

# The Kalman filter

Sensor fusion & nonlinear filtering

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# ANALYTICAL SOLUTION TO THE FILTERING PROBLEM

- The filtering equations

$$p(\mathbf{x}_k | \mathbf{y}_{1:k-1}) = \int p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \mathbf{y}_{1:k-1}) d\mathbf{x}_{k-1} \leftarrow \text{prediction}$$

$$p(\mathbf{x}_k | \mathbf{y}_{1:k}) \propto p(\mathbf{y}_k | \mathbf{x}_k) p(\mathbf{x}_k | \mathbf{y}_{1:k-1}) \leftarrow \text{update}$$

are applicable to all filtering problems.

- Unfortunately, there are **very few** examples where the posterior distribution has an **analytical expression**.

# LINEAR AND GAUSSIAN STATE SPACE MODELS

## Definition (Linear and Gaussian models)

- For state vector  $\mathbf{x}_k$  and observation  $\mathbf{y}_k$ ,

$$\mathbf{x}_k = \mathbf{A}_{k-1} \mathbf{x}_{k-1} + \mathbf{q}_{k-1}, \quad \mathbf{q}_{k-1} \sim \mathcal{N}(\bar{\mathbf{q}}_{k-1}, \mathbf{Q}_{k-1})$$

*Handwritten notes:*  $\mathbf{A}_{k-1}$  is the **Transition matrix**;  $\mathbf{q}_{k-1}$  is **process noise**. The mean  $\bar{\mathbf{q}}_{k-1}$  is marked with a red '0'.

$$\mathbf{y}_k = \mathbf{H}_k \mathbf{x}_k + \mathbf{r}_k, \quad \mathbf{r}_k \sim \mathcal{N}(\bar{\mathbf{r}}_k, \mathbf{R}_k)$$

*Handwritten notes:*  $\mathbf{H}_k$  is the **Measurement model matrix**;  $\mathbf{r}_k$  is **measurement noise**. The mean  $\bar{\mathbf{r}}_k$  is marked with a red '0'.

$$\text{and } \mathbf{x}_0 \sim \mathcal{N}(\bar{\mathbf{x}}_0, \mathbf{P}_{0|0}).$$

$[m > n]$

$p(\mathbf{x}_{1:n}, \mathbf{y}_{1:n})$

$\Rightarrow$  marginal Gaussian

$\Rightarrow$  conditional Gaussian

Note:

- $p(\mathbf{x}_m | \mathbf{y}_{1:n})$  is **Gaussian** for all  $m$  and  $n$ , i.e., for all **filtering, smoothing and prediction** problems.