

## 1 Introduction

The objective of Lab 3 is to implement a Kalman Filter. The lab is done in two parts. In Part 1, a Kalman Filter for a constant 1D velocity model is designed for the data "1D-data.txt". In Part 2, the Kalman filter is modified for a 2D model and the data used is provided in "2D-UWB-data.txt".

## 2 Methods

The Kalman filter for both parts make use of the following equations for each loop.

1. Prediction of next state:

$$X_{t,t-1} = \Phi X_{t-1,t-1} \quad (1)$$

2. Prediction of next state covariance:

$$S_{t,t-1} = \Phi S_{t-1,t-1} \Phi^T + Q \quad (2)$$

3. Measurement  $Y_t$  is obtained from the data files "1D-data.txt" and "2D-UWB-data.txt"
4. Calculating Kalman gain:

$$K_t = S_{t,t-1} M^T [M S_{t,t-1} M^T + R]^{-1} \quad (3)$$

5. Updating states:

$$X_{t,t} = X_{t,t-1} + K_t (Y_t - M X_{t,t-1}) \quad (4)$$

6. Updating state covariances:

$$S_{t,t} = [I - K_t M] S_{t,t-1} \quad (5)$$

The values of Dynamic noise  $Q$ , Measurement noise  $R$ , Observation matrix  $M$  and covariance of state variables  $S_t$  are different for Part 1 and Part 2.

### 2.1 Part 1

In Part 1, a 1D velocity model is used. The observation matrix  $M$  for this model is,

$$M = \begin{bmatrix} 1 & 0 \end{bmatrix}$$

The state variable covariance is given by,

$$\Phi = \begin{bmatrix} 1 & 1 \\ 0 & 1 \end{bmatrix}$$

The dyanmic noise  $Q$  and measurement noise are varied for three different ratios: high  $Q$  and low  $R$ , low  $Q$  and high  $R$  and a balanced pair of  $Q$  and  $R$ . The values used for each ratio is given below:

1. High  $Q$  and Low  $R$

$$Q = \begin{bmatrix} 0 & 0 \\ 0 & 0.5 \end{bmatrix} R = [ 0.0005 ]$$

2. Low  $Q$  and High  $R$

$$Q = \begin{bmatrix} 0 & 0 \\ 0 & 0.0005 \end{bmatrix} R = [ 0.5 ]$$

3. Balanced  $Q$  and  $R$

$$Q = \begin{bmatrix} 0 & 0 \\ 0 & 0.5 \end{bmatrix} R = [ 0.5 ]$$

In Part 1,  $X_{(t-1,t-1)}$  and  $S_{(t-1,t-1)}$  are initialized to  $[0 \ 0]$  and

$$S_{t-1,t-1} = \begin{bmatrix} 0 & 0 \\ 0 & 1 \end{bmatrix}$$

## 2.2 Part 2

In part 2, the 2D UWB data was applied to a 2D velocity model. The observation matrix used is,

$$M = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

The state variable covariance is given by,

$$\Phi = \begin{bmatrix} 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

The dyanmic noise  $Q$  and measurement noise are varied for three different ratios: high  $Q$  and low  $R$ , low  $Q$  and high  $R$  and a balanced pair of  $Q$  and  $R$ . The values used for each ratio is given below:

1. High  $Q$  and Low  $R$

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0.25 \\ 0 & 0 & 0.25 & 0.5 \end{bmatrix} R = \begin{bmatrix} 0.001 & 0.0005 \\ 0.0010.0005 \end{bmatrix}$$

2. Low  $Q$  and High  $R$

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.0005 & 0.00025 \\ 0 & 0 & 0.00025 & 0.0005 \end{bmatrix} R = \begin{bmatrix} 1 & 0.5 \\ 10.5 \end{bmatrix}$$

### 3. Balanced Q and R

$$Q = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.5 & 0.25 \\ 0 & 0 & 0.25 & 0.5 \end{bmatrix} \quad R = \begin{bmatrix} 1 & 0.5 \\ 10.5 & 0.5 \end{bmatrix}$$

In Part 2,  $X_{(t-1,t-1)}$  and  $S_{(t-1,t-1)}$  are initialized as shown below,

$$X_{t-1,t-1} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix} \quad S_{t-1,t-1} = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0.1 & 0.05 \\ 0 & 0 & 0.05 & 0.1 \end{bmatrix}$$

## 3 Results

### 3.1 Part 1

The results obtained by passing the 1D data through the Kalman filter designed in part 1 are as follows:

