

Particle Filter for mini project – Screenshots from class

% initialization of all the parameters of the four tank system

clc; clear; close all;

A1 = 28; %(cm^2)

A2 = 32;

A3 = 28;

A4 = 32;

a1 = 0.071; a3 = 0.071; %(cm^2)

a2 = 0.057; a4 = 0.057;

kc = 0.5; % (V/cm)

g = 981; %(cm/s^2)

gamma1 = 0.7; gamma2 = 0.6; % constants, determined from valve position

k1 = 3.33; k2 = 3.35; %[cm^3/Vs]

kc = 0.5; % [V/cm]

v1 = 3; v2 = 3; % (V)

h0 = [12.4; 12.7; 1.8; 1.4];

Initialization of Parameters

Particle Filter Application

$$p(\mathbf{x}_k | \mathbf{Z}_k) = \kappa p(\mathbf{z}_k | \mathbf{x}_k) \int p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \mathbf{Z}_{k-1}) d\mathbf{x}_{k-1}$$

• Initialisation, $t = 0$; (Prior Step)

For $i = 1, \dots, N$, sample $\mathbf{x}(0) \sim p\{\mathbf{x}(0)\}$ & set $t = 1$

Particle Filter Algorithm

• Importance Sampling

– Prediction Step

For $i = 1, \dots, N$, sample $\mathbf{x}(t, i) \sim p\{\mathbf{x}(t) | \mathbf{x}(t-1, i)\}$

– Likelihood Step

For $i = 1, \dots, N$, evaluate importance weights : $w(t, i) = p\{\mathbf{z}(t) | \mathbf{x}(t, i)\}$

Normalise the Importance Weights

• Selection

– Update Step/Resampling Step

Resample with replacement, according to Importance Weights

Set $t = t + 1$ and return to **Prediction Step**

Prior

- For a state vector of dimension (1 x 1)
 - $x(:,1) = \text{sqrt}(P0) * \text{randn}(N,1)$
 - We obtain N samples (particles)

- For a state vector of dimension (n x 1)
 - $L = \text{cholesky}(P0)$
 - $x = \text{randn}(N, n) * L + \text{ones}(N, n) * x(n \times 1)$
 - We obtain x of order (N x n)

$$x(t+1) = A x(t) + B u(t) + \underbrace{w(t)}_{\text{Prior}}$$

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$n = 4 \Rightarrow x^T = \begin{bmatrix} x_1 & x_2 & x_3 & x_4 \end{bmatrix}$
 $N = 100$

$\begin{bmatrix} x_1 & x_2 & x_3 & x_4 \\ \vdots & \vdots & \vdots & \vdots \\ x_{100} & \dots & \dots & \dots \end{bmatrix}$

$\odot \frac{n \times n}{n \times n}$

$\begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \dots & x_{nn} \end{bmatrix}$

$x = n \times 1$

```
% initialization of the states and covariances
x0 = h0;
x_post = x0;
C = [kc 0 0 0; 0 kc 0 0];
n = 4; % number of states
P0 = 10^5 * eye(4); % initial covariance
N = 500; % number of particles
```

Initialization

```
L = chol(P0);
x0 = (x0 * ones(1,N))' + randn(N,n) * L; %Adding covariance to each particle
% Initialization of the states
x1_post = x0(:,1);
x2_post = x0(:,2);
x3_post = x0(:,3);
x4_post = x0(:,4);
```

Prior

```
% initialization of the states and covariances
x0 = h0;
x_post = x0;
C = [kc 0 0 0; 0 kc 0 0];
n = 4; ✓ % number of states
P0 = 10^5 * eye(4); ✓ % initial covariance
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Initialization

