

HW - 4 Submission

AE-6505 - Kalman Filtering

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5.4. a. Representing the equations in state space form

$$\begin{bmatrix} x_{p,k+1} \\ x_{g,k+1} \end{bmatrix} = \begin{bmatrix} 1-k_2 & k_1 \\ -k_3 & 1 \end{bmatrix} \begin{bmatrix} x_{p,k} \\ x_{g,k} \end{bmatrix} + \begin{bmatrix} 0 \\ 1 \end{bmatrix} v_k + \begin{bmatrix} w_{p,k} \\ w_{g,k} \end{bmatrix}$$

$$= \begin{bmatrix} 1/2 & 1 \\ -1/2 & 1 \end{bmatrix} x_k + \begin{bmatrix} 0 \\ 1 \end{bmatrix} v_k + w_k$$

$$y_k = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_{p,k} \\ x_{g,k} \end{bmatrix} + v_k$$

$$= \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} x_k + v_k$$

From info in the question, we also know that

$$Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \text{ and } R = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

So $w_k \sim N(0, Q)$ and $v_k \sim N(0, R)$

b. Given that initial population count is perfect

$$\therefore P_0^+ = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}$$

Iteratively using the Kalman Filter equations

$$P_i^- = F P_{i-1}^+ F^T + Q = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$$

$$K_i = P_i^- H^T (H P_i^- H^T + R)^{-1} = \begin{bmatrix} 1 & 0 \\ 0 & 1/2 \end{bmatrix}$$

$$P_i^+ = (I - K_i H) P_i^- = \begin{bmatrix} 0 & 0 \\ 0 & 1/2 \end{bmatrix}$$

$$P_2^- = F P_1^+ F^T + Q = \begin{bmatrix} 3/2 & 1/2 \\ 1/2 & 3/2 \end{bmatrix}$$

$$K_2 = P_2^- H^T (H P_2^- H^T + R)^{-1} = \begin{bmatrix} 1 & 0 \\ 1/7 & 4/7 \end{bmatrix}$$

$$K_2 = P_2^- H^T (H P_2^- H^T + R)^{-1} = \begin{bmatrix} 1 & 0 \\ 1/7 & 4/7 \end{bmatrix}$$

$$P_2^+ = (I - K_2 H) P_2^- = \begin{bmatrix} 0 & 0 \\ 0 & 4/7 \end{bmatrix}$$

\therefore After 1 week the variance of the guppy population is $1/2$ and $4/7$ after two weeks

c. As $k \rightarrow \infty$ $x_{k+1} = x_k$ (i.e. steady-state)

