



# Introduction to Recursive Filtering and Estimation

Spring 2010

Problem Set:

Bayes Theorem, recursive estimation using Bayes Theorem

#### Notes:

- Notation: Unless otherwise noted, x, y, and z denote random variables,  $f_x(x)$  (or the short hand f(x)) denotes the probability density function of x, and  $f_{x|y}(x|y)$  (or f(x|y)) denotes the conditional probability density function of x conditioned on y. The expected value is denoted by  $E[\cdot]$ , the variance is denoted by  $Var(\cdot)$  and Pr(Z) denotes the probability that the event Z occurs.
- Please report any error that you may find to the teaching assistants (strimpe@ethz.ch or aschoellig@ethz.ch).

#### Problem Set

#### Problem 1

Mr. Jones has devised a gambling system for winning at roulette. When he bets, he bets on red, and places a bet only when the ten previous spins of the roulette have landed on a black number. He reasons that his chance of winning is quite large since the probability of eleven consecutive spins resulting in black is quite small. What do you think of this system?

#### Problem 2

Consider two boxes, one containing one black and one white marble, the other, two black and one white marble. A box is selected at random and a marble is drawn at random from the selected box. What is the probability that the marble is black?

#### Problem 3

In Problem 2, what is the probability that the first box was the one selected given that the marble is white?

#### Problem 4

Urn 1 contains two white balls and one black ball, while urn 2 contains one white ball and five black balls. One ball is drawn at random from urn 1 and placed in urn 2. A ball is then drawn from urn 2. It happens to be white. What is the probability that the transferred ball was white?

#### Problem 5

Stores A, B and C have 50, 75, 100 employees, and respectively 50, 60 and 70 percent of these are women. Resignations are equally likely among all employees, regardless of sex. One employee resigns and this is a woman. What is the probability that she works in store C?

#### Problem 6

- a) A gambler has in his pocket a fair coin and a two-headed coin. He selects one of the coins at random, and when he flips it, it shows heads. What is the probability that it is the fair coin?
- b) Suppose that he flips the same coin a second time and again it shows heads. What is now the probability that it is the fair coin?
- c) Suppose that he flips the same coin a third time and it shows tails. What is now the probability that it is the fair coin?

#### Problem 7

Urn 1 has five white and seven black balls. Urn 2 has three white and twelve black balls. We flip a fair coin. If the outcome is heads, then a ball from urn 1 is selected, while if the outcome is tails, then a ball from urn 2 is selected. Suppose that a white ball is selected. What is the probability that the coin landed tails?

An urn contains b black balls and r red balls. One of the balls is drawn at random, but when it is put back in the urn c additional balls of the same color are put in with it. Now suppose that we draw another ball. Show that the probability that the first ball drawn was black given that the second ball drawn was red is b/(b+r+c).

#### Problem 9

Three prisoners are informed by their jailer that one of them has been chosen at random to be executed, and the other two are to be freed. Prisoner A asks the jailer to tell him privately which of his fellow prisoners will be set free, claiming that there would be no harm in divulging this information, since he already knows that at least one will go free. The jailer refuses to answer this question, pointing out that if A knew which of his fellows were to be set free, then his own probability of being executed would rise from 1/3 to 1/2, since he would then be one of two prisoners. What do you think of the jailer's reasoning?

#### Problem 10

Let x and y be independent random variables. Let  $g(\cdot)$  and  $h(\cdot)$  be arbitrary functions of x and y, respectively. Define the random variables v = g(x) and w = h(y). Prove that v and w are independent. That is, functions of independent random variables are independent.

