# ELEC-E8107 - Stochastic models, estimation and control

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### **Exercises Session 3: Solution**

### Exercise 1

Consider the time-invariant linear Stochastic Differential Equation (SDE), called the Ornstein–Uhlenbeck process:

$$\dot{x}(t) = -\lambda x(t) + \tilde{v}(t) \quad x(0) = x_0 \tag{1}$$

- 1. Write the ordinary differential equation (ODE) describing the evolution of the mean of the state x.
- 2. Write the solution of the ODE obtained in the previous question.

The SDE given in the equation (1) cannot be solved using the general numerical methods for deterministic differential equations. This is because the white noise is not differentiable anywhere. Method such as Euler–Maruyama method does not explicitly require continuity. Such method can be used to solve the SDE in equation (1). Using Euler-Maruyama method, the equation (1) can be written in discrete form as:

$$x(k+1) = x(k) - \lambda x(k)\Delta t + \Delta v(k)$$
<sup>(2)</sup>

Where  $\Delta v(k) \sim \mathcal{N}(0, Q\Delta t)$ ; Q is the spectral density of the white noise  $\tilde{v}(t)$ . Assuming  $\lambda = \frac{1}{2}$ ,  $\Delta t = \frac{1}{100}$ , x(0) = 1, Q = 1:

- 3. Using equation (2), simulate 500 trajectories of the Ornstein–Uhlenbeck process on the time interval  $t \in \begin{bmatrix} 0 & 1 \end{bmatrix}$ . (Show the result on a plot)
- 4. Check that the mean trajectory approximately agree with the theoretical value (use a plot to show the results).

# Solution Exercise 1

### 1. The ODE describing the evolution of the mean

Applying the expectation operation (which is linear) to the equation (1), we have:

$$E[\dot{x}(t)] = -\lambda E[x(t)] + E[\tilde{v}(t)]$$
$$\dot{\bar{x}}(t) = -\lambda \bar{x}(t) + \bar{v}(t)$$

### 2. The solution of the ODE obtained previously

This is a time-invariant ODE and the solution is given by:

$$\bar{x}(t) = e^{-\lambda t} \bar{x}(0) + \frac{\bar{v}}{\lambda} (1 - e^{-\lambda t}),$$

Where  $\bar{x}(0)$  is the initial condition.

**3. Simulating 500 trajectories** We directly use the discrete equation (2). The following Matlab script is used to simulate the trajectories. The inner-loop simulates one trajectory. And the outer loop used to simulate the given number of trajectories.

```
clc;
```

4. Comparison of the mean trajectory with the theoretical value See figure 1 and 2



Figure 1: Result of simulating five trajectories



Figure 2: Result of simulating 500 trajectories. The mean trajectories is very close to the theoretical trajectory.

# Exercise 2

A vehicle is moving at near constant speed following a line (1D-motion). The position is measured with a measurement covariance of r = 0.5. A kinematic  $\frac{3}{3}$  model for such a system is as follow:

$$p(k+1) = p(k) + \Delta t v(k) + \frac{\Delta t^2}{2} w(k)$$

$$v(k+1) = v(k) + \Delta t w(k)$$
(3)

where  $w(k) \sim \mathcal{N}(0,q)$ . The position and speed, at each instant k, can be combined in a single vector x(k) considered as the state of the system.

- 1. Write the equation (3) in a state-space form: x(k+1) = Fx(k) + Lw(k). Specify the variables F, and L.
- 2. Given that the state of interest is composed of the position and the speed, and that only the position is measured with white noise, write the measurement equation for the system.
- 3. Implement, using MATLAB, a Kalman filter to estimate the state x(k) of the system at each time instant.

Note: For the implementation of the Kalman filter, you are given two files containing the real data (*RealData.mat*) and the measurement data (*measurement.mat*); You don't need to modify these files and they are already loaded in the Matlab script (*BasicKalmanFilter.m*) in which you need to implement the Kalman filter. Some basic instructions are given in the Matlab script to help you write the Kalman filter.

## Solution Exercise 2

#### 1. State-space form

The state is composed of the position and speed which can be combined in a single vector:

$$x(k) = \begin{bmatrix} p(k) \\ v(k) \end{bmatrix}$$

The equation (3) can be rewritten as follow:

$$\begin{bmatrix} p(k+1)\\ v(k+1) \end{bmatrix} = \begin{bmatrix} 1 & \Delta t\\ 0 & 1 \end{bmatrix} \begin{bmatrix} p(k)\\ v(k) \end{bmatrix} + \begin{bmatrix} \frac{\Delta t^2}{2}\\ \Delta t \end{bmatrix} w(k)$$
$$x(k+1) = \begin{bmatrix} 1 & \Delta t\\ 0 & 1 \end{bmatrix} x(k) + \begin{bmatrix} \frac{\Delta t^2}{2}\\ \Delta t \end{bmatrix} w(k)$$

#### 2. The measurement equation

$$y(k) = p(k) + r(k)$$
$$y(k) = \begin{bmatrix} 1 & 0 \end{bmatrix} x(k) + r(k)$$

### 3. Kalman filter implementation

Note that the prediction for the state covariance matrix is done as follow:

$$P(k+1|k) = FP(k|k)F^T + LQL^T$$

The Kalman filter is implemented in the following script.

```
% Implementation of Kalman filter !!!
%
% INITIALIZE KALMAN FILTER PARAMETERS HERE !!!
%
dt = 1/100;
F = [1 dt; 0 1];
H = [1 0];
L = [dt*dt/2; dt];
Q = 0.3;
R = 0.5;
XO = [0; 0];
PO = [100 \ 0; \ 0 \ 10000];
Xm(:, 1) = XO;
SP(:,:, 1) = PO;
%
% MODEL INITIALIZATION END HERE !!!
%
for i = 2:n
   % Prediction step
   x_p = F * Xm(:, i-1);
   P_p = F*SP(:,:, i-1)*F' + L*Q*L';
   %Update step
   v = Y(i) - H*x_p;
   S = H*P_p*H' + R;
   W = P_p * H' * inv(S);
   Xm(:,i) = x_p + W*v;
   SP(:,:,i) = P_p - W*S*W';
   % % % % % % % % % % % % % % % % %
   % Visualize data %
   % % % % % % % % % % % % % % % % % % %
   if(~mod(i,plotRatio))
```

```
clf(1)
        if(focus)
            axis([i-xmin i+xmax X_r(1, i)-ymin X_r(1,i)+ymax
               ])
        else
            axis([0 n min(Y(1:i)) max(Y(1:i))])
        end
        hold on
        plot(i,X_r(1,i),'ko','MarkerFaceColor','r','
           MarkerSize',5)
        plot(i,Y(i),'ko','MarkerFaceColor','k','MarkerSize'
           ,6)
        plot(i,Xm(1, i),'ko','MarkerFaceColor','b','
           MarkerSize',5)
        legend('Real','Meas','Est','Location','Best')
        plot(X_r(1,1:i),'r.-')
        plot(Y(1:i-1), 'k.')
        plot(Xm(1,1:i),'b.-')
        pause(ptime)
    end
end
```