Sensors networks

Estimation

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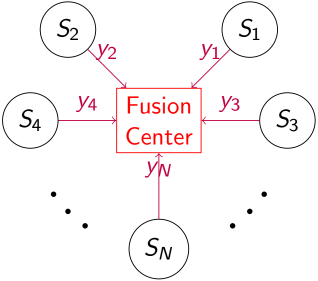
Centralized estimation network



Structure of the network with N sensors ($i = 1, \ldots, N$):

- $S_i \equiv i$-th sensor
- $y_i \equiv$ observation coming from the i-th sensor

The FC must use the collection of observations to estimate an $M \times 1$ vector, $\mathbf{x}$.

Classic estimation

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- Maximum a posteriori (MAP)

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- Minimum Mean Square Error (MMSE)

$$\begin{aligned} \hat{\mathbf{x}}^{MMSE} &= \arg\min_{\hat{\mathbf{x}}} \mathbb{E}\left[\|\mathbf{x} - \hat{\mathbf{x}}\|^2\right] \\ &= \mathbb{E}\left[\mathbf{x}|\mathbf{y}\right] = \int \mathbf{x} p(\mathbf{x}|\mathbf{y}) d\mathbf{x}. \end{aligned}$$

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Dynamic model

A more interesting problem...

What if the variable of interest changes with time?

$$\mathbf{x} \rightarrow \mathbf{x}_t$$

with t being a discrete-time index. Since $\mathbf{x}$ was a random variable, $\mathbf{x}_t$ is a *random process*.

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- a state equation modeling the evolution of the variable of interest
- a observation equation modeling the connection between the variable of interest and the observations

Let us start by considering an easy-to-handle model...

Linear Gaussian model

Linear Gaussian model

- Process $\mathbf{x}_t$ evolves according to a linear Gaussian model

$$\mathbf{x}_t = \mathbf{F}\mathbf{x}_{t-1} + \mathbf{v}_t \qquad \text{(state equation)}$$

where $\mathbf{F}$ is a $M \times M$ matrix, and $\mathbf{v}_t$ is a $M \times 1$ Gaussian random vector with mean $\mathbf{0}$ and covariance $\mathbf{Q}$, being M the number of elements in $\mathbf{x}_t$.

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- Connection between the variable of interest $\mathbf{x}_t$ and the observations is given by

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t + \mathbf{w}_t \qquad \text{(observation equation)}$$

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Observations...

...vector, $\mathbf{y}_t$, collects the measurements from all the sensors

Example I

Goal

Localization and tracking of an object moving with a *known* constant velocity $\mathbf{c}$.

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  where T is the *sampling period*, i.e., the time elapsed between two consecutive observations.

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where T is the *sampling period*, i.e., the time elapsed between two consecutive observations.

- The position is observed directly:

$$\mathbf{y}_t = \mathbf{x}_t + \mathbf{w}_t$$

Example II

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$$\mathbf{x}'_t = \begin{bmatrix} \mathbf{x}_t \\ \mathbf{c} \end{bmatrix}$$

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- The state equation is now

$$\mathbf{x}'_t = \mathbf{F}\mathbf{x}'_{t-1} + \begin{bmatrix} \mathbf{v}_t \\ \mathbf{0} \end{bmatrix}, \text{ with } \mathbf{F} = \begin{bmatrix} 1 & 0 & T & 0 \\ 0 & 1 & 0 & T \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix},$$

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- and the observation equation

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- dynamic systems: systems that model a time-varying magnitude
- linear: the equations defining the system are linear with respect to the variable of interest
- Gaussian: the noise affecting the above equations is Gaussian.

Dynamic system in state-space form

$$\mathbf{x}_t = \mathbf{F}_{t-1}\mathbf{x}_{t-1} + \mathbf{v}_t \quad \longleftarrow$$

state
equation

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Goal

Recursively estimate the state of the system $\mathbf{x}_t$ given the observations, $\mathbf{y}_t$

The time index is discrete, i.e, $t = 0, 1, \cdots$

Notation

$$\mathbf{x}_t = \mathbf{F}_{t-1}\mathbf{x}_{t-1} + \mathbf{v}_t$$

- $\mathbf{x}_t$ is the (system) state vector at time t
- $\mathbf{F}_t$ is the state transition matrix: it determines the evolution of the state of the system
- $\mathbf{v}_t \sim \mathcal{N}\left(\mathbf{v}_t | \mathbf{0}, \mathbf{Q}_t\right)$ is the state (or process) noise
  - $\mathbf{Q}_t$ is the covariance matrix for the state noise (it might be time-varying)

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$$\mathbf{y}_t = \mathbf{H}_t\mathbf{x}_t + \mathbf{w}_t$$

- $\mathbf{y}_t$ is the observations vector
- $\mathbf{H}_t$ is the observation matrix: it connects the observations with the (unknown) state
- $\mathbf{w}_t \sim \mathcal{N}\left(\mathbf{w}_t | \mathbf{0}, \mathbf{R}_t\right)$ is the observation noise
  - $\mathbf{R}_t$ is the covariance matrix of the observation noise (it might be time-varying)