$$x_k = Fx_k + Gu_k$$

$$(I - F)x_k = Gu_k$$

$$x_k = (I - F)^{-1}Gu_k$$

$$= \begin{bmatrix} 2 \\ 1 \end{bmatrix} u_k$$

\therefore The ratio of the piranha population to the guppy population is 2:1

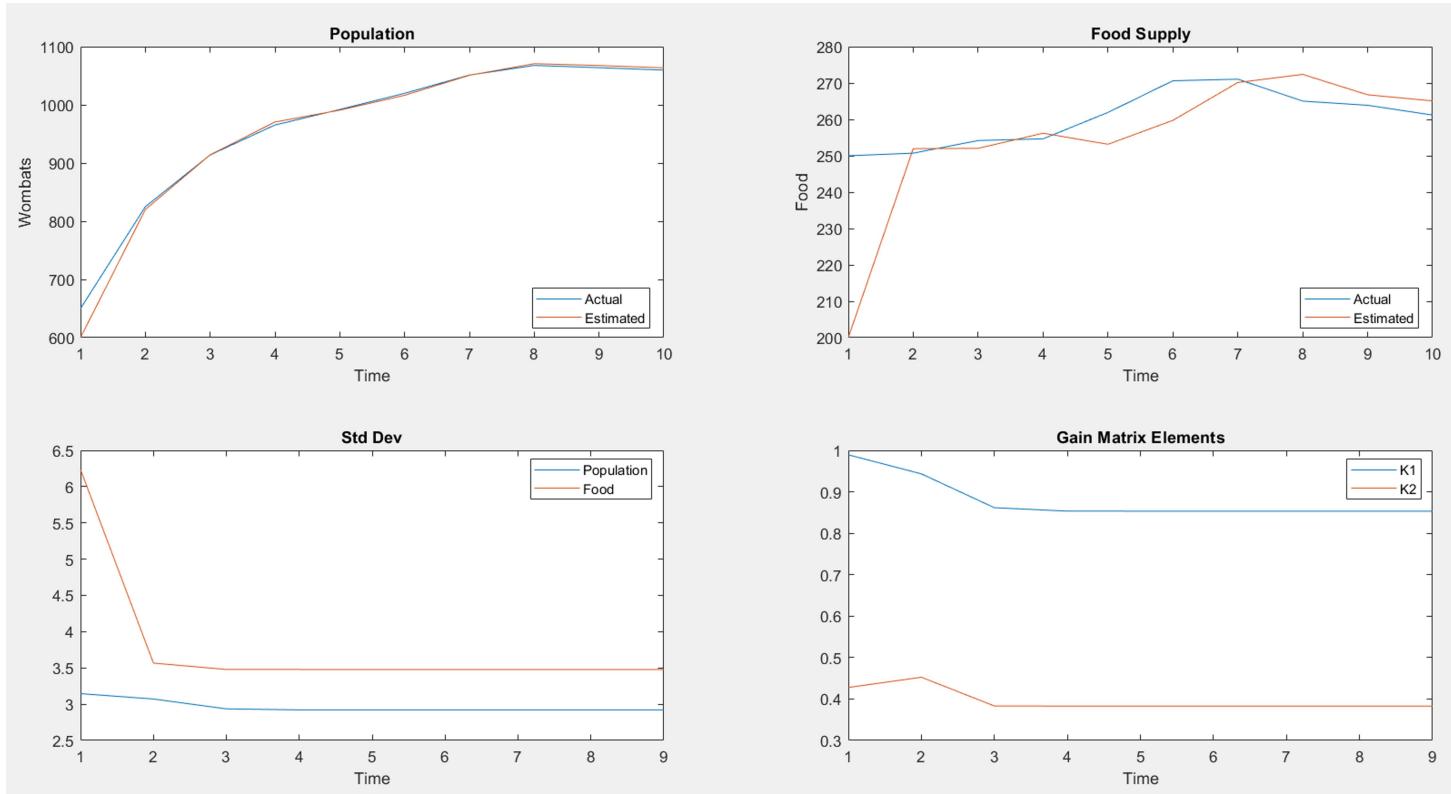
$$5.11. \begin{bmatrix} P_{k+1} \\ f_{k+1} \end{bmatrix} = \begin{bmatrix} 1/2 & 2 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} P_k \\ f_k \end{bmatrix} + w_k$$

$$w_{f,k} \sim N(0, Q) \text{ where } Q = \begin{bmatrix} 0 & 0 \\ 0 & 10 \end{bmatrix}$$