1. High dynamic noise Q and low measurement noise R

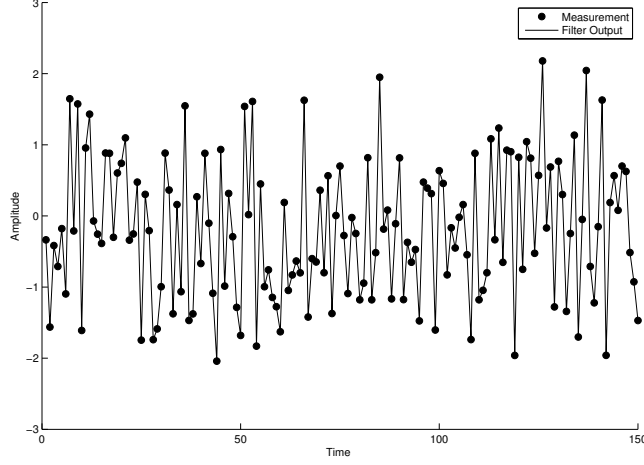


Figure 1: Plot for prediction of x (1D model-high Q, low R ratio)

2. Low dynamic noise  $Q$  and high measurement noise  $R$

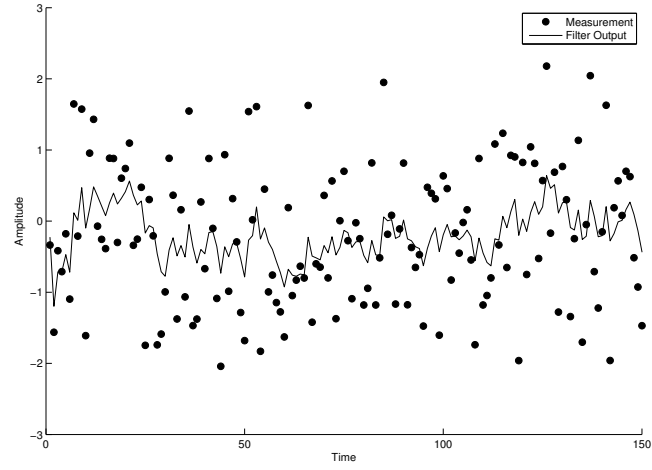


Figure 2: Plot for prediction of  $x$  (1D model-low  $Q$ , high  $R$  ratio)

3. Balanced  $Q$  and  $R$

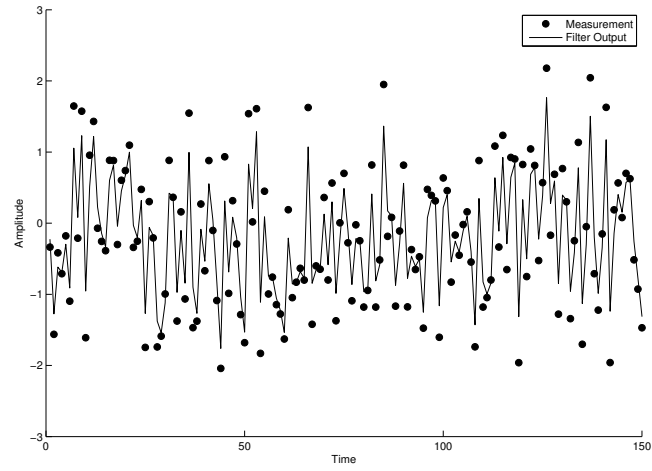


Figure 3: Plot for prediction of  $x$  (1D model-Balanced  $Q/R$  ratio)

### 3.2 Part 2

The results obtained by passing the 2D UWB data through the Kalman filter designed in part w are as follows:

1. High dynamic noise  $Q$  and low measurement noise  $R$

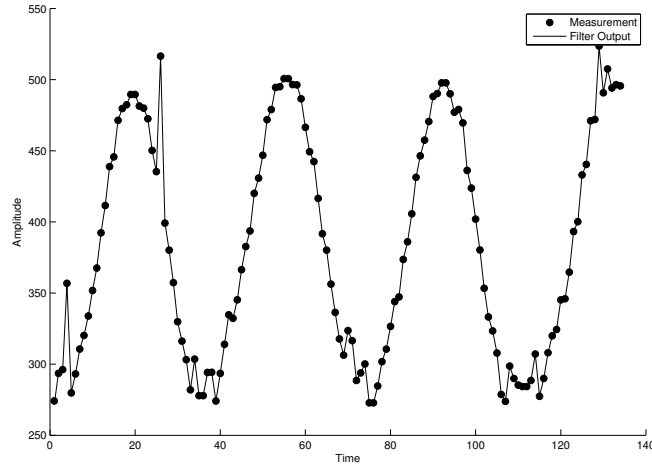


Figure 4: Plot for prediction of  $x$  (2D model-high  $Q$ , low  $R$  ratio)