Filtering: initial hypothesis

The *prior* (initial) distribution of the state is Gaussian, i.e.,

$$p(\mathbf{x}_0) \sim \mathcal{N}\left(\mathbf{x}_0 | \hat{\mathbf{x}}_{0|0}, \mathbf{P}_{0|0}\right)$$

with **known**

- $\hat{\mathbf{x}}_{0|0}$: the mean for the distribution of the state at time 0
- $\mathbf{P}_{0|0}$: covariance matrix for the distr. of the state at time 0

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Notation

- $\hat{\mathbf{x}}_{a|b} \equiv$ mean *estimated* at time a using the observations up to time b
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In the beginning

At time 0 we have no observations available...but the notation is still convenient.

Filtering: recursion

If the initial hypothesis holds then, for $t = 1, 2, \cdots$

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$$p(\mathbf{x}_t \mid \mathbf{y}_{1:t-1}) \sim \mathcal{N}\left(\mathbf{x}_t | \hat{\mathbf{x}}_{t|t-1}, \mathbf{P}_{t|t-1}\right) \quad \longleftarrow$$

predictive
pdf

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$$p(\mathbf{x}_t \mid \mathbf{y}_{1:t}) \sim \mathcal{N}\left(\mathbf{x}_t | \hat{\mathbf{x}}_{t|t}, \mathbf{P}_{t|t}\right) \longleftarrow$$ filtered pdf

...that is, both pdf's are Gaussian if the initial distribution is Gaussian, and the **Kalman filter** yields both its means and covariances in a two-steps process

Notation

$y_{i:j} \equiv \{y_i, y_{i+1}, \cdots, y_j\}$

Solution

Predictive step

$$\left.\begin{array}{lll} \hat{\mathbf{x}}_{t|t-1} = \mathbf{F}_{t-1}\hat{\mathbf{x}}_{t-1|t-1} & \longleftarrow & \text{predictive mean} \\ \mathbf{P}_{t|t-1} = \mathbf{Q}_{t-1} + \mathbf{F}_{t-1}\mathbf{P}_{t-1|t-1}\mathbf{F}_{t-1}^{H} & \longleftarrow & \text{predictive covariance} \end{array}\right\} \begin{array}{c} \text{associated with the} \\ \text{predictive pdf} \end{array}$$

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Update step

$$\left.\begin{aligned} \mathbf{K}_t &= \mathbf{P}_{t|t-1}\mathbf{H}^{H}_{t}\left(\mathbf{H}_t\mathbf{P}_{t|t-1}\mathbf{H}^{H}_{t} + \mathbf{R}_t\right)^{-1} && \longleftarrow \quad \text{Kalman gain} \\ \hat{\mathbf{x}}_{t|t} &= \hat{\mathbf{x}}_{t|t-1} + \mathbf{K}_t\left(\mathbf{y}_t - \mathbf{H}_t\hat{\mathbf{x}}_{t|t-1}\right) && \longleftarrow \quad \text{filtered mean} \\ \mathbf{P}_{t|t} &= \left(\mathbf{I} - \mathbf{K}_t\mathbf{H}_t\right)\mathbf{P}_{t|t-1} && \longleftarrow \quad \text{filtered covariance} \end{aligned}\right\} \begin{array}{c}\text{associated with}\\ \text{the filtered pdf}\end{array}$$

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- KF outputs the a probability distribution[1], which contains all the available information about the parameter of interest

In our case...

$p(\mathbf{x}_t \mid \mathbf{y}_{1:t})$ contains all the available information at time t about $\mathbf{x}_t$, and from it we can compute the mean, median, mode...

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- $\hat{\mathbf{x}}_{t|t} \equiv$ MMSE estimate of the state at time t
- $\mathrm{Tr}\left\{\mathbf{P}_{t|t}\right\} \equiv$ minimum error (square error at $\hat{\mathbf{x}}_{t|t}$)

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State and observation equations

$$\mathbf{x}_t = \mathbf{F}_{t-1}\mathbf{x}_{t-1} + \mathbf{B}_t\mathbf{u}_t + \mathbf{v}_{t-1} \quad \longleftarrow$$ state equation

$$\mathbf{y}_t = \mathbf{H}_t\mathbf{x}_t + \mathbf{w}_t \quad \longleftarrow$$ observation equation

The control term, $\mathbf{B}_t\mathbf{u}_t$, with

- $\mathbf{B}_t$ is the control-input, and
- $\mathbf{u}_t$ is the control vector

is **known** (at every time instant t) and meant for modifying the (unknown) state.

What is the control term good for?

- ...sometimes we can have some impact (control) over whatever we aim at estimating

example

Problem: estimating the trajectory of a drone we are handling ourselves

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The control term is something that affects the state[2], but since it is known there is no need to estimate it.

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