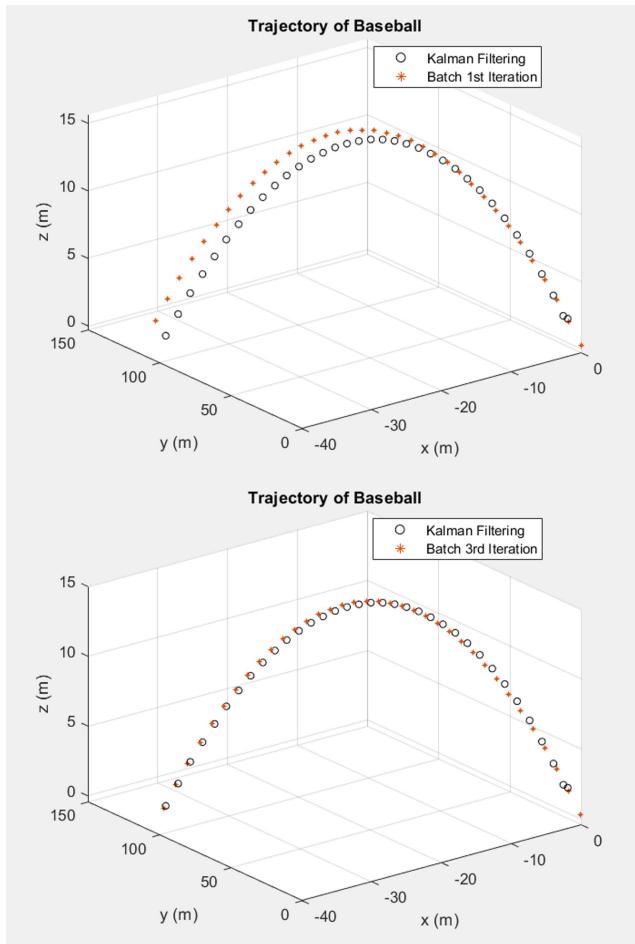
$$y_k = \begin{bmatrix} 1 & 0 \end{bmatrix} \begin{bmatrix} P_k \\ f_k \end{bmatrix} + v_k$$

$$v_k \sim N(0, R) \text{ where } R = 10$$

After assembling this in MATLAB and using Eq (5.17) through (5.19) from Simon, we get the following plots



- b. The std. devs of the population and food supply estimation errors starts around 15. The steady state std. devs. settle at ~ 2.92 for the wombat population and ~ 3.47 for the food supply. This difference is due to the large error in the initial estimate and the small number of simulation iterations.
- c. As the number of timesteps increases, the std dev. moves closer to the theoretical std. dev because the initial estimation errors are dealt with as more simulations are run.
2. Made necessary changes to batch approach for a priori information
- Implemented Kalman Filter code
 - (Code in appendix)



1 Appendix: MATLAB Code

```
1 %%  
2 clc; clear all; close all;  
3 maxIter = 10;  
4 foodW = normrnd(0,sqrt(10),[1,maxIter]);  
5 obsW = normrnd(0,sqrt(10),[1,maxIter]);  
6 Xactual = [650; 250];  
7 F = [1/2 2; 0 1];  
8 Pplus(:,:,1) = [500 0; 0 200];  
9 Q = [0 0; 0 10];  
10 H = [1 0];  
11 R = 10;  
12 Xplus(:,1)= [600; 200];  
13 n = 2;  
14  
15 y(:,1) = Xactual(1,1) + obsW(1);  
16 std1 = [];  
17 std2 = [];  
18 K1 = [];  
19 K2 = [];  
20  
21 % discrete kalman filter + simulation  
22 for k = 2:maxIter  
23     Xactual(:,:,k) = F*Xactual(:,:,k-1) + [0 foodW(k)]';  
24     y(:,:,k) = Xactual(1,k) + obsW(k);  
25  
26     Pminus(:,:,k) = F*Pplus(:,:,k-1)*F' + Q;  
27     K(:,:,k) = Pminus(:,:,k)*H'/(H*Pminus(:,:,k)*H' + R);  
28     Xminus(:,:,k) = F*Xplus(:,:,k-1);  
29     Xplus(:,:,k) = Xminus(:,:,k) + K(:,:,k)*(y(:,:,k)-H*Xminus(:,:,k));  
30     Pplus(:,:,k) = (eye(n) - K(:,:,k)*H)*Pminus(:,:,k);  
31     std1 = vertcat(std1, sqrt(Pplus(1,1,k)));  
32     std2 = vertcat(std2, sqrt(Pplus(2,2,k)));  
33     K1 = vertcat(K1, K(1,1,k));  
34     K2 = vertcat(K2, K(2,1,k));  
35 end  
36 figure()  
37 subplot(2,2,1)  
38 plot(Xactual(1,:))  
39 hold on  
40 plot(Xplus(1,:))  
41 xlabel('Time')  
42 ylabel('Wombats')  
43 legend('Actual', 'Estimated', 'Location', 'best')  
44 title('Population')  
45  
46 subplot(2,2,2)  
47 plot(Xactual(2,:))  
48 hold on  
49 plot(Xplus(2,:))  
50 xlabel('Time')  
51 ylabel('Food')  
52 legend('Actual', 'Estimated', 'Location', 'best')  
53 title('Food Supply')  
54  
55 subplot(2,2,3)  
56 plot(std1)  
57 hold on  
58 plot(std2)  
59 xlabel('Time')  
60 legend('Population', 'Food', 'Location', 'best')  
61 title('Std Dev')  
62
```