#### Problem 11

Let x be a continuous, uniformly distributed random variable with  $x \in \mathcal{X} = [-5, 5]$ . Let

$$z_1 = x + n_1$$
$$z_2 = x + n_2,$$

where  $n_1$  and  $n_2$  are continuous random variables with probability density functions

$$f(n_1) = \begin{cases} \alpha_1 (1 + n_1) & \text{for } -1 \le n_1 \le 0 \\ \alpha_1 (1 - n_1) & \text{for } 0 \le n_1 \le 1 \\ 0 & \text{otherwise}, \end{cases}$$

$$f(n_2) = \begin{cases} \alpha_2 \left( 1 + \frac{1}{2} n_2 \right) & \text{for } -2 \le n_2 \le 0 \\ \alpha_2 \left( 1 - \frac{1}{2} n_2 \right) & \text{for } 0 \le n_2 \le 2 \\ 0 & \text{otherwise} \,, \end{cases}$$

where  $\alpha_1$  and  $\alpha_2$  are normalization constants. Assume that the random variables x,  $n_1$ ,  $n_2$  are independent, i.e.  $f(x, n_1, n_2) = f(x)f(n_1)f(n_2)$ .

- a) Calculate  $\alpha_1$  and  $\alpha_2$ .
- **b)** Calculate  $f(x|z_1 = 0, z_2 = 0)$ .
- c) Calculate  $f(x|z_1 = 0, z_2 = 1)$ .
- d) Calculate  $f(x|z_1 = 0, z_2 = 3)$ .

Discuss the results.

Consider the following estimation problem: an object B moves randomly on a circle with radius 1. The distance to the object can be measured from a given observation point P. The goal is to estimate the location of the object, see Figure 1.

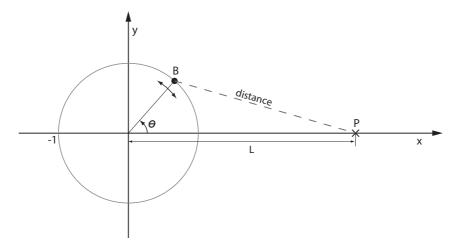


Figure 1

The object B can only move in discrete steps. The object's location at time k is given by  $x(k) \in \{0, 1, ..., N-1\}$ , where

$$\theta(k) = 2\pi \frac{x(k)}{N}.$$

The dynamics are

$$x(k) = \mod(x(k-1) + v(k), N), \qquad k = 1, 2, \dots,$$

where v(k) = 1 with probability p and v(k) = -1 otherwise. Note that  $\mod(N, N) = 0$  and  $\mod(-1, N) = N - 1$ . The distance sensor measures

$$z(k) = \left( (L - \cos \theta(k))^2 + (\sin \theta(k))^2 \right)^{\frac{1}{2}} + w(k),$$

where w(k) represents the sensor error which is uniformly distributed on [-e, e]. We assume that x(0) is uniformly distributed and x(0), v(k) and w(k) are independent.

Simulate object movement and implement a Bayesian tracking algorithm that calculates for each time step k the probability density function f(x(k)|z(1:k)).

a) Test the following settings and discuss the results:  $N = 100, x(0) = \frac{N}{4}, e = 0.5,$ 

$$L = 2,$$
  $p = 0.5,$   
 $L = 2,$   $p = 0.55,$   
 $L = 0.1,$   $p = 0.55,$   
 $L = 0,$   $p = 0.55.$ 

b) How robust is the algorithm? Set N=100,  $x(0)=\frac{N}{4}$ , e=0.5, L=2, p=0.55 in the simulation, but use slightly different values for p and e in your estimation algorithm,  $\hat{p}$  and  $\hat{e}$ , respectively. Test the algorithm and explain the result for:

4

$$\begin{array}{ll} \hat{p} = 0.45, & \hat{e} = e, \\ \hat{p} = 0.5, & \hat{e} = e, \\ \hat{p} = 0.9, & \hat{e} = e, \\ \hat{p} = p, & \hat{e} = 0.9, \\ \hat{p} = p, & \hat{e} = 0.45. \end{array}$$

# Problem Set #2

- Angla Schaling, asthoelige othe on -

## Problem 1

- o x: discrete random variable representing outcome of ith spin, x: € { red, black}, assume both equally likely
- o Assuming independence between spins;

  Pr(xx, xx, xx, xx, = 7(xx) P(xx, P(xx)),

  the probability of M consecutive spins resulting in black

  Pr(xm=black, xno=black, x=black) = (±)

  is actually guite small.
- The place of the previous 10 were black,

  Pot xm = black | xn = black, xg = black, -- xn = black) = Pr (xn = black)

