

# ROB 501 HW10

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## 1

### 1.1

Given  $f(x_1, x_2, x_3) = 3x_1(2x_2 - x_3^3) + \frac{1}{3}x_2^4$  and  $x^* = [1, 3, -1]^T$

$$\begin{aligned} J_f &= \nabla^\top f \\ &= \left[ \frac{\partial f}{\partial x_1} \quad \frac{\partial f}{\partial x_2} \quad \frac{\partial f}{\partial x_3} \right] \\ &= \left[ 6x_2 - 3x_3^3 \quad 6x_1 + \frac{4}{3}x_2^3 \quad -9x_1x_3^2 \right] \\ J_f(x^*) &= [21, 42, -9] \end{aligned}$$

## 1.2

```
clc; clear;
syms x y z;
grad = jacobian(3 * x * (2 * y - z^3) + y^4 / 3, [x y z]);

f = @(x) 3 * x(1) * (2 * x(2) - x(3)^3) + x(2)^4 / 3;
x_star = [1 3 -1]';

grad_star = double(subs(grad, [x y z], x_star'))
```

```
grad_star = 1×3
    21    42    -9
```

```
delta = [1e-3 1e-3 1e-3]';

grad_hat = zeros(1, 3);

e = eye(3);

for i = 1:3
    grad_hat(i) = (f(x_star + delta(i)*e(:, i)) ...
        - f(x_star - delta(i)*e(:, i))) / (2*delta(i));
end

grad_hat
```

```
grad_hat = 1×3
    21.0000    42.0000    -9.0000
```

## 1.3

```
clc; clear;

x_star = [1 1 1 1 1]';

delta = [1e-5 1e-3 1e-6 1e-3 1e-3]';

grad_hat = zeros(1, 5);

e = eye(5);

for i = 1:5
    grad_hat(i) = (funcPartC(x_star + delta(i)*e(:, i)) ...
        - funcPartC(x_star - delta(i)*e(:, i))) / (2*delta(i));
end

grad_hat
```

```
grad_hat = 1×5
    117.3525   -41.3695  -636.6017   -3.8520  -11.2049
```

## 2

## 2.1

```
clc; clear; close all;

load SegwayData4KF.mat

whos
```

Name	Size	Bytes	Class	Attributes
A	4x4	128	double	
B	4x1	32	double	
C	1x4	32	double	
D	1x1	8	double	
G	4x4	128	double	
N	1x1	8	double	
P0	4x4	128	double	
Q	1x1	8	double	
R	4x4	128	double	
Ts	1x1	8	double	
t	500x1	4000	double	
u	500x1	4000	double	
x0	4x1	32	double	
y	500x1	4000	double	

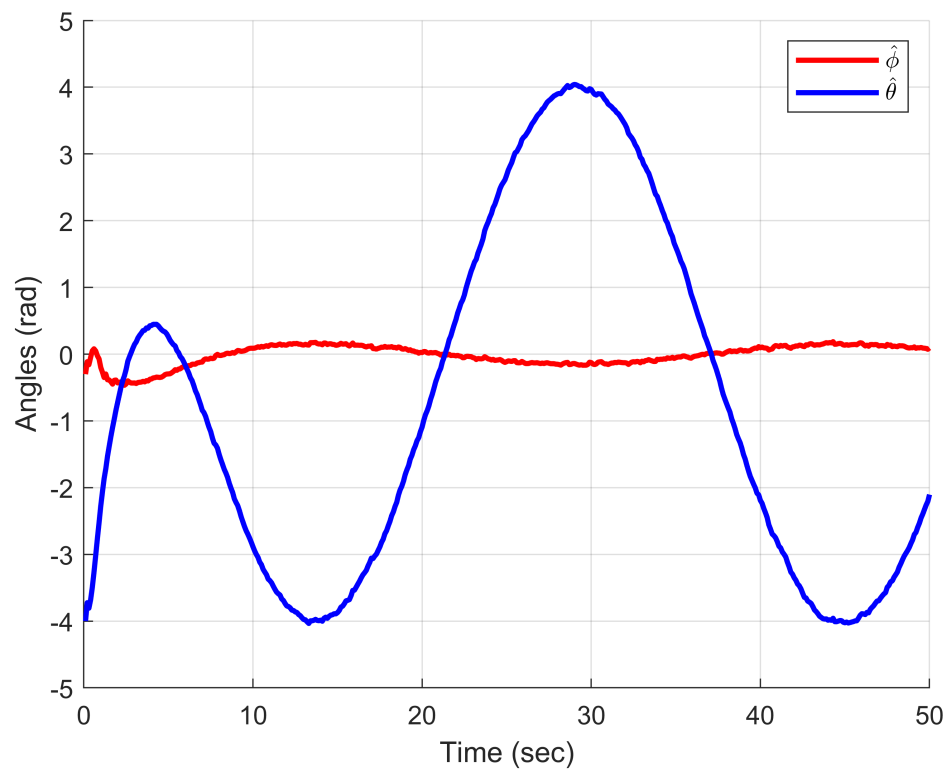
```
x_hat = zeros(length(x0), length(y));
xk = x0;
Pk = P0;
Kt = zeros(length(x0), length(y));

for i=1:length(y)
    x_hat(:, i) = xk;
    Kk = (Pk * C') * inv(C * Pk * C' + Q);
    Kt(:, i) = Kk;
    xk = A * xk + B * u(i) + A * Kk * (y(i) - C * xk);
    Pk = A * (Pk - Kk * C * Pk) * A' + G * R * G';
end
```