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63 subplot(2,2,4)
64 plot(K1)
65 hold on
66 plot(K2)
67 xlabel('Time')
68 legend('K1', 'K2', 'Location', 'best')
69 title('Gain Matrix Elements')
70
71 %%
72 %%
73 clc; clear all; close all;
74
75 % SET CONSTANTS
76 g = 9.81;
77
78 % Measurement noise covariance
79 % 5 ft and 0.1 deg in m and rad
80 R = [(1.524)^2 0 0;
81 0 (0.1*pi/180)^2 0;
82 0 0 (0.1*pi/180)^2];
83
84 data = importdata('homerun_data_HW4.txt');
85 data(1,:) = [];
86 tspan = data(:, 1);
87 rho = data(:, 2)/3.281; % in m
88 alpha = data(:, 3)*pi/180; % in rad
89 beta = data(:, 4)*pi/180; % in rad
90
91 % Assembling Y_obs using read in data
92 Y_obs = [];
93 for i = 1:length(rho)
94 Y_obs = vertcat(Y_obs, [rho(i) alpha(i) beta(i)]);
95 end
96 m = size(Y_obs, 1);
97
98 % Visualizing data
99 figure(1)
100 [x y z] = sph2cart(alpha, beta, rho);
101 scatter3(x, y, z, 10, 'm', 'filled')
102
103 t0 = 0;
104 X0star = [0.4921 0.4921 2.0013 -26.2467 114.3051 65.9941]'/3.281; % in SI
105 xbar_0 = [0 0 0 0 0 0]';
106 Pbar_0 = diag([4 4 4 0.1 0.1 0.1])/3.281^2;
107 i = 1;
108
109 while i<=m
110 if i == 1
111 xhat_i_1 = X0star;
112 P_i_1 = Pbar_0;
113 t_i_1 = t0;
114 else
115 xhat_i_1 = xhat_i;
116 P_i_1 = P_i;
117 t_i_1 = tspan(i-1);
118 end
119
120 Phi = [1 0 0 tspan(i)-t_i_1 0 0;
121 0 1 0 0 tspan(i)-t_i_1 0;
122 0 0 1 0 tspan(i)-t_i_1;
123 0 0 0 1 0;
124 0 0 0 0 1;
125 0 0 0 0 1];
126
127 B = [0; 0; -1/2*(tspan(i)-t_i_1)^2; 0; 0; -(tspan(i)-t_i_1)];

```