  = 1

  macpendence

  = P(xm = red | xn = black, xg = black, -- xn = black)

i.e. it is equally likely that 10 blacks in a row are followed by red or followed by black (independence assumption)

Example: two spines, combinations (red, red), (red, black), (black, black) all equally (back)

 $P(x_0 = black | x_n = red) = A \leftarrow (black, red), (red, red)$ 

-> bad strategy :

- $x \in \{1,2\}$ : discrete random variable representing probability of choosing box 1 or 2,  $f_{x}(1) = f_{x}(2) = \frac{4}{3}$
- · y & fb, w } = discrete random which representing probability of drawing a back or white marke

$$f_{y|x}(b|1) = \frac{1}{a} = f_{y|x}(\omega|1)$$

• 
$$f_{y}(b) = f_{y|x}(b|1) \cdot f_{x}(1) + f_{y|x}(b|2) \cdot f_{x}(2)$$
  
=  $f_{x} \cdot f_{x}(2) + f_{y|x}(b|2) \cdot f_{x}(2)$  total probability theorem

Problem 3

$$f_{\times |y|}(1) = \frac{f_{\times |x|}(\omega |x|) \cdot f_{\times}(1)}{f_{\times}(\omega)} = \frac{1}{1 - f_{\times}(0)} = \frac{1}{1 - f_{\times}(0)}$$

Problem 4

- · Um 1: xe(b,ω) fx(b)=3, fx(ω)=3
- · un a: yelo,w)

fylx 
$$(b(\omega) = \frac{5}{5})$$
  
fylx  $(u(\omega) = \frac{5}{5})$ 

· question: fxy (w/w)?

total probability

marginal probability

fylx (w/b) fx/b)+fylx(w/w).fx/a)

$$f_{x}(A) = \frac{50}{225} = \frac{2}{9}$$
 $f_{x}(B) = \frac{75}{325} = \frac{1}{3}$ 

$$f_{XM}(C|f) = f_{YM}(f|C) \cdot f_{X}(C) = \frac{7}{10} \cdot \frac{4}{3}$$

$$f_{YM}(f) = \frac{7}{10} \cdot \frac{4}{3}$$

$$f_{YM}(f|C) \cdot f_{X}(C) = \frac{7}{10} \cdot \frac{4}{3}$$

$$f_{YM}(f|C) \cdot f_{X}(C) = \frac{7}{10} \cdot \frac{4}{3}$$

Prodem 6 Q · X ∈ δf, u3: fur or wfair con, fx (f)-fx(u)=5 · y E {htj: head or tail, fylx (hlf) = = fylx (+lf) fyk(h)u)=1 fyx(tlu)=0 · question: fxly (f/h)? fxy (flh) = fyx(hlf) (fx(f) fy (h) for (hf) fact) + for (hin) fx (u) fair con two heaved con = 4 = 1 (b) · y denotes first flip, up the second · assume independence between totallips fyrigalx (yrigalx) = for 1x (yrlx) · for 1x (galx) a question: fxlyinge (flhih)? fxlynya (fluh) = foryelx (holf) . fx (f) fyrys (hih) = 12.12.1 fair coin two headed can (c) Charly, then, the probability is /

Problem 7 Similar to Problema · uni x ∈ (1,25 with fx (1)=fx(2)=5 · color: 47 26,003 Pylx (6/1) = 12 fylx (w(1) = 12 fyx (612) - 12 fyx (W(2) = 3 · question: fx1y (alw)? 1x13 (2(4)= for (w/2) fx(2) fo(w)  $=\frac{3}{15}\cdot\frac{1}{2}$ 3 + 3 - 1 37 Problem 8 · first ball: X, E (b, r), (x, (b) = b+r fx, (r) = b+r · second bull: Xx E (b, F) fx=1x1 (b 1r) = btrtc fxxxx (r1r) = C+r fxxxx (b(b) = btrtc fxxxx(r(b) = btrtc o question: fx 1x2 (b/r)? frace (6/1) = fxxxx (1/6) fxx(6) 1×0 (-) bitte gread C+F F F B+F+C fretred first black

