

Examen localisation, UV 3.7, ENSI 2.

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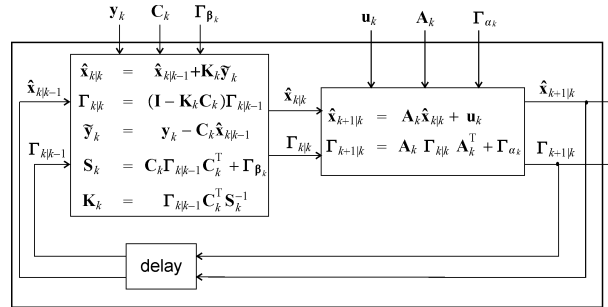
Durée: 60 minutes.

Consider a vehicle (a robot) moving in a plane and described by the following discretized state equations

$$\begin{cases} x_1(k+1) &= x_1(k) + v(k) \cos(\theta(k)) + \alpha_1(k) \\ x_2(k+1) &= x_2(k) + v(k) \sin(\theta(k)) + \alpha_2(k) \end{cases}$$

where the $\alpha_i(k)$ are white unit centred Gaussian noise, *i.e.*, $\alpha_i(k) : \mathcal{N}(0, 1)$. The vector $(x_1(k), x_2(k))$ represents the coordinates of the center of the vehicle at time k , $\theta(k)$ is the heading, $v(k)$ is its speed. The sampling time is taken as $dt = 1sec$. Both $v(k)$ and $\theta(k)$ are assumed to be known exactly. At each k , a GPS provides a measurement on \mathbf{x} with an accuracy of $10m$.

1) We want to use a Kalman filter (see the figure) in order to estimate the state \mathbf{x}_k with a higher precision than that given by the GPS.



Explain how this can be done and explain how you choose the values for the inputs $\mathbf{u}_k, \mathbf{y}_k, \mathbf{A}_k, \mathbf{C}_k, \mathbf{\Gamma}_\alpha, \mathbf{\Gamma}_\beta$ of the Kalman filter. Explain also how the filter can be initialized.

2) We now assume that the speed is not measured anymore, but only its derivative $a(k)$. More precisely, we assume that we have

$$v(k+1) = v(k) + a(k) + \alpha_v(k)$$

where $\alpha_v(k)$ is white unit centred Gaussian noise. Explain in details how the Kalman filter can be used in this context to get a precise localization.

Correction de l'examen du 8 janvier 2019

1) Our system can be written under the form:

$$\left\{ \begin{array}{l} \mathbf{x}_{k+1} = \underbrace{\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}}_{\mathbf{A}_k} \mathbf{x}_k + \underbrace{\begin{pmatrix} v(k) \cos(\theta(k)) \\ v(k) \sin(\theta(k)) \end{pmatrix}}_{\mathbf{u}_k} + \boldsymbol{\alpha}_k \\ \mathbf{y}_k = \underbrace{\begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}}_{\mathbf{C}_k} \mathbf{x}_k + \boldsymbol{\beta}_k \end{array} \right.$$

Moreover

$$\boldsymbol{\Gamma}_{\boldsymbol{\alpha}_k} = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \text{ and } \boldsymbol{\Gamma}_{\boldsymbol{\beta}_k} = \begin{pmatrix} 10^2 & 0 \\ 0 & 10^2 \end{pmatrix}.$$

For the initialization, we can take

$$\hat{\mathbf{x}}_{0|-1} = (0 \ 0)^T \text{ and } \boldsymbol{\Gamma}_{0|-1} = 10^{10} \cdot \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix}.$$

2) We add a state variable $x_3 = v$. The system is now described by:

$$\left\{ \begin{array}{l} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} (k+1) = \underbrace{\begin{pmatrix} 1 & 0 & \cos(\theta(k)) \\ 0 & 1 & \sin(\theta(k)) \\ 0 & 0 & 1 \end{pmatrix}}_{\mathbf{A}_k} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} (k) + \underbrace{\begin{pmatrix} 0 \\ 0 \\ a_k \end{pmatrix}}_{\mathbf{u}_k} + \underbrace{\begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \alpha_v \end{pmatrix}}_{\boldsymbol{\alpha}_k} \\ \mathbf{y}_k = \underbrace{\begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix}}_{\mathbf{C}_k} \mathbf{x}_k + \boldsymbol{\beta}_k \end{array} \right.$$

We can thus use a Kalman filter with

$$\hat{\mathbf{x}}_{0|-1} = (1 \ 2 \ 0)^T \text{ and } \boldsymbol{\Gamma}_{0|-1} = 10^{10} \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix}.$$

and

$$\boldsymbol{\Gamma}_{\boldsymbol{\alpha}_k} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \text{ and } \boldsymbol{\Gamma}_{\boldsymbol{\beta}_k} = \begin{pmatrix} 10^2 & 0 \\ 0 & 10^2 \end{pmatrix}.$$