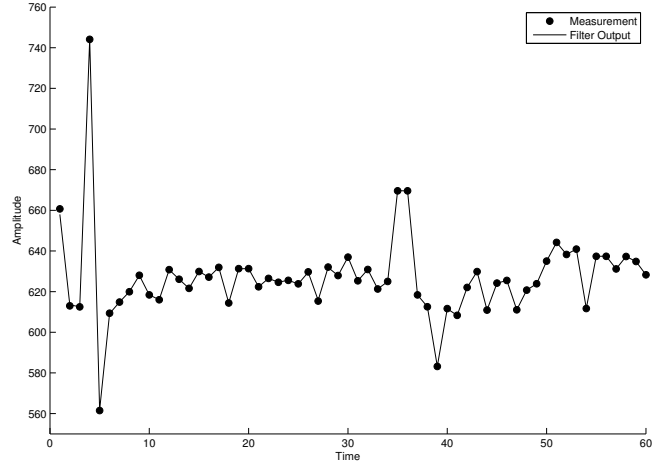


Figure 5: Plot for prediction of  $y$  (2D model-high  $Q$ , low  $R$  ratio)

## 2. Low dynamic noise $Q$ and high measurement noise $R$

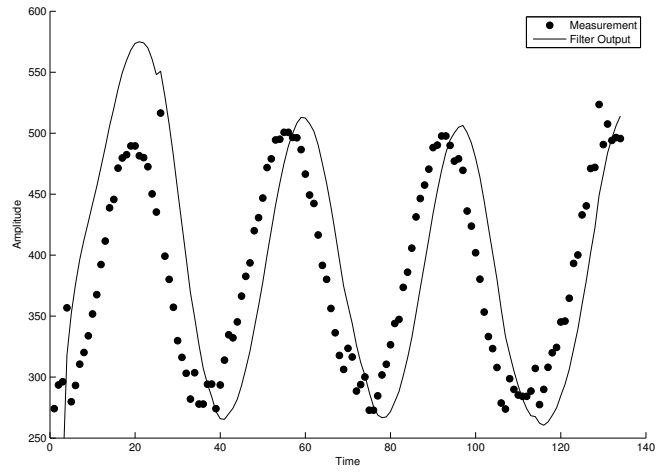


Figure 6: Plot for prediction of  $x$  (2D model-low  $Q$ , high  $R$  ratio)

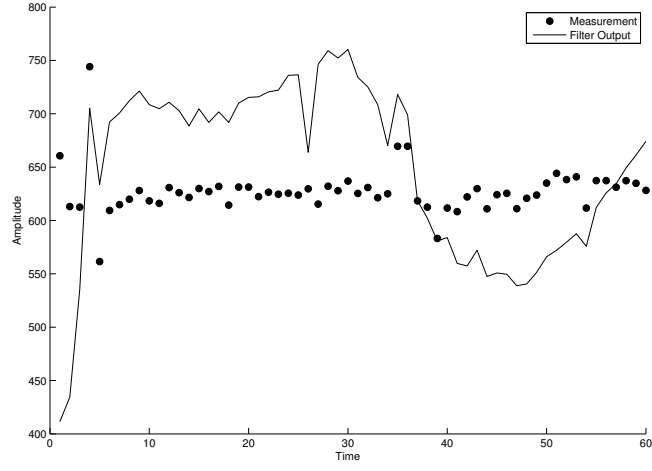


Figure 7: Plot for prediction of  $y$  (2D model-low  $Q$ , high  $R$  ratio)