I) Popular descriptive solution:

The probability that A is chosen to be executed is 3 and those is a chance of 3 that one of the others was chosen. If the jailer gives the name of one of the fellow prisoners who will be set free, prisoner A does not get new information about his own fate, but the probability of the remaining prisoner (Borc) to be executed is 3 now. The probability of A being executed is 3 now. The probability of A

# II) Bayasian analysis:

- · prisoner to be executed: X & EA, B, C3 -> assumption of a random choice fx (A) = fx (B) = fx (C) = {3}
- o name of the prisoner which is given away by the pailer:

  y \( \int \land \mathbb{B}, \alpha \mathbb{G} \)

  To conditional probabilities

of x=y jailer does not lie

of y=A jailer does not reveal asking peron

if x=A A the one executed, jailer

mentions B,C with equal

probability

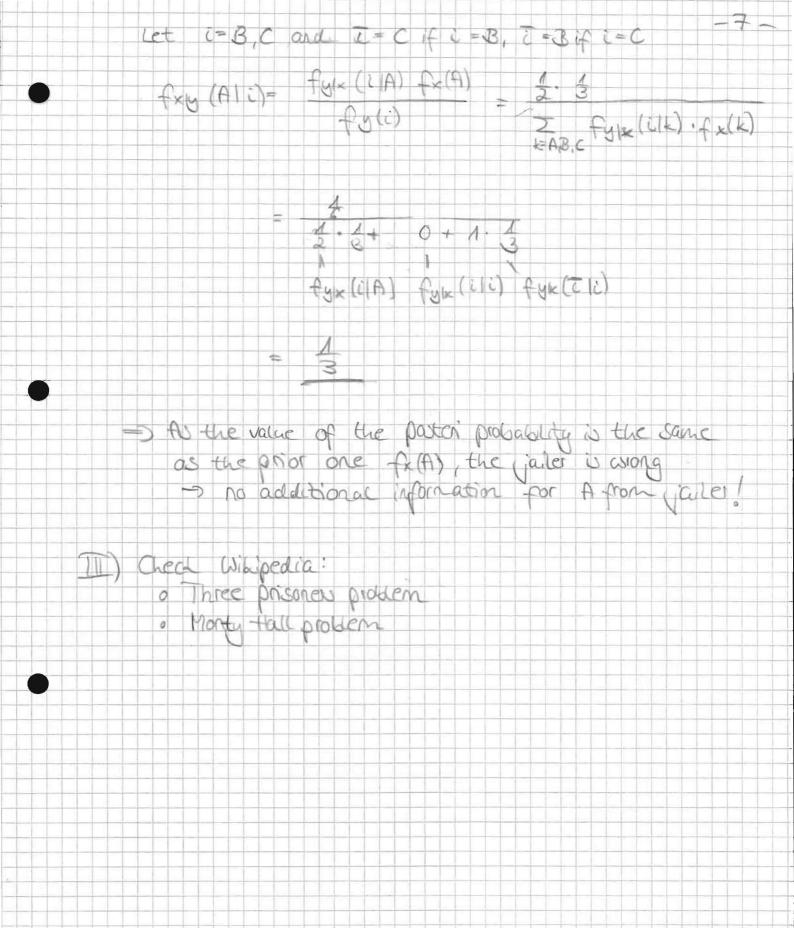
probability

away the none of the

remaining other one to

be set free

o question: fxly (A/B) = fx (A)?



Consider the jard cumulative distribution

$$\mp_{\gamma\omega}(\overline{v},\overline{\omega}) = Pr(v \leq \overline{v}, \omega \leq \overline{\omega})$$

$$= Pr(g(x) \leq \overline{v}, h(y) \leq \overline{\omega})$$

$$A\overline{v} = \{x \in X : g(x) \leq \overline{v}\}$$

$$A = \{x \in X : g(x) \leq \overline{v}\}$$

$$\exists v_{,\omega}(\bar{v},\bar{\omega}) = \Pr(x \in A\bar{v}, y \in A\bar{\omega}) \quad \forall \bar{v},\bar{\omega}$$

$$= \Pr(x \in A\bar{v}) \Pr(y \in A\bar{\omega}) \quad \text{independence assumption}$$