## 2.2

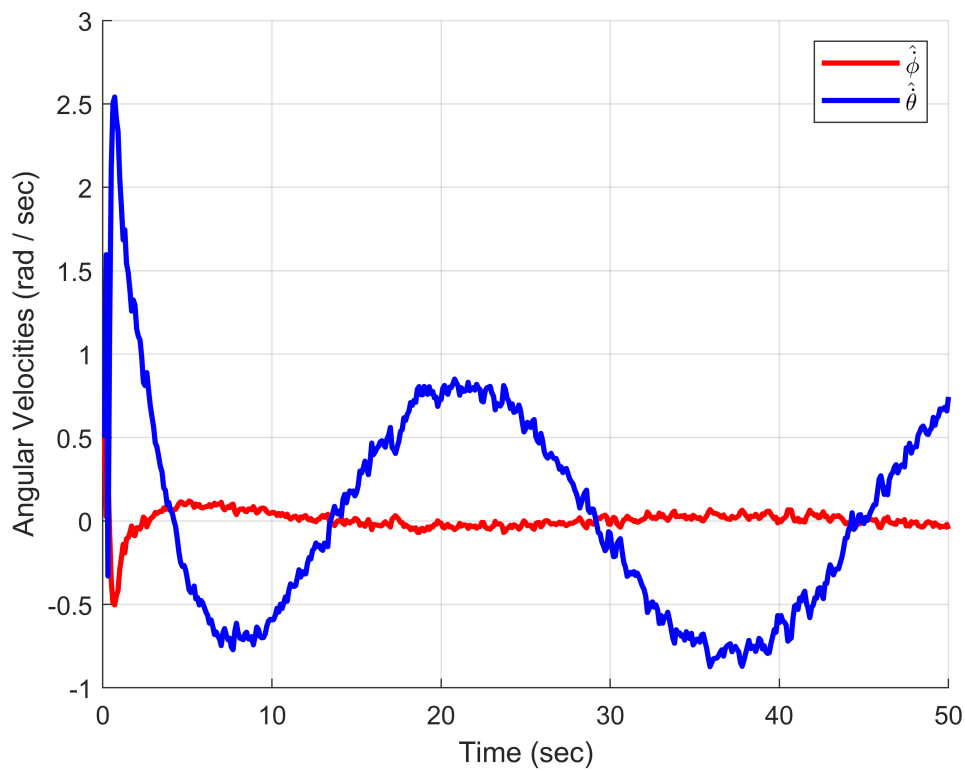
```
figure()
plot(t, x_hat(1, :), 'r', "LineWidth",2)
hold on; grid on; box off;
plot(t, x_hat(2, :), 'b', "LineWidth",2)
hold off;
legend([" $\hat{\phi}$ ", " $\hat{\theta}$ "], 'interpreter', 'latex')

xlabel("Time (sec)")
ylabel("Angles (rad)")
```