```

128     xbar_i = Phi * xhat_i_1 + B * g;
129     Pbar_i = Phi * P_i_1 * Phi';
130 %     + Q to previous line to add filter from diverging
131
132     X = xbar_i(1);
133     Y = xbar_i(2);
134     Z = xbar_i(3);
135
136     rho = sqrt(X^2 + Y^2 + Z^2);
137     alpha = atan2(Y, X);
138     beta = atan2(Z, sqrt(X^2 + Y^2));
139
140     Y_computed = [rho; alpha; beta];
141     y_i = Y_obs(i,:)' - Y_computed;
142     H_tilda_i = [X/rho Y/rho Z/rho 0 0 0;
143                   (-Y/X^2)/(1 + (Y/X)^2) (1/X)/(1+(Y/X)^2) 0 0 0 0;
144                   ((-X*Z)/(X^2 + Y^2)^{(3/2)})/(1+(Z^2)/(X^2 + Y^2)) ((-Y*Z)/(X^2 + Y^2)^{(3/2)})/(1 + (Z^2)/(X^2
145 → + Y^2)) ((1)/(X^2 + Y^2)^{(1/2)})/(1 + (Z^2)/(X^2 + Y^2)) 0 0 0];
146     K_i = Pbar_i*H_tilda_i'*inv(H_tilda_i*Pbar_i*H_tilda_i' + R);
147
148     xhat_i = xbar_i + K_i*y_i;
149     P_i = (eye(6) - K_i*H_tilda_i)*Pbar_i;
150     X_calculated(:, i) = xhat_i;
151
152     figure(1)
153     hold on
154     scatter3(X_calculated(1, i), X_calculated(2, i), X_calculated(3, i), 20, 'black')
155
156     i = i+1;
157 end
158 xlabel('x (m)')
159 ylabel('y (m)')
160 zlabel('z (m)')
161 title('Trajectory of Baseball')
162
163 %% Batch approach
164 %% Hyperparameters
165 n = 6; % number of params
166 k = 3; % number of obs per epoch
167 max_iter = 8;
168 g = 9.81; % m/s^2
169 dt = 0.1;
170 t_all = [0:dt:3.5];
171
172 % Measurement noise covariance
173 % 5 ft and 0.1 deg in m and rad
174 R = [(1.524)^2 0 0;
175         0 (0.1*pi/180)^2 0;
176         0 0 (0.1*pi/180)^2];
177
178 % Initial state
179 X_0 = [0.4921 0.4921 2.0013 -26.2467 114.3051 65.9941]'; % in ft and ft/s
180 X_0 = X_0/3.281; % converting to SI
181
182 % IF NO APRIORI COMMENT THIS OUT
183 P_bar = diag([4 4 0.1 0.1 0.1])/3.281^2;
184 x_bar = [0; 0; 0; 0; 0; 0];
185
186 % Initial measurements
187 data = importdata('../HW3/homerun_data.txt');
188 tspan = data(:, 1);
189 rho = data(:, 2)/3.281; % in m
190 alpha = data(:, 3)*pi/180; % in rad
191 beta = data(:, 4)*pi/180; % in rad

```

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192
193 % Assembling Y_obs using read in data
194 Y_obs = [];
195 for i = 1:length(rho)
196     Y_obs = vertcat(Y_obs, [rho(i) alpha(i) beta(i)]);
197 end
198 m = size(Y_obs, 1);
199
200 % Visualizing data
201 figure(2)
202 [x y z] = sph2cart(alpha, beta, rho)
203 scatter3(x, y, z, 10, 'm', 'filled')
204
205 % Run iterations
206 for i = 1:max_iter
207     HtH = zeros(n, n);
208     Hty = zeros(n, 1);
209
210     % Loop over all observations
211     % Compute the nominal trajectory and computed observations
212     % Compute Normal equations
213     for j=1:m
214         Phi = [1 0 0 tspan(j) 0 0;
215                 0 1 0 0 tspan(j) 0;
216                 0 0 1 0 0 tspan(j);
217                 0 0 0 1 0 0;
218                 0 0 0 0 1 0;
219                 0 0 0 0 0 1];
220
221         % Compute nominal trajectory
222         B = [0; 0; -1/2*tspan(j)^2; 0; 0; -tspan(j)];
223         X_nom = Phi * X_0 + B * g;
224
225         X = X_nom(1);
226         Y = X_nom(2);
227         Z = X_nom(3);
228
229         % Compute partials
230         rho = sqrt(X^2 + Y^2 + Z^2);
231
232         H_tilda = [X/rho Y/rho Z/rho 0 0 0;
233                     (-Y/X^2)/(1 + (Y/X)^2) (1/X)/(1+(Y/X)^2) 0 0 0 0;
234                     ((-X*Z)/(X^2 + Y^2)^(3/2))/(1+(Z^2)/(X^2 + Y^2)) ((-Y*Z)/(X^2 + Y^2)^(3/2))/(1 +
235             (Z^2)/(X^2 + Y^2)) ((1)/(X^2 + Y^2)^(1/2))/(1 + (Z^2)/(X^2 + Y^2)) 0 0 0];
236
237         % Generate observation deviation (i.e. observed - computed)
238         rho = sqrt(X^2 + Y^2 + Z^2);
239         alpha = atan2(Y, X);
240         beta = atan2(Z, sqrt(X^2 + Y^2));
241
242         Y_computed = [rho; alpha; beta];
243         y = Y_obs(j,:) - Y_computed;
244
245         % Use STM to map partials back to initial coords
246         H = H_tilda * Phi;
247
248         % Compute rank-k update of normal equations for this observation
249         HtH = HtH + H'*inv(R)*H;
250         Hty = Hty + H'*inv(R)*y;
251
252         % Compute state deviation
253         P = inv(HtH);
254
255         % Uncomment line 1 if no apriori, uncomment line 2 if given apriori info