Problem 11

$$(a) \circ \int_{-\infty}^{\infty} f_{n_1}(n_1) dn_1 = \alpha_1 \left[ \int_{-1}^{0} (n+n_1) dn_1 + \int_{0}^{1} (n+n_1) dn_1 \right] = 1$$

$$= \alpha_1 \left( 1 - \frac{1}{2} + 1 - \frac{1}{2} \right) = 1$$

$$\int_{\infty}^{\infty} f_{n_{2}}(n_{1}) dn_{2} = x_{2} \int_{-2}^{\infty} (n_{1} + o S n_{2}) dn_{2} + \int_{0}^{2} (n_{1} - o S n_{2}) dn_{2} = 1$$

$$= \alpha_{\alpha} (2-1+2-1) = 2\alpha_{2} = 1$$

$$\Rightarrow \alpha_{\nu} = \frac{1}{2}$$

(b) o without poor information on x, assume all values are equally likely (maximizing the entropy...)

$$f_{\times}(x) = \frac{1}{10}$$
 for  $-5 \le x \le 5$   
 $f_{\times}(x) = 0$  Otherwise

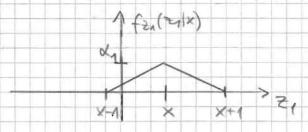
Check: 500 fx(x) dx = 1

6 Independent assumption: f(2, 2, 1x) = f(2, 1x) + f(2,1x)

o calculate observation likelihood: f(znk), f (znk)

zn-x=n1, z-x=n2, x is given fix

 $f_{2n|x}(2,|x) = \begin{cases} \alpha_1 \left( 1 - 2_n + x \right) & \text{for } 0 \leq 2_n - x \leq 1 \\ \alpha_2 \left( 1 + 2_n - x \right) & \text{for } -1 \leq 2_n - x \leq 0 \end{cases}$ 



Similar, for fzix (zilx)

$$f_{2d\times}(z_{2}|x) = \begin{cases} x_{2}(1-\frac{1}{2}z_{2}+\frac{1}{2}x) & \text{for } 0 \leq z_{2}-x \leq 2\\ x_{2}(1+\frac{1}{2}z_{2}-\frac{1}{2}x) & \text{for } -2 \leq z_{2}-x \leq 0\\ 0 & \text{otherwise} \end{cases}$$

o Bayes Theoren:

 $f(x) = \frac{f(z_1|x) f(z_2|x) f(x)}{\int_{S} f(x) f(z_1|x) f(z_2|x) dx}$   $= \frac{f(z_1|x) f(z_2|x) f(z_2|x) dx}{\int_{S} f(x) f(z_2|x) dx}$   $= \frac{f(z_1|x) f(z_2|x) f(z_2|x) dx}{\int_{S} f(x) f(z_2|x) dx}$ 

-> numerator: Z=0, Z=0 given

num(x) = 10 . fz (x (01x) . fz (01x)

Consider four different intervals: [-5,-1], [-1,0], [0,1], [1,5)

I) num(x)= 0 for -5 < x < -1, 1 < x < 5

II)  $\operatorname{num}(x) = \frac{4}{10} \cdot \alpha_1 \cdot (1+x) \cdot \alpha_2 \cdot (1+\frac{4}{2}x)$  for  $-1 \le x \le 0$ 

 $= \frac{1}{20} \left( 1 + x \right) \left( 1 + \frac{x}{2} \right)$ 

 $\overline{\text{III}}) \text{ num}(x) = \frac{4}{10} \propto_1 (1-x) \propto_1 (1+\frac{x}{2}) \quad \text{for } 0 \leq x \leq 1$ 

 $=\frac{1}{20}(1-x)(1-\frac{x}{2})$ 

1 f(x(\frac{1}{2}=0,\frac{2}{2}=0))

-> normalize  $n(0,0) = \int num(x) dx = \int \int \int (1+x)(1+\frac{x}{2}) dx$   $+ \int (1-x)(1-\frac{x}{2}) dx$ 

