Data Provided: None

The University Of Sheffield.

DEPARTMENT OF ELECTRONIC AND ELECTRICAL ENGINEERING

Spring Semester 2008-2009 (2 hours)

Multi-Sensor 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. Discuss the relative attributes of i) Exclusive clustering ii) Overlapping clustering and iii) Hierarchical clustering techniques. **(6)**

b. Provide a simple pseudo-code algorithm <u>or</u> flow-chart to show the procedure for K-means clustering. **(4)**

c. Two satellites have sent back data relating to the locations of 2 vehicles on the ground. The 4 data points that are received from the satellites are located at :

$(X,Y)=\{(1.5,1),(2,1),(3,3),(5,4.5)\}$

as shown in Fig. 1.1.

You assume that there are 2 clusters of points and that the 2 centroids (c_1 and c_2) are randomly initialised at $c_1=(4,2)$, $c_2=(2,3)$—also shown in Fig.1.1.

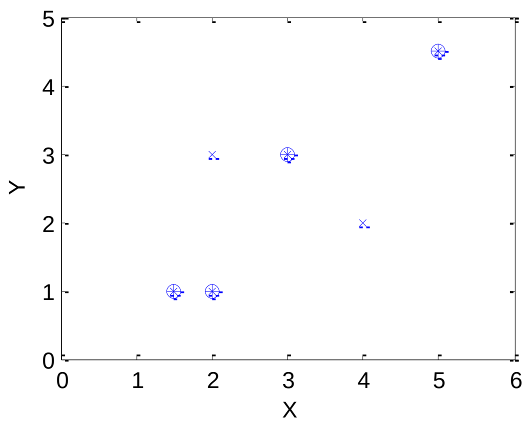

Figure 1.1

Using the K-means clustering method, identify which data points should be grouped in each of the 2 clusters. Show all your working and calculations (note: you should only need a maximum of 3 iterations of the algorithm, possibly less). **(10)**

2. **a.** You have 2 sensors, S_1 and S_2, to determine the position of an object. The data from S_1 is $\mu_{s1}=4$, and is known to have a statistical variance of $\sigma_1^2 = 0.1$. The data from S_2 has a value of $\mu_{s2}=3$, and is known to have a statistical variance of $\sigma_2^2 = 0.2$.

i) By fusing the data given above, from the 2 sensors, calculate the best estimate, μ_{best} , of the position of the object, and the statistical variance σ_{best}^2 you expect, just from the given information.

ii) From the results of i) explain why you have more confidence in the position of the object from the 'fused' data, compared to the readings taken individually from each sensor. **(7)**

b. To measure the range of a stationary aircraft, 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 $\sigma_1^2 = 0.1$ 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 aircraft's range, the data from the two sensors is 'fused' using a minimum variance estimator (simple Kalman filter). A flowchart showing the structure of the estimator is given in Figure 2.1. Some data from the sensors, and the output from the estimator, are given in Table 2.1.

Complete Table 2.1 by calculating the output of the estimator for $k= 3, 4, 5$. **(13)**

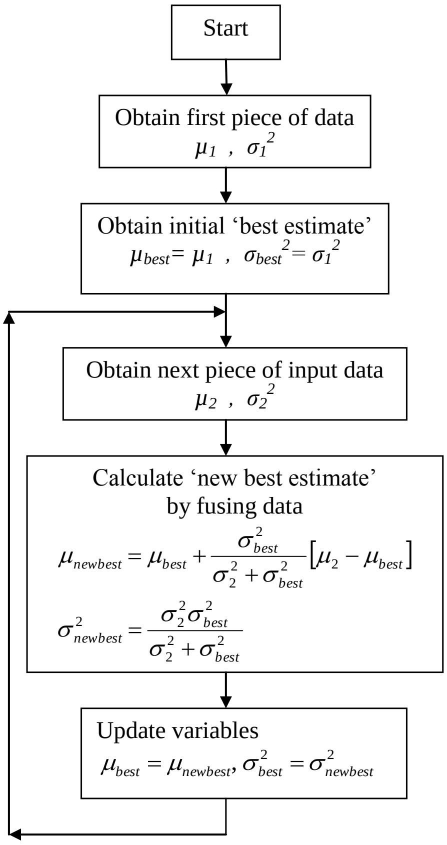

Figure 2.1 Minimum variance estimator

k	S_1	σ_1^2	S_2	σ_2^2	μ_{best}	σ_{best}
0	4.19	0.1			**4.19**	**0.1**
1			3.27	0.2	**3.88**	**0.067**
2	4.33	0.1			**4.06**	**0.04**
3			3.47	0.2	**?**	**?**
4	3.86	0.1			**?**	**?**
5			2.80	0.2	**?**	**?**
6	4.03	0.1			**3.85**	**0.018**
7			3.05	0.2	**3.78**	**0.017**
8	3.95	0.1			**3.81**	**0.014**

Table 2.1

3. **a.** Identify the 5 levels of data fusion represented by the standard JDL model (use a diagram if it helps), and give examples of data-fusion techniques used for each level. **(8)**

b. You have been given the task of determining whether a particular vehicle is an *Enemy* or a *Friend*. You have 2 sensors, each of which can give only one-of-two outputs at any particular time—Output 1 (m_{i1}) of each sensor has been tuned to detect *Enemy* vehicles with a high probability, and Output 2 (m_{i2}) of each sensor has been tuned to detect *Friendly* vehicles with a high probability. The decision matrix for each of the 2 sensors, is identical, and shown in Fig. 3.1.

$$\begin{array}{cc} & \begin{array}{cc} m_{11} & m_{12} \end{array} \\ \begin{array}{r} Enemy \\ Friend \end{array} & \begin{bmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{bmatrix} \end{array} \quad sensor\,1$$

$$\begin{array}{cc} & \begin{array}{cc} m_{21} & m_{22} \end{array} \\ \begin{array}{r} Enemy \\ Friend \end{array} & \begin{bmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{bmatrix} \end{array} \quad sensor\,2$$

Figure 3.1

Use a simple Maximum Likelihood Decision Rule to obtain the 'Network Probability' (matrix) of correctly classifying the vehicle as an *Enemy* or a *Friend*. **(12)**

4. a. Give 4 advantages of using multi-sensor data-fusion systems, along with example applications where the advantages can be obtained. **(5)**

b. What are the 3 different types of <u>Sensor Network</u> commonly encountered in data-fusion systems, and their attributes ? Give clear example applications for each type of network. **(5)**

c. A multi-sensor network consists of $k=5$ similar sensors ($S_1,\ldots,S_5$) to measure the range of a ship. In order to monitor the validity of the sensor readings, you take $\bar{n}=17$ readings from each sensor and apply <u>Cochran's method</u> to determine if any <u>outliers</u> are present, and are significant. The variance of the sensor measurements is given in Table 4.1.

	S_1	S_2	S_3	S_4	S_5
σ^2	0.04	0.2	0.05	0.055	0.045

Table 4.1

Use Cochran's method and the 'significance table' (Fig.4.1) with $\alpha=0.05$ to show that the data from S_2 should be considered with caution.

Level of significance $\alpha = 0.05$

$k \backslash \nu_x$	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 4.1

If you decide to ignore the data from S2, does the data from the remaining sensors in the network subsequently appear statistically robust i.e. are there any further outliers ? **(10)**

CMB