```

```

256 %       $x_{\text{hat}} = P * Hty;$ 
257  $x_{\text{hat}} = \text{inv}(HtH + \text{inv}(P_{\text{bar}})) * (Hty + \text{inv}(P_{\text{bar}}) * x_{\text{bar}});$ 
258
259 % Add state deviation to get final estimate
260  $X_{\text{new}} = X_0 + x_{\text{hat}}$ 
261
262 % Use the new estimates as starting point for next iter
263  $X_0 = X_{\text{new}};$ 
264  $P_{\text{bar}} = \text{inv}(HtH + \text{inv}(P_{\text{bar}}));$ 
265
266 %Plot estimated trajectory for current iteration
267 figure(2);
268 hold on;
269 if i==1 || i == 3
270     for k=1:size(t_all, 2)
271         X0 = X_0(1);
272         Y0 = X_0(2);
273         Z0 = X_0(3);
274         Vx0 = X_0(4);
275         Vy0 = X_0(5);
276         Vz0 = X_0(6);
277         X = X0 + Vx0 * t_all(k);
278         Y = Y0 + Vy0 * t_all(k);
279         Z = Z0 + Vz0 * t_all(k) - (1/2)*g*t_all(k)^2;
280         X_KF(i, k) = X;
281         Y_KF(i, k) = Y;
282         Z_KF(i, k) = Z;
283         scatter3(X, Y, Z, 20)
284     end
285 end
286 xlabel('x (m)')
287 ylabel('y (m)')
288 zlabel('z (m)')
289 title('Trajectory of Baseball')
290
291 %%%
292 close all;
293
294 figure()
295 scatter3(X_calculated(1,:), X_calculated(2,:), X_calculated(3,:), 20, 'black')
296 hold on;
297 scatter3(X_KF(1, :), Y_KF(1, :), Z_KF(1, :), 10, '*')
298 xlabel('x (m)')
299 ylabel('y (m)')
300 zlabel('z (m)')
301 title('Trajectory of Baseball')
302 legend('Kalman Filtering', 'Batch 1st Iteration', 'Location', 'best')
303 hold off;
304
305 figure()
306 scatter3(X_calculated(1,:), X_calculated(2,:), X_calculated(3,:), 20, 'black')
307 hold on;
308 scatter3(X_KF(3, :), Y_KF(3, :), Z_KF(3, :), 10, '*')
309 xlabel('x (m)')
310 ylabel('y (m)')
311 zlabel('z (m)')
312 title('Trajectory of Baseball')
313 legend('Kalman Filtering', 'Batch 3rd Iteration', 'Location', 'best')
314 hold off;

```