SLAM II

EKF SLAM via the MonoSLAM example

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This exercise is designed to exercise your understanding of the EKF SLAM equations and their meaning. In particular, here we are looking at EKF SLAM via the MonoSLAM system [Davison et al.,PAMI 2007] we discussed in this week's lecture segments.

Figure 1: MonoSLAM IN ACTION: the external view, the camera view and the SLAM map

Following the notation of MonoSLAM, vector $\mathbf{x}$ stacks the state of the camera and the landmarks $\mathbf{y}_i$ and the associated covariance matrix $\mathbf{P}$ encodes the variance in and correlation across the individual elements of $\mathbf{x}$. Below, is a set of partially completed equations to perform EKF SLAM. Read on carefully and select the option that substitutes the # symbol, such that these equations are completed correctly.

Note: the hat ($\hat{}$) symbol denotes a predicted value (e.g. $\hat{\mathbf{x}}$) and the subcripts on $\mathbf{x}$ and $\mathbf{P}$ correspond to different time-stamps (e.g. $\mathbf{x}_t$ is the state at time t).

What does the # correspond to in each equation?

Prediction Step

Let f denote the prediction function and $\mathbf{u}_t$ denote the odometric/control input between time-stamps $t1$ and t (assuming that it is available).

$$\hat{\mathbf{x}}_t = f(\mathbf{x}_{t-1}, \mathbf{u}_t) \tag{1}$$

Let $\mathbf{F_x}$ and $\mathbf{F_u}$ denote the Jacobians of function f (above) with respect to $\mathbf{x}$ and $\mathbf{u}$, respectively and $\mathbf{Q_t}$ the covariance matrix corresponding to $\mathbf{u}_t$.

$$\hat{\mathbf{P}}_\mathbf{t} = \mathbf{F_x P_{t-1} F_x}^T + \mathbf{F_u Q_t F_u}^T \tag{2}$$

Measurement Step

Let $\mathbf{h_i}$ denote the measurement projection function for feature $\mathbf{y_i}$.

$$\hat{\mathbf{z}}_{\mathbf{i}} = h_i(\hat{\mathbf{x}}_t, \mathbf{y_i}) \tag{3}$$

If $\mathbf{H}$ is the Jacobian of h with respect to $\mathbf{x}$ and $\mathbf{R}$ the constant noise covariance of measurements, then the innovation covariance matrix $\mathbf{S}$ is defined as,

$$\mathbf{S} = \mathbf{H}\hat{\mathbf{P}}_{\mathbf{t}}\mathbf{H}^T + \mathbf{R} \tag{4}$$

Update Step

If the Kalman gain at time t corresponds to:

$$\mathbf{K_t} = \hat{\mathbf{P}}_{\mathbf{t}}\mathbf{H}\mathbf{S}^{-1}$$

then

$$\mathbf{x_t} = \hat{\mathbf{x}}_{\mathbf{t}} + \mathbf{K_t}(\mathbf{z_{0:n}} - \hat{\mathbf{z}}_{\mathbf{0:n}}) \tag{5}$$

$$\mathbf{P_t} = \hat{\mathbf{P}}_{\mathbf{t}} - \mathbf{K_t}\mathbf{S}\mathbf{K_t}^T \tag{6}$$