

# Random Signals and Filtering (201200135)

Final Exam (with 4 questions)

Full Marks: 30

Thursday 19/04/2018, 13:45 – 16:45

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Formulate your answers clearly and present them in a well-structured manner.

1.(a.) Let  $\Omega$  be a set. Give the definition of a field and a sigma-field on  $\Omega$ . [3]

(b.) Consider the collection  $\mathbb{A}$  of semi-open intervals of  $(0, 1]$  and the finite unions of disjoint semi-open intervals, i.e.,  $(a, b]$ ,  $0 \leq a \leq b \leq 1$ .

$$\mathbb{A} = \left\{ \bigcup_{i=1}^n (a_i, b_i], \quad n \geq 1, \quad (a_i, b_i] \cap (a_j, b_j] = \emptyset, \quad \forall i \neq j = 1, 2, \dots, n \right\}.$$

It is known that  $\mathbb{A}$  is a field on  $(0, 1]$ . The proof hinges on the following two simplified properties. Show these two properties: [2]

(i.) Let  $A = (a_1, b_1] \cup (a_2, b_2]$ , union of two disjoint semi-open intervals of  $(0, 1]$ . Then  $A^c$  can be represented as a finite union of disjoint semi-open intervals of  $(0, 1]$ .

(ii.) Let  $A, B \in \mathbb{A}$  be disjoint. Then  $A \cup B$  is also in  $\mathbb{A}$ .

2. Consider the following linear non-Gaussian system: for  $k \geq 0$ ,

$$X_{k+1} = -X_k + W_k \quad \text{and} \quad Y_k = X_k + V_k,$$

where the initial state  $X_0$  and the noises  $W_k, V_k$  ( $k \geq 0$ ) are all Unif(0, 1) random variables. Furthermore,  $X_0, \{W_k\}$ , and  $\{V_k\}$  are mutually independent and the noise sequences  $\{W_k\}$  and  $\{V_k\}$  are white.

(a.) Show that the pdf of  $Y_0$  is given by  $p_{Y_0}(y_0) = \begin{cases} y_0 & 0 < y_0 \leq 1 \\ 2 - y_0 & 1 \leq y_0 < 2. \end{cases}$  [3]

(b.) Show that the posterior distribution of  $X_0$  (conditional on  $Y_0 = y_0$ ) is given by [2]

$$p_{X_0|Y_0=y_0}(x_0) = \begin{cases} \frac{1}{y_0}, & \text{for } 0 \leq x_0 \leq y_0, \quad \text{i.e., Unif}(0, y_0), & \text{if } 0 < y_0 \leq 1 \\ \frac{1}{2-y_0}, & \text{for } y_0 - 1 \leq x_0 \leq 1, \quad \text{i.e., Unif}(y_0 - 1, 1), & \text{if } 1 \leq y_0 < 2 \\ \text{undefined,} & & \text{otherwise.} \end{cases}$$

Provide, subsequently, the (point) estimate  $\hat{X}_0 = E(X_0 | Y_0)$ . [1]

(c.) Use the *law of iterated expectation*:  $E[X|Y] = E[E[X|Y, Z] | Y]$  to obtain the predicted estimate  $E[X_1|Y_0]$  in terms of  $\hat{X}_0$ . [2]

3. Recall that  $E_{\text{aff}}(X | Y)$  is the “best” predictor of  $X$  as a linear/affine function of  $Y$ , of the form  $a + bY$ . More precisely,

$$E_{\text{aff}}(X | Y) = E(X) + \text{Cov}(X, Y) \text{Cov}(Y)^{-1} (Y - E(Y)).$$

In a linear-Gaussian dynamical system of (unobserved) signals ( $X_k$ ) and measurements ( $Y_k$ ), the posterior mean  $E(X_k | Y_{0:k})$  can be expressed as a linear/affine combination of  $Y_0, Y_1, \dots, Y_k$ . Kalman filter (KF) exploits this fact. In the calculation, KF uses the concept of linear innovations.

- (a.) Explain what linear innovations are corresponding to a sequence of measurements  $Y_0, Y_1, \dots, Y_n$ . Also, explain, briefly, how they help in the derivation of KF. [3]
- (b.) Consider the following nonlinear system with additive Gaussian noises: for  $k \geq 0$ ,

$$X_{k+1} = X_k + W_k \quad \text{and} \quad Y_k = X_k^2 + V_k, \quad (\star)$$

where the initial state  $X_0$ , and for  $k \geq 0$ , the noises  $W_k, V_k$  are all  $N(0, 1)$ . Furthermore,  $X_0, \{W_k\}$ , and  $\{V_k\}$  are mutually independent and the noise sequences  $\{W_k\}$  and  $\{V_k\}$  are white.

This system is not suitable for applying KF. However the concept of linear innovation can still be applied. Obtain the first two innovations. [3]

[ Hint: Use different properties of covariances. You may also use the fact that for  $Z \sim N(0, 1)$ ,  $E(Z^2) = \text{Var}(Z) = 1$  and  $\text{Var}(Z^2) = 2$ . ]

4. Consider again the (real-valued) nonlinear system  $(\star)$  in question 3(b). It is not suitable for KF, because KF requires the measurement model to be of the form  $Y_k = H_k X_k + V_k$ . However, one may apply the extended Kalman filter (EKF) or a particle filter (PF).

- (a.) Suppose we would like to implement an EKF to the system  $(\star)$ . Explain how you would transform, given the estimates  $\hat{x}_{k-1|k-1}$  and  $P_{k-1|k-1}$  of time  $(k-1)$ , the observation equation, in order to implement EKF. Give explicit formulas. [3]
- (b.) Give the pseudo-code for the generic iteration step of a standard PF applied to the system  $(\star)$ , i.e., how to obtain  $(x_k^i, w_k^i)_{i=1}^N$  from  $(x_{k-1}^i, w_{k-1}^i)_{i=1}^N$  and the measurement  $y_k$ . [5]

Assume that you have access to a command `randn` to generate a sample from  $N(0, 1)$  distribution, and a command `resample(x_vec, p_vec, n)` to draw a random sample of size “n” from the discrete distribution with values “x\_vec” and corresponding probabilities “p\_vec”. Everything else in your code should be self explanatory, i.e., in terms of known function or known structures like `if` and `for` loop.

- (c.) Suppose one is interested in the (posterior) probability of the signal exceeding 10, i.e.,  $P(X_k > 10 | Y_{0:k})$ . How would you estimate it from the weighted particles? [1]
- (d.) In the context of a PF, one often talks about the *optimal* importance/proposal density. What is it and how does it help? [2]