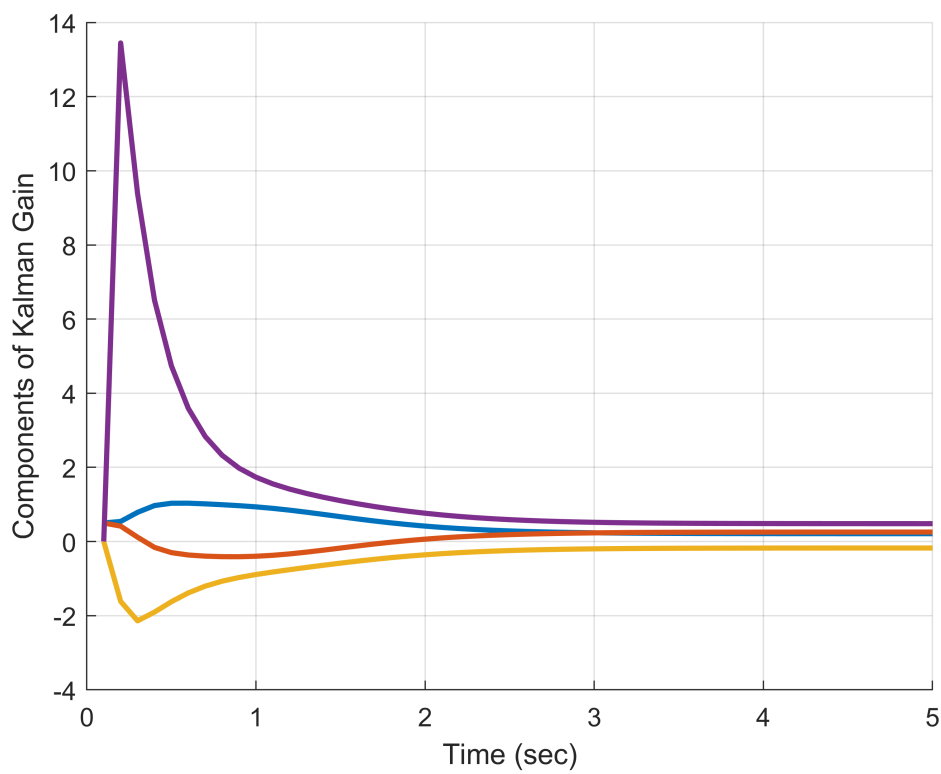
```
figure()
plot(t, x_hat(3, :), 'r', "LineWidth",2)
hold on; grid on; box off;
plot(t, x_hat(4, :), 'b', "LineWidth",2)
hold off;
legend([" $\hat{\dot{\phi}}$ ", " $\hat{\dot{\theta}}$ "], 'interpreter', 'latex')

xlabel("Time (sec)")
ylabel("Angular Velocities (rad / sec)")
```



```
figure()
plot(t, Kt(1, :), "LineWidth",2)
hold on; grid on; box off;
plot(t, Kt(2, :), "LineWidth",2)
plot(t, Kt(3, :), "LineWidth",2)
plot(t, Kt(4, :), "LineWidth",2)
hold off;
xlim([0, 5])

xlabel("Time (sec)")
ylabel("Components of Kalman Gain")
```



## 2.3

Kk

```
Kk = 4x1
    0.2113
    0.2559
   -0.1744
    0.4816
```

```
[Kss,Pss] = dlqe(A,G,C,R,Q);
Kss
```

```
Kss = 4x1
    0.2113
    0.2559
   -0.1744
    0.4816
```

### 3

$$\begin{aligned} \begin{cases} x_0 \sim N(1, 0.25) & \Rightarrow \hat{x}_0 = 1, P_0 = 0.25 \\ u_1 \sim N(10, 16) & \Rightarrow \hat{u}_1 = 10, R = 16 \end{cases} \\ \Rightarrow A = 1, B = 0.1 \\ x_1 = x_0 + u_1 \cdot \delta_t \\ z_t = -\frac{2}{c}x_t + \frac{10}{c} \Rightarrow C = -\frac{2}{c} \end{aligned}$$

Given  $z_1 = 2.2 \times 10^{-8}$ ,  $Q = 10^{-18}$  and  $t = 0.1$ .