```
L = chol(P0);
x0 = (x0 * ones(1,N))' + randn(N,n) * L; %Adding covariance to each particle
% Initialization of the states
x1_post = x0(:,1); ✓
x2_post = x0(:,2); ✓
x3_post = x0(:,3); ✓
x4_post = x0(:,4); ✓
```

Prior



$$\begin{aligned} \hat{x}(k) &= A\hat{x}(k-1) + Bw(k-1) \\ P_k &= AP_{k-1}A^T + Q \end{aligned}$$

Handwritten notes include: $k-1$, k , $k+1$, \hat{x} , P , and Q .

$$p(\mathbf{x}_k | \mathbf{Z}_k) = \kappa p(\mathbf{z}_k | \mathbf{x}_k) \int p(\mathbf{x}_k | \mathbf{x}_{k-1}) p(\mathbf{x}_{k-1} | \mathbf{Z}_{k-1}) d\mathbf{x}_{k-1}$$

- **Initialisation**, $t = 0$; (*Prior Step*)

For $i = 1, \dots, N$, sample $\mathbf{x}(0) \sim p\{\mathbf{x}(0)\}$ & set $t = 1$

- **Importance Sampling**

- *Prediction Step*

For $i = 1, \dots, N$, sample $\mathbf{x}(t, i) \sim p\{\mathbf{x}(t) | \mathbf{x}(t-1, i)\}$

- *Likelihood Step*

For $i = 1, \dots, N$, evaluate importance weights : $w(t, i) = p\{\mathbf{z}(t) | \mathbf{x}(t, i)\}$

