Data Provided: None

The University Of Sheffield.

DEPARTMENT OF ELECTRONIC AND ELECTRICAL ENGINEERING

Spring Semester 2009-2010 (2 hours)

Multi-Sensor Data Fusion 6

Answer **THREE** questions. **No marks will be awarded for solutions to a fourth question.** Solutions will be considered in the order that they are presented in the answer book. Trial answers will be ignored if they are clearly crossed out. **The numbers given after each section of a question indicate the relative weighting of that section.**

1. **a.** Give 4 different types of application where the advantages of multi-sensor data-fusion can be obtained. State the advantage of data-fusion for each application. **(6)**

b. Draw a diagram showing the 5 levels of data fusion specified by the JDL model, and give examples of applications that fall into each level. **(7)**

c. Seven sensors are used to monitor the altitude (km) of a satellite in orbit ($S_1,\ldots,S_7$). To determine the 'health' of the sensor system, a test is undertaken after every $\bar{n} = 37$ readings from each sensor. Apply Cochran's method to determine if any outliers are present in the reading set. Sensor variances given in Table 1.1. Cochran's table for α=0.05 is given in Fig. 1.1.

	S_1	S_2	S_3	S_4	S_5	S_6	S_7	
σ^2	0.04	0.055	0.05	0.2	0.42	0.1	0.06	

Table 1.1

Level of significance α = 0.05

k \ ν_x	1	2	3	4	5	6	7	8	9	10	16	36
2	0.9985	0.9750	0.9392	0.9057	0.8772	0.8534	0.8332	0.8159	0.8010	0.7880	0.7341	0.6602
3	0.9669	0.8709	0.7977	0.7457	0.7071	0.6771	0.6530	0.6333	0.6167	0.6025	0.5466	0.4748
4	0.9065	0.7679	0.6841	0.6287	0.5895	0.5598	0.5365	0.5175	0.5017	0.4884	0.4366	0.3720
5	0.8412	0.6838	0.5981	0.5441	0.5065	0.4783	0.4564	0.4387	0.4241	0.4118	0.3645	0.3066
6	0.7808	0.6161	0.5321	0.4803	0.4447	0.4184	0.3980	0.3817	0.3682	0.3568	0.3135	0.2612
7	0.7271	0.5612	0.4800	0.4307	0.3974	0.3726	0.3535	0.3384	0.3259	0.3154	0.2756	0.2278
8	0.6798	0.5157	0.4377	0.3910	0.3595	0.3362	0.3185	0.3043	0.2926	0.2829	0.2462	0.2022
9	0.6385	0.4775	0.4027	0.3584	0.3286	0.3067	0.2901	0.2768	0.2659	0.2568	0.2226	0.1820
10	0.6020	0.4450	0.3733	0.3311	0.3029	0.2823	0.2666	0.2541	0.2439	0.2353	0.2032	0.1655
12	0.5410	0.3924	0.3264	0.2880	0.2624	0.2439	0.2299	0.2187	0.2098	0.2020	0.1737	0.1403
15	0.4709	0.3346	0.2758	0.2419	0.2195	0.2034	0.1911	0.1815	0.1736	0.1671	0.1429	0.1144
20	0.3894	0.2705	0.2205	0.1921	0.1735	0.1602	0.1501	0.1422	0.1357	0.1303	0.1108	0.0879
24	0.3434	0.2354	0.1907	0.1656	0.1493	0.1374	0.1286	0.1216	0.1160	0.1113	0.0942	0.0743
30	0.2929	0.1980	0.1593	0.1377	0.1237	0.1137	0.1061	0.1002	0.0958	0.0921	0.0771	0.0604
40	0.2370	0.1576	0.1259	0.1082	0.0968	0.0887	0.0827	0.0780	0.0745	0.0713	0.0595	0.0462
60	0.1737	0.1131	0.0895	0.0765	0.0682	0.0623	0.0583	0.0552	0.0520	0.0497	0.0411	0.0316
120	0.0998	0.0632	0.0495	0.0419	0.0371	0.0337	0.0312	0.0292	0.0279	0.0266	0.0218	0.0165
∞	0	0	0	0	0	0	0	0	0	0	0	0

Figure 1.1

If sensor S_5 is taken out of the system, does the data from the remaining sensors in the network subsequently appear statistically robust ? **(7)**

2. a. Discuss as fully as you can, the relative merits of <u>Centralised</u> and <u>Decentralised</u> data fusion systems. **(4)**

b. Explain the relative attributes of <u>state-fusion</u> and <u>measurement fusion</u> when referring to Kalman Filter based fusion systems. Given your answers to part (a), do you consider each method to be more suited for Centralised or Decentralised systems ? **(4)**

c. A tracking system has detected the presence of an incoming aircraft. You know from past experience that it will be either a *Fighter* aircraft or a *Bomber* aircraft. Two sensors have been installed, each of which can only give one-of-two outputs which have been 'tuned' to correctly detect whether the incoming aircraft is a *Fighter* or *Bomber*, with a high probability. Sensor 1 is older than Sensor 2, and is considered to provide a less reliable output.