- 1 (元 + 元) = 元

 $\frac{12}{70}(1-x)(1-\frac{x}{2}) \quad \text{for } 0 \leq x \leq 1$ 

=> symmetric to x=0, peak at x=0, both senson

(c) Similar to (b)

-> numerator: Z1 = 0, Za= 1 giver

num(x) = 10 fz1x (0/x) fz1x (1/x)

Consider four different intervals: [-5,-1], (-1,0)

[0,13, [7,5]

I)  $\operatorname{nun}(x) = 0$  for  $-5 \le x \le -1$ ,  $1 \le x \le 5$ II)  $\operatorname{nun}(x) = \frac{1}{10} \propto_1 (1+x) \propto_2 (\frac{1}{2} + \frac{1}{2}x)$  for  $-1 \le x \le 0$ 

 $=\frac{1}{40}(1+x)^2$ 

III) num(x) = 10 x1 (1-x) x2 (2+4x) for 0 < x < 1

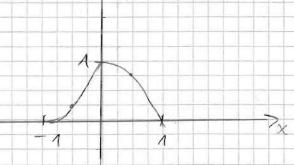
 $= \frac{1}{40} \left( 1 - x^2 \right)$ 

-> gormalize

$$n(0,1) = \int_{-1}^{1} nun(x) dx = \int_{-120}^{1} + \frac{2}{120} = \frac{1}{120}$$

$$\Rightarrow f(x|0,1) = \begin{cases} 0 & for -1 \leq x \leq -1, \ 1 \leq x \leq 5 \\ 1 - x^2 & for 0 \leq x \leq 1 \end{cases}$$

1 f(x(z=0, 2=1)



=> higher probability values on pastile x-axis because of

2 = 1 measurement

(d) Similar to (b) and (c)

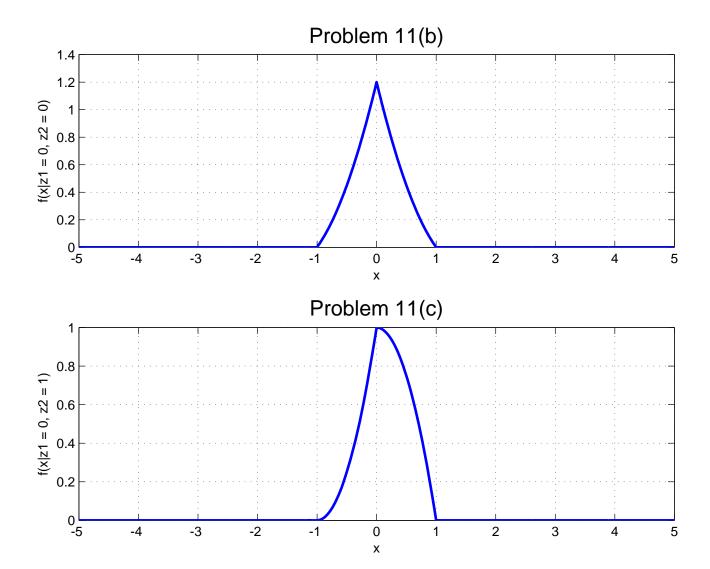
-> numerator: 2=0,2=3 quer

rum(x) = to flor(01x) flor (31x)

=> However, this time the intervals of partire probability of featx (O(x), featx(31x) do not over-Cap, i.e.

num(x) = 0  $\forall x \in [-5,5]$ 

i.e. given our noise model for min no, there is no chance to measure == 0 and ===3. f(x 12,=0, 2,= B) is not defined



\* Code attached \*

a) - bimodal distribution

- decay,

- Wifam distribution V K=1,2 ...