Normalise the Importance Weights

- **Selection**

- *Update Step/Resampling Step*

Resample with replacement, according to Importance Weights

Set $t = t + 1$ and return to *Prediction Step*

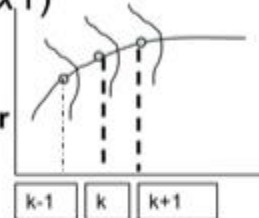
Prediction

- For a state vector of dimension (1×1)

- $w \sim \text{sqrt}(Q) * \text{randn}(N, 1)$

- $\mathbf{x}(k-) = \text{fn.}\{\mathbf{x}, \mathbf{u}\} + w$

- We obtain predicted \mathbf{x} as $(N \times 1)$ vector



- For a state vector of dimension $(n \times 1)$

- $w \sim \text{Cholesky}(Q) * \text{randn}(N \times n)$

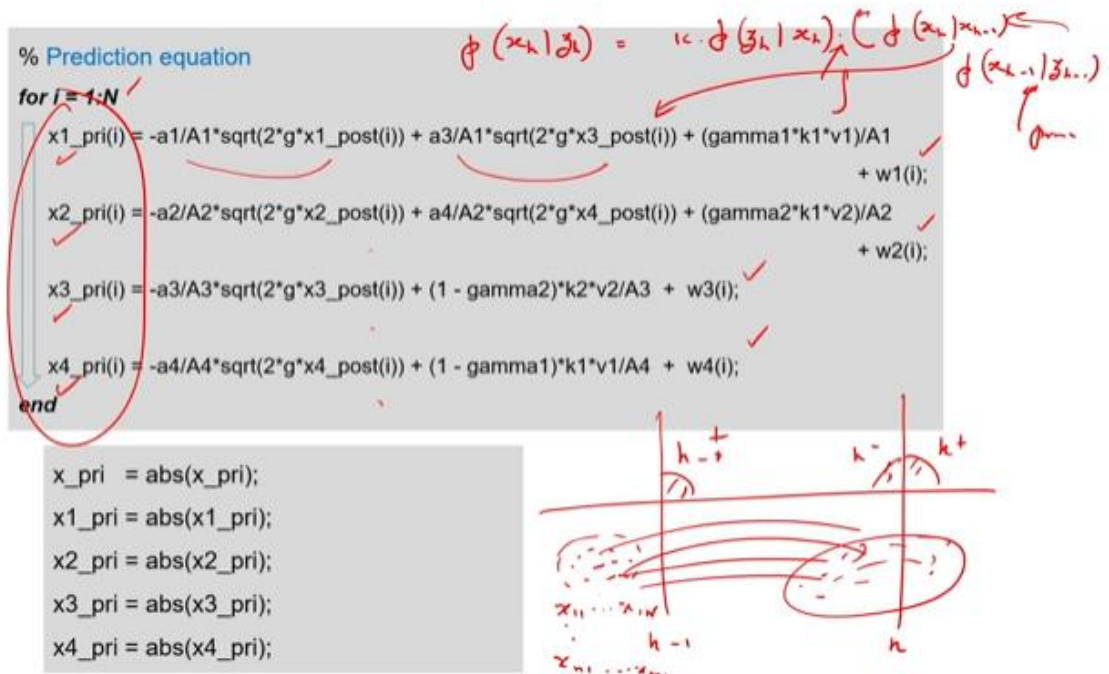
- For $i = 1$ to N ,

- $\mathbf{x}_1(k-) = \text{fn.}\{\mathbf{x}, \mathbf{u}\} + w(i, 1)$

- \vdots

- $\mathbf{x}_n(k-) = \text{fn.}\{\mathbf{x}, \mathbf{u}\} + w(i, n)$

- We obtain predicted \mathbf{x} as $(N \times n)$ vector



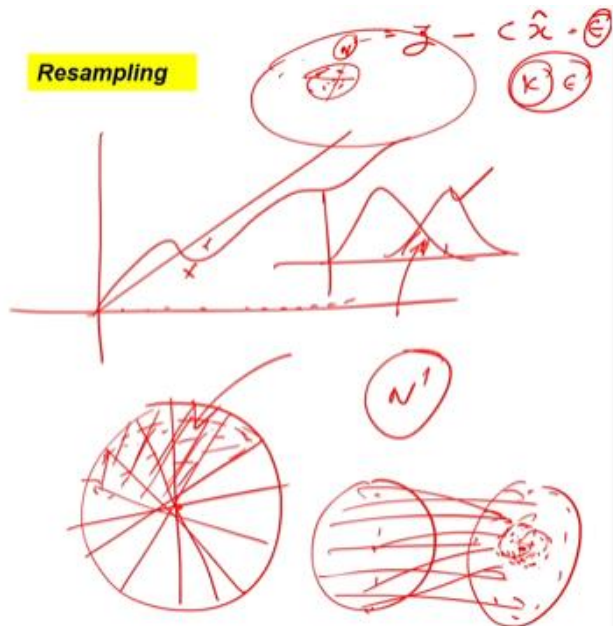
As per sir, this is more than a pseudo code, almost the code!

