textbf{Kalman\_filter}(\mu_{t-1}, \Sigma_{t-1}, u_t, z_t):

2:  \quad \bar{\mu}_t = A_t \mu_{t-1} + B_t u_t

3:  \quad \bar{\Sigma}_t = A_t \Sigma_{t-1} A^T_t + R_t

4:  \quad K_t = \bar{\Sigma}_t C^T_t (C_t \bar{\Sigma}_t C^T_t + Q_t)^{-1}

5:  \quad \mu_t = \bar{\mu}_t + K_t(z_t - C_t \bar{\mu}_t)

6:  \quad \Sigma_t = (I - K_t C_t) \bar{\Sigma}_t

7:  return \mu_t, \Sigma_t
1D Kalman Filter Example (1)

prediction

measurement

It's a weighted mean!
1D Kalman Filter Example (2)

- Prediction
- Correction
- Measurement
Kalman Filter Assumptions

- Gaussian distributions and noise
- Linear motion and observation model

\[ x_t = A_t x_{t-1} + B_t u_t + \epsilon_t \]
\[ z_t = C_t x_t + \delta_t \]

What if this is not the case?
Non-linear Dynamic Systems

- Most realistic problems (in robotics) involve nonlinear functions

\[ x_t = A_t x_{t-1} + B_t u_t + \epsilon_t \]

\[ z_t = C_t x_t + \delta_t \]

\[ x_t = g(u_t, x_{t-1}) + \epsilon_t \]

\[ z_t = h(x_t) + \delta_t \]
Linearity Assumption Revisited

\[ p(y) = \mathcal{N}(y; a\mu + b, a^2 \sigma^2) \]

Mean of \( p(y) \)

\[ y = ax + b \]

Mean \( \mu \)

\[ p(x) = \mathcal{N}(x; \mu, \sigma^2) \]

Mean of \( p(x) \)

Courtesy: Thrun, Burgard, Fox
Non-Linear Function

Non-Gaussian!
Non-Gaussian Distributions

- The non-linear functions lead to non-Gaussian distributions
- Kalman filter is not applicable anymore!

What can be done to resolve this?
Non-Gaussian Distributions

- The non-linear functions lead to non-Gaussian distributions
- Kalman filter is not applicable anymore!

What can be done to resolve this?

Local linearization!
EKF Linearization: First Order Taylor Expansion

- **Prediction:**
  \[ g(u_t, x_{t-1}) \approx g(u_t, \mu_{t-1}) + \frac{\partial g(u_t, \mu_{t-1})}{\partial x_{t-1}} (x_{t-1} - \mu_{t-1}) =: G_t \]

- **Correction:**
  \[ h(x_t) \approx h(\bar{\mu}_t) + \frac{\partial h(\bar{\mu}_t)}{\partial x_t} (x_t - \bar{\mu}_t) =: H_t \]
Reminder: Jacobian Matrix

- It is a **non-square matrix** $m \times n$ in general

- Given a vector-valued function

$$g(x) = \begin{pmatrix} g_1(x) \\ g_2(x) \\ \vdots \\ g_m(x) \end{pmatrix}$$

- The **Jacobian matrix** is defined as

$$G_x = \begin{pmatrix} \frac{\partial g_1}{\partial x_1} & \frac{\partial g_1}{\partial x_2} & \cdots & \frac{\partial g_1}{\partial x_n} \\ \frac{\partial g_2}{\partial x_1} & \frac{\partial g_2}{\partial x_2} & \cdots & \frac{\partial g_2}{\partial x_n} \\ \vdots & \vdots & \cdots & \vdots \\ \frac{\partial g_m}{\partial x_1} & \frac{\partial g_m}{\partial x_2} & \cdots & \frac{\partial g_m}{\partial x_n} \end{pmatrix}$$
Reminder: Jacobian Matrix

- It is the orientation of the tangent plane to the vector-valued function at a given point