### 3. Balanced $Q$ and $R$

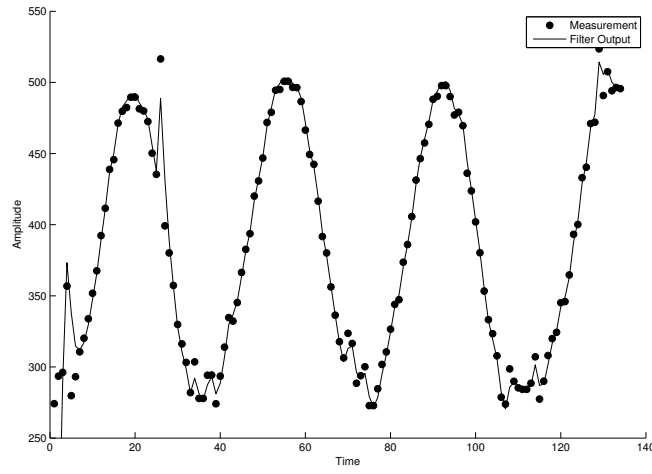


Figure 8: Plot for prediction of  $x$  (2D model-Balanced  $Q/R$  ratio)

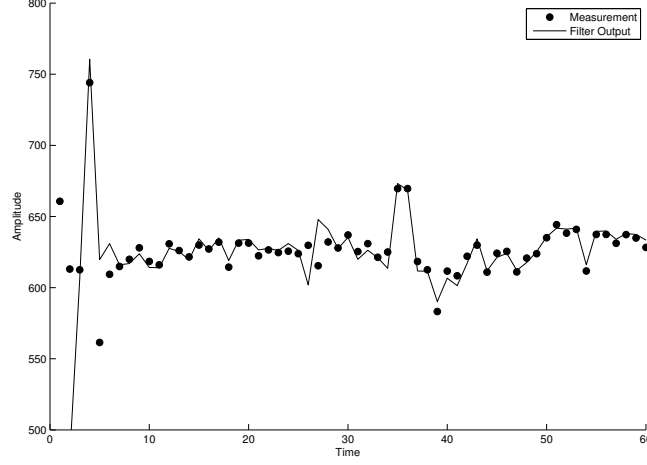


Figure 9: Plot for prediction of  $y$  (2D model-Balanced  $Q/R$  ratio)

### 3.3 Inference

From, the above plots it can be observed that when the dynamic noise  $Q$  is set high compared to the measurement noise  $R$ , the filter output tends to follow the measurement values closely. When  $Q$  is set low and  $R$  is set to high values, the output does not closely follow the measurement data. For a balanced ratio, the output tends to follow the measurements with slight variations depending on the values of  $Q$  and  $R$ .

## 4 Conclusions

Thus, the Kalman filter has been applied to 1D and 2D models to predict the next states.



## 5 Appendix : Matlab Code

### 5.1 Part 1

```
clear;
Y_t=load('1D-data.txt');

X_t=[0 0]';
S_t=[1 1;0 1];
M=[1 0];
S=[0 0;0 1];
Q=[0 0; 0 0.0005];
R=.0005;

X_predict=S_t*X_t;
S_predict=S_t*S*S_t'+Q;

for i=1:size(Y_t)
    Kt=S_predict*M'*inv(M*S_predict*M'+R);
    X_upd=X_predict+Kt*(Y_t(i)-M*X_predict);
    S_update=(eye(2)-Kt*M)*S_predict;
    X_update(i)=X_upd(1);
    X_predict=S_t*X_update(i);
    S_predict=S_t*S_update*S_t'+Q;
end

scatter(1:1:length(Y_t),Y_t)
hold on
plot(X_update)
hold off
```

### 5.2 Part 2

```
clear;
Y_t=load('2D-UWB-data.txt');

X_t=[0 0 0 0]';
S_t=[1 0 1 0;0 1 0 1;0 0 1 0;0 0 0 1];
M=[1 0 0 0;0 1 0 0];
S=[0 0 0 0 ;0 0 0 0;0 0 0.1 0.05;0 0 0.05 0.1];
Q=[0 0 0 0 ;0 0 0 0;0 0 0.5 0.25;0 0 0.25 0.5];
R=[1 0.5;1 0.5];

X_predict=S_t*X_t;
```

```

S_predict=S_t*S*S_t'+Q;

for i=1:length(Y_t)
    Kt=S_predict*M'*inv(M*S_predict*M'+R);
    X_upd=X_predict+Kt*(Y_t(i,:)'-M*X_predict);
    S_update=(eye(4)-Kt*M)*S_predict;
    X_update(i)=X_upd(1);
    Y_update(i)=X_upd(2);
    X_predict=S_t*X_upd;
    S_predict=S_t*S_update*S_t'+Q;
end

figure
scatter(1:1:length(Y_t),Y_t(:,1))
hold on
plot(X_update)

figure
scatter(1:1:length(Y_t),Y_t(:,2))
hold on
plot(Y_update)

```