

Kalman Filter for Observer-ARMA Model with Parameter Estimation

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Preliminaries

Notation

- Observed data vector: $y_t^* := (y_0^T, y_1^T, \dots, y_t^T)^T$.
- $z_{t|t-1} := E(z_t | y_{t-1}^*)$ and $y_{t|t-1} := E(y_t | y_{t-1}^*)$.
- $\Delta y_t := y_t - y_{t|t-1}$ and $\Delta z_t := z_t - z_{t|t-1}$.
- $\Sigma_{t|t} := \text{Cov}(\Delta z_t | y_t^*)$.

Preliminaries

Observer-ARMA model

The general scheme for the observer-ARMA model is given by

$$\begin{aligned} z_{t+1} &= \sum_{s=0}^{l_1} a_s z_{t-s} + \sum_{s=0}^{l_2} b_s \xi_{t-s} \\ y_t &= h_t z_t + \zeta_t \\ z_0 &\in \mathbb{R}, \quad t = 0, 1, \dots \end{aligned} \tag{1}$$

Preliminaries

Kalman Filter

The standard KF Procedure [Kalman 1960] has two main hypothesis:

H1

$$E(\xi_t) = E(\zeta_t) = 0, \quad t = 0, 1, \dots$$

.

$$E(\xi_t \xi_t^T) = Q_t, \quad E(\zeta_t \zeta_t^T) = R_t$$

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$$E(z_t z_s^T) = 0, \quad \forall t \neq s$$

H2

$$\xi_t \sim \mathcal{N}(0, Q_t), \quad \zeta_t \sim \mathcal{N}(0, R_t), \quad \forall t = 0, 1, \dots$$

Preliminaries

Kalman Filter

The KF procedure is now presented:

1. Initialization:

$$z_{0|0} = z_0 \in \mathbb{R}^n, \Sigma_{0|0} = 0$$

2. Prediction:

$$z_{t|t-1} = F_t z_{t-1|t-1}$$

$$\Sigma_{t|t-1} = F_{t-1} \Sigma_{t-1|t-1} F_{t-1}^T + Q_{t-1}$$

3. Correction:

$$z_{t|t} = z_{t|t-1} + M_t^{\text{opt}} \Delta y_t$$

$$\Sigma_{t|t} = \Sigma_{t|t-1} - M_t^{\text{opt}} H_t \Sigma_{t|t-1}$$

$$\text{where } M_t^{\text{opt}} = \Sigma_{t|t-1} H_t^T (H_t \Sigma_{t|t-1} H_t^T + R_t)^{-1}.$$

Preliminaries

Extended Kalman Filter

Let $f : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be a given vector function.

$$\begin{cases} x_{t+1} = f(x_t) + \xi_t \\ y_t = H_t x_t + \zeta_t \\ x_0 \in \mathbb{R}^n, \quad t = 0, 1, \dots \end{cases}$$

Preliminaries

Extended Kalman Filter

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$$\begin{cases} x_{t+1} = f(x_t) + \xi_t \\ y_t = H_t x_t + \zeta_t \\ x_0 \in \mathbb{R}^n, \quad t = 0, 1, \dots \end{cases} \implies \begin{cases} x_{t+1} = \tilde{F}_t x_t + \xi_t \\ y_t = H_t x_t + \zeta_t \\ x_0 \in \mathbb{R}^n, \quad t = 0, 1, \dots \end{cases} \quad (2)$$

Where \tilde{F}_t is:

$$\tilde{F}_t := \left. \frac{\partial f(x)}{\partial x} \right|_{x=x_t^{\text{ref}}}$$

Instrumental Extended Kalman Filter

Problem definition

In this work we will use a simple ARMA model, with correlated state and one unknown stationary parameter a . The model in consideration is

$$\begin{aligned}z_{t+1} &= az_t + \xi_t + d\xi_{t-1} \\ y_t &= hz_t + \gamma_t \\ z_0 &\in \mathbb{R}, \quad t = 0, 1, \dots\end{aligned}\tag{3}$$

Instrumental Extended Kalman Filter

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Remark

The objective is find an estimator \tilde{a} for the unknown parameter a using the data vector y_t^* .

References I



Kalman, Rudolph Emil (1960). “A New Approach to Linear Filtering and Prediction Problems”. In: *Journal of basic Engineering* 82.1, pp. 35–45.

Thank you

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