- Generalizes the gradient of a scalar valued function

Courtesy: K. Arras
EKF Linearization: First Order Taylor Expansion

- **Prediction:**
  \[ g(u_t, x_{t-1}) \approx g(u_t, \mu_{t-1}) + \frac{\partial g(u_t, \mu_{t-1})}{\partial x_{t-1}} (x_{t-1} - \mu_{t-1}) \]
  \[ =: G_t \]

- **Correction:**
  \[ h(x_t) \approx h(\bar{\mu}_t) + \frac{\partial h(\bar{\mu}_t)}{\partial x_t} (x_t - \bar{\mu}_t) \]
  \[ =: H_t \]

Linear functions!
Linearity Assumption Revisited

\[ p(y) = N(y; a\mu + b, a^2\sigma^2) \]

Mean of \( p(y) \)

\[ y = a \times + b \]

Mean \( \mu \)

\[ p(x) = N(x; \mu, \sigma^2) \]

Mean of \( p(x) \)

Courtesy: Thrun, Burgard, Fox
Non-Linear Function

Courtesy: Thrun, Burgard, Fox
EKF Linearization (1)
EKF Linearization (2)
EKF Linearization (3)

Courtesy: Thrun, Burgard, Fox
Linearized Motion Model

- The linearized model leads to

\[
p(x_t \mid u_t, x_{t-1}) \approx \det (2\pi R_t)^{-\frac{1}{2}} \exp \left( -\frac{1}{2} (x_t - g(u_t, \mu_{t-1}) - G_t (x_{t-1} - \mu_{t-1}))^T R_t^{-1} (x_t - g(u_t, \mu_{t-1}) - G_t (x_{t-1} - \mu_{t-1})) \right)
\]

- \( R_t \) describes the noise of the motion
Linearized Observation Model

- The linearized model leads to

\[
p(z_t \mid x_t) = \det (2\pi Q_t)^{- \frac{1}{2}} \exp \left( - \frac{1}{2} \left( z_t - h(\mu_t) - H_t (x_t - \mu_t) \right)^T Q_t^{-1} \left( z_t - h(\mu_t) - H_t (x_t - \mu_t) \right) \right)
\]

- \( Q_t \) describes the measurement noise
Extended Kalman Filter Algorithm

1: Extended_Kalman_filter($\mu_{t-1}, \Sigma_{t-1}, u_t, z_t$):

2: \[ \bar{\mu}_t = g(u_t, \mu_{t-1}) \]

3: \[ \bar{\Sigma}_t = G_t \Sigma_{t-1} G_t^T + R_t \]

4: \[ K_t = \bar{\Sigma}_t H_t^T (H_t \bar{\Sigma}_t H_t^T + Q_t)^{-1} \]

5: \[ \mu_t = \bar{\mu}_t + K_t (z_t - h(\bar{\mu}_t)) \]

6: \[ \Sigma_t = (I - K_t H_t) \bar{\Sigma}_t \]

7: return $\mu_t, \Sigma_t$

KF vs. EKF
Extended Kalman Filter Summary

- Extension of the Kalman filter
- One way to handle the non-linearities
- Performs local linearizations
- Works well in practice for moderate non-linearities
- Large uncertainty leads to increased approximation error error
Literature

Kalman Filter and EKF

- Thrun et al.: “Probabilistic Robotics”, Chapter 3
- Schön and Lindsten: “Manipulating the Multivariate Gaussian Density”
- Welch and Bishop: “Kalman Filter Tutorial”
- Tipaldi: “Notes on Univariate Gaussians and 1D Kalman Filters”
Slide Information

- These slides have been created by Cyrill Stachniss as part of the robot mapping course taught in 2012/13 and 2013/14. I created this set of slides partially extending existing material from courses of Wolfram Burgard, Dieter Fox, and myself.

- I tried to acknowledge all people that contributed image or video material. In case I missed something, please let me know. If you adapt this course material, please make sure you keep the acknowledgements.

- Feel free to use and change the slides. If you use them, I would appreciate an acknowledgement as well. To satisfy my own curiosity, I appreciate a short email notice in case you use the material in your course.

- My video recordings are available through YouTube: http://www.youtube.com/playlist?list=PLgnQpQtFTOGQrZ4O5QzbIHg13b1JHimN&_feature=g-list

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