- wrong result: estimation is real position, 6)

binded - we cannot differentiate

- incarect assumption

- washes out

- crashes! Think about why ... :

```
% Problem Set2 - Problem 12
% *Object on Circle - Recursive Filtering Algorithm*
% Recursive Filtering and Estimation
% Spring 2010
응 --
% ETH Zurich
% Institute for Dynamic Systems and Control
% Angela Schöllig
% aschoellig@ethz.ch
응
% Revision history
% [14.03.10, AS] first version
clear
rand('state',0);
% Configuration Constants
% Number of simulation steps
T = 100;
% Number of discrete steps around circle
N = 100;
% Actual probability of going CCW
PROB = 0.55;
% Model of probability of going CCW
PROB_MODEL = PROB;
PROB_MODEL = 0.45;
% Location of distance sensor, as a multiple of the circle radius. Can be
% less than 1 (inside circle), but must be positive (WLOG).
SENSE\_LOC = 2;
% The sensor error is modeled as additive (a time of flight sensor, for
% example), uniformly distributed around the actual distance. The units
% are in circle radii.
ERR\_SENSE = 0.50;
% Model of what the sensor error is
ERR_SENSE_MODEL = ERR_SENSE;
%ERR_SENSE_MODEL = 0.45;
```

```
% Initialization
% W(k,i)  denotes the probability that the object is at location i at time
% k, given all measurements up to, and including, time k. At time 0, this
% is initialized to 1/N, all positions are equally likely.
W = zeros(T+1,N);
W(0+1,:) = 1/N;
% The intermediate prediction weights, initialize here for completeness.
% We don't keep track of their time history.
predictW = zeros(1,N);
% The initial location of the object, an integer between 0 and N-1.
loc = zeros(T+1,1);
loc(0+1) = round(N/4);
% Simulation
for t = 1:T
   % Simulate System
   % Process dynamics. With probability PROB we move CCW, otherwise CW
   if (rand < PROB)</pre>
      loc(t+1) = mod(loc(t) + 1,N);
   else
      loc(t+1) = mod(loc(t) - 1,N);
   end
   % The physical location of the object is on the unit circle
   xLoc = cos(2*pi * loc(t+1)/N);
   yLoc = sin(2*pi * loc(t+1)/N);
   % Can calculate the actual distance to the object
   dist = sqrt( (SENSE_LOC - xLoc)^2 + yLoc^2);
   % Corrupt the distance by noise
   dist = dist + ERR_SENSE * 2 * (rand - 0.5);
   % Update Estimator
   % Prediction Step. Here we form the intermediate weights which capture
   % the pdf at the current time, but not using the latest measurement.
   for i = 1:N
```

```
predictW(i) = PROB_MODEL*W(t, 1+mod(i-2,N)) + (1-PROB_MODEL)*W(t, 1+ mod(i, ✓
N));
   end
    % Fuse prediction and measurement. We simply scale the prediction step
    % weight by the conditional probability of the observed measurement
    % at that state. We then normalize.
   for i = 1:N
       xLocHypo = cos(2*pi * (i-1)/N);
       yLocHypo = sin(2*pi * (i-1)/N);
       distHypo = sqrt( (SENSE_LOC - xLocHypo)^2 + yLocHypo^2);
       if abs(dist-distHypo) < ERR_SENSE_MODEL</pre>
           condProb = 1/(2*ERR_SENSE_MODEL);
       else
           condProb = 0;
       end
       W(t+1,i) = condProb * predictW(i);
   end
    % Normalize the weights. If the normalization is zero, it means that
    % we received an inconsistent measurement. We can either use the old
   % valid data, re-initialize our estimator, or crash. To be as
   % robust as possible, we simply re-initialize the estimator.
   normConst = sum(W(t+1,:));
   % Uncomment this line if we want to allow the program to crash.
   W(t+1,:) = W(t+1,:)/normConst; normConst = 1.0;
   if (normConst > 1e-6)
       W(t+1,:) = W(t+1,:)/normConst;
    else
       W(t+1,:) = W(1,:);
   end
end
288888888888888888888888888888
% Visualize the results
figure(1)
xVec = (0:N-1)/N;
yVec = 0:T;
mesh(xVec,yVec,W);
xlabel('POSITION x(k)/N ');
ylabel('TIME STEP k');
view([-30,40]);
```

hold on

```
% actual simulated position
plot3(loc/N,(0:T)',ones(T+1,1)*max(max(W)));
hold off
findfigs
```