More generally, however, Output 1 (m_{i1}) of each sensor has been tuned to detect *Fighter* aircraft with a high probability, and Output 2 (m_{i2}) of each sensor has been tuned to detect *Bomber* aircraft with a high probability. The <u>decision matrix</u> for each of the 2 sensors, is given in Fig. 2.1—notice sensor 2 is considered to be more reliable at detecting *Bomber* aircraft.

$$\begin{array}{c c} & \begin{array}{cc} m_{11} & m_{12} \end{array} \\ \begin{array}{r} Fighter \\ Bomber \end{array} & \begin{bmatrix} 0.9 & 0.1 \\ 0.3 & 0.7 \end{bmatrix} \end{array} \quad sensor\,1$$

$$\begin{array}{c c} & \begin{array}{cc} m_{21} & m_{22} \end{array} \\ \begin{array}{r} Fighter \\ Bomber \end{array} & \begin{bmatrix} 0.9 & 0.1 \\ 0.1 & 0.9 \end{bmatrix} \end{array} \quad sensor\,2$$

Figure 2.1

Use a simple <u>Maximum Likelihood Decision Rule</u>, and your judgement of the results, obtain the 'Network Probability' (matrix) for correctly classifying the vehicle as a *Fighter* or a *Bomber* aircraft.

(12)

3.

3. **a.** Construct a flowchart that describes the algorithm of a simple recursive 2-sensor Kalman Filter to provide an optimal (minimum variance) estimate of the position of a stationary vehicle.

(6)

b. To measure the range of a stationary vehicle, data from 2 sensors (S_1 and S_2) is collected at alternate time intervals. The data from S_1 is known to have a variance of $\sigma_1^2 = 0.3$ and a mean $\mu_{s1}=4$, and the data from S_2 a variance of $\sigma_2^2 = 0.2$ and mean $\mu_{s2}=3$.

To obtain the 'best estimate' of the vehicle's range, the data from the two sensors is 'fused' using the minimum variance estimator (simple Kalman filter) algorithm from part (a) of the question. Some data from the sensors, and the output from the estimator, are given in Table 3.1.

Complete Table 3.1 by calculating the output of the Kalman estimator from part (a), for $k= 2, 3, 4, 5$.

Table 3.1

k (secs)	S_1	σ_1^2	S_2	σ_2^2	μ_{best}	σ_{best}
0	4.19	0.3			**4.19**	**0.3**
1			3.27	0.2	**3.64**	**0.12**
2	4.33	0.3			**?**	**0.086**
3			3.47	0.2	**3.72**	**?**
4	3.86	0.3			**?**	**0.05**
5			2.80	0.2	**3.56**	**?**
6	4.03	0.3			**3.61**	**0.035**
7			3.05	0.2	**3.53**	**0.03**

(9)

c. When employing a Kalman estimator with system model dynamics, the formulation involves co-variance matrices P(k), Q, R, and the matrix K(k). Explain the role of these matrices as fully as you can. **(5)**

4. A sensor has identified a possible 5 datapoints (A to E) corresponding to the position of vehicles on a 2-dimensional plane, designated by *x, y* co-ordinates [*x*,*y*]. The position of the 5 datapoints are:

A=(1.5, 1)
B=(2, 1)
C=(3, 3)
D=(2, 2.5)
E=(3, 4)

For ease of visualisation, the 5 datapoints (designated by the '+' symbol) are also shown in Fig. 4.1.

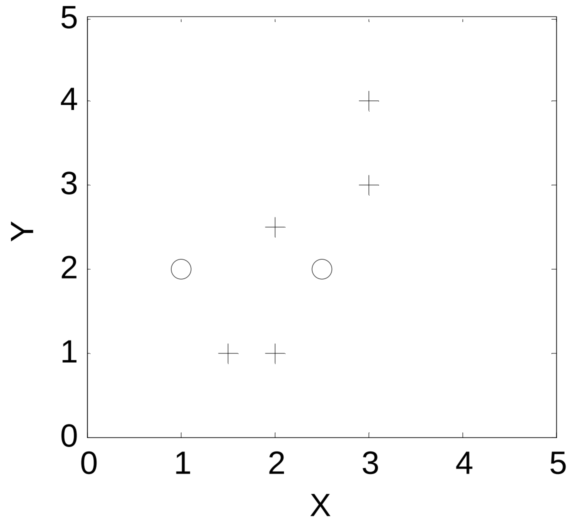

Figure 4.1

However, you know from prior knowledge, that there are actually only 2 vehicles present in this area. You therefore choose to use K-means clustering to obtain a 'best estimate' of the position of the 2 vehicles. You decide to initiate 2 cluster centroids, c_1 and c_2, whose positions are at:

c_1=(1, 2) c_2=(2.5, 2)

which are also shown in Fig. 4.1 (designated 'o')

a. Produce a flowchart to implement the K-means clustering algorithm. **(5)**

b. Use the K-means clustering method to determine the best estimate of the position of the vehicles i.e. determine the final cluster centroids, and how the original datapoints (A to E) should be grouped based on your answers. (note: do not attempt more than 2 iterations) **(10)**

c. If you did not know that there were originally only two vehicles located in the vicinity, discuss other clustering methods that could be used, and why. **(5)**

CMB