```

M = length(wt);
Q = cumsum(wt);
indx = zeros(1, N);
T = linspace(0, 1-1/N, N) + rand/N;
i = 1; j = 1;
while(i <= N && j <= M),
    while Q(j) < T(i)
        j = j + 1;
    end
    indx(i) = j;
    x1_post(i) = x1_pri(j);
    x2_post(i) = x2_pri(j);
    x3_post(i) = x3_pri(j);
    x4_post(i) = x4_pri(j);
    i = i + 1;
end

```

Resampling



Likelihood/Importance Weights

- *Considering an Exponential pdf*
 - $v = z * \text{ones}(N \times 1) - C * \hat{x} \text{ (predicted)}$
 $(1 \times n) \quad (n \times N)$
 - For $i = 1$ to N

$$q(i) = e^{-\frac{1}{2}[v(i,:)^T R^{-1} v(i,:)]}$$
- *Normalising the Weights*
 - For $i = 1$ to N
 - $Wt(i) = q(i) / \text{sum}(q)$

```
% Importance Weights (Likelihood Function)
```

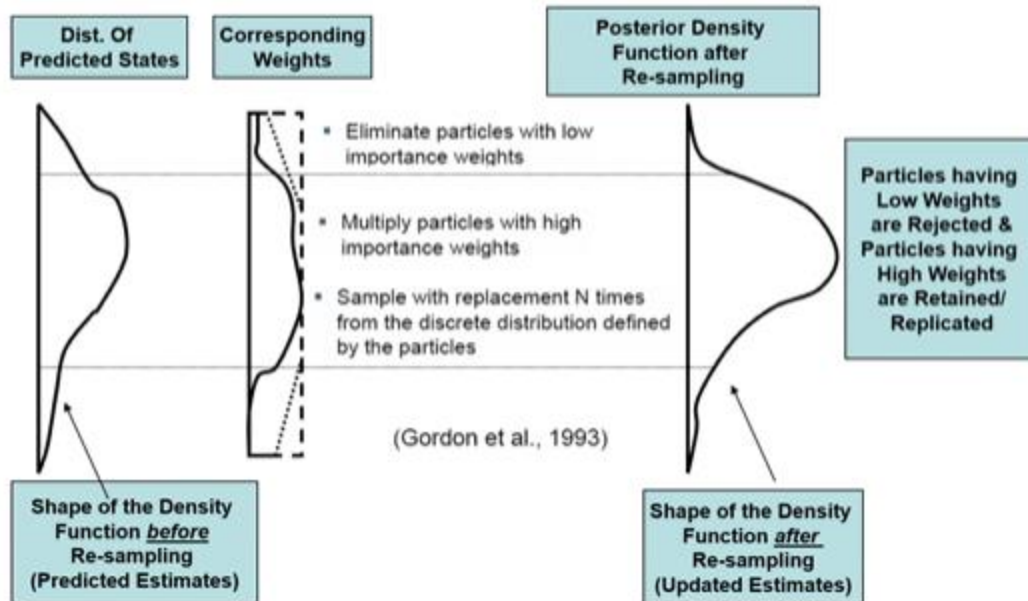
```
z1 = 12.4;
z2 = 12.7;
z = [z1; z2];
z_true = z * ones(1,N);
R = 10 * eye(2);
z_est = C*x_pri;
v = z_true - z_est;

for i = 1:N
    q(i) = exp(-0.5 * (v(:,i))' * inv(R) * v(:,i)));
end
```

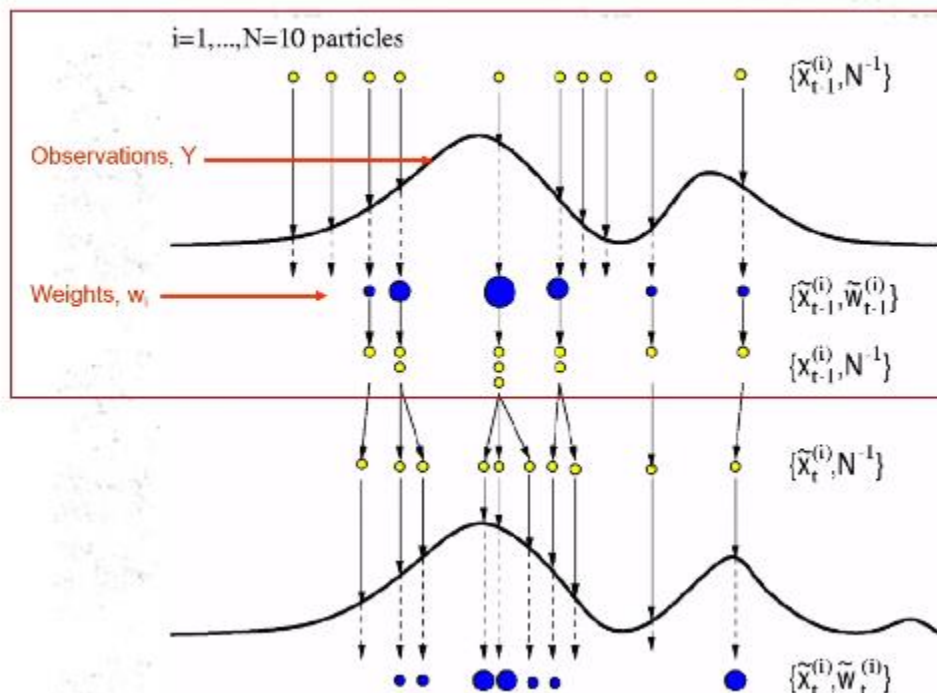
```
% Normalizing the weights
```