Prediction Step:

$$\begin{aligned} \hat{x}_{1|0} &= A\hat{x}_0 + B\hat{u}_1 \\ &= 1 + 0.1 \times 10 \\ &= 2 \\ P_{1|0} &= AP_0A^\top + BRB^\top \\ &= 0.25 + 0.01 \times 16 \\ &= 0.41 \end{aligned}$$

Measurement Update Step:

$$\begin{aligned} K_1 &= P_{1|0}C^\top (CP_{1|0}C^\top + Q)^{-1} \\ &= 0.41 \times -\frac{2}{c} \left( \frac{4}{c^2} \times 0.41 + Q \right)^{-1} \\ &= -1.422 \times 10^8 \\ \hat{z}_{1|0} &= \frac{2}{c} (5 - \hat{x}_{1|0}) \\ &= \frac{6}{c} \\ \hat{x}_{1|1} &= \hat{x}_{1|0} + K_1 (z_1 - \hat{z}_{1|0}) \\ &= 2 + K_1 \left( 2.2 \times 10^{-8} - \frac{6}{c} \right) \\ &= 1.7156 \\ P_{1|1} &= P_{1|0} - K_1 CP_{1|0} \\ &= 0.41 + K_1 \times \frac{2}{c} \times 0.41 \\ &= 0.0213 \end{aligned}$$

Hence,  $x_1 \sim N(\hat{x}_{1|1}, P_{1|1})$ , where  $\hat{x}_{1|1} = 1.7156$  and  $P_{1|1} = 0.0213$ .

### 4

$$\hat{x} = \arg \min_{x^\top x = 1} x^\top A^\top A x$$

Show that if  $A$  is real, then  $\hat{x}$  is given by the last column of  $V$  where  $A = U\Sigma V^\top$  is the SVD of  $A$ .

*Proof.* Let  $M = A^T A$ ,  $M$  is an  $n \times n$  real symmetric matrix. Apply SVD to  $A$ , we have  $A = U\Sigma V^T$ , where  $V \in \mathbb{R}^{n \times n}$  is an orthogonal matrix and its columns are eigenvectors of  $M$  in descending order according to its eigenvalues.

Construct  $L(x, \lambda) = x^T Mx - \lambda(x^T x - 1)$ , and  $\lambda > 0$ .

$$\nabla L = \frac{dL}{dx} = 2Mx - 2\lambda x$$

Solve  $\nabla L = 0$ , we have  $Mx = \lambda x$ .

Therefore,  $\lambda$  is the eigenvalue of  $M$  and  $x$  is the corresponding eigenvector.

$$x^T Mx = x^T (\lambda x) = \lambda x^T x = \lambda$$

Solve  $\det(M - \lambda I) = 0$ . Since the eigenvalues are real and finite in number, there exists a largest eigenvalue, denoted  $\lambda_{max}$ , and a smallest eigenvalue, denoted  $\lambda_{min}$ , i.e.  $\boldsymbol{\lambda} = [\lambda_{max}, \dots, \lambda_{min}]^T$

Hence,  $\hat{x}$  is its corresponding eigenvector given by  $(M - \lambda_{min}I)x = 0$ , which is the last column of  $V$ .

□



## 5

```
clc; clear;  
A = [4.041 7.046 3.014;  
     10.045 17.032 7.027;  
     16.006 27.005 11.048];
```

```
[U V D] = svd(A);  
V
```

```
V = 3×3  
    40.2854         0         0  
         0    0.1859         0  
         0         0    0.0051
```

```
A_hat = U(:, 1:2) * V(1:2, 1:2) * D(:, 1:2)'
```

```
A_hat = 3×3  
    4.0420    7.0450    3.0150  
   10.0426   17.0345    7.0245  
   16.0073   27.0037   11.0493
```

```
A_delta = A - A_hat
```

```
A_delta = 3×3  
   -0.0010    0.0010   -0.0010  
    0.0024   -0.0025    0.0025  
   -0.0013    0.0013   -0.0013
```