```
for i = 1:N
    wt(i) = q(i)/sum(q);
end
```

Resampling



The Particle Filter Principle



Comparing Particle Filter and Kalman Filter

• Kalman Filter

- **Guess/Prior Knowledge :**
 $x(0), P(0), Q, R$

- **Prediction/Propagation :**
 $x(k-) = Ax(k-1+) + Bu(k)$

$$P(k-) = AP(k-1+)A' + Q$$

- **Update**
 $r = z - cx$
 Obtaining Residues

$$K = \dots\dots\dots$$

$$x(k+) = x(k-) + K.r$$

$$P(k+) = P(k-) - K\dots\dots$$

- **Repeat for $t = 1:T$**
- **Obtain Aposteriori Density**

• Particle Filter

- **Prior Knowledge :** $P(0), Q, R$

- **Prior :**
 $x(0) = \text{fn. } \{ \text{Sqrt/Chol. } (P(0)) \cdot \text{randn} \}$
 $(n \times N) : N \text{ particles}$

- **Prediction :**
 For $1:N(\text{particles})$
 $x(k-) = Ax(k-1+) + Bu(k) + Q$

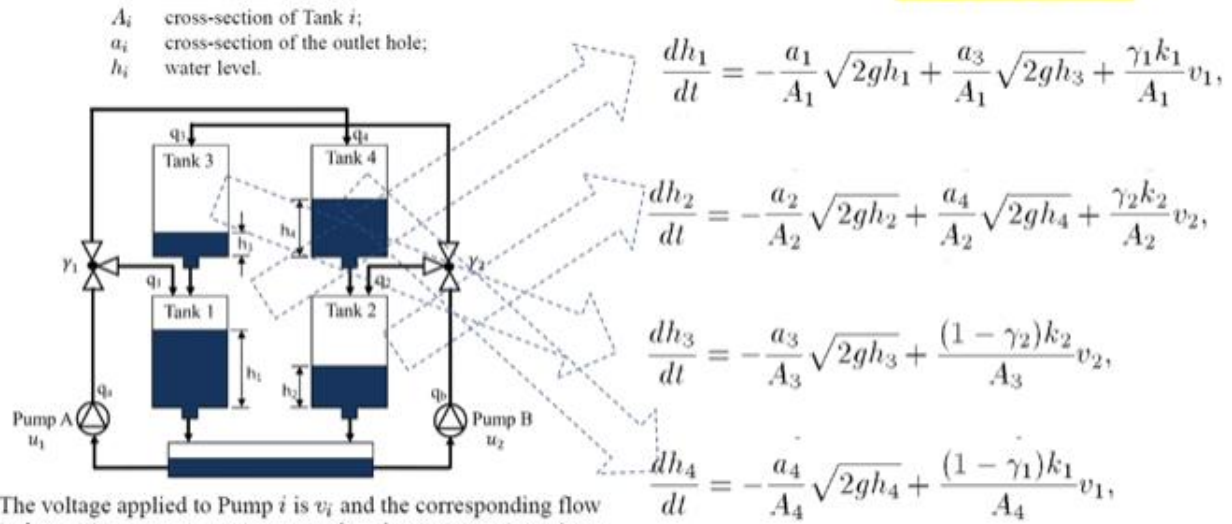
- **Likelihood Function/ Importance Wt. Generation (N)**
 $\text{pdf}([z - cx(k-1)], R) = \text{Wts.}(N)$

- **Resampling (of the N Weights)**

- **Repeat for $t = 1: T$**
- **Obtain Aposteriori Density**

In Kalman filter we linearized non-linear equations. (2 images below)

The 4-Tank Problem



The voltage applied to Pump i is v_i and the corresponding flow is $k_i v_i$. The parameters $\gamma_1, \gamma_2 \in (0, 1)$ are determined from how the valves are set prior to an experiment. The flow to Tank 1 is $\gamma_1 k_1 v_1$ and the flow to Tank 4 is $(1 - \gamma_1)k_1 v_1$ and similarly for Tank 2 and Tank 3. The acceleration of gravity is denoted g . The measured level signals are $k_c h_1$ and $k_c h_2$. The parameter

Linearized State Eqn. & Meas. Eqn.

$$x_k = A_{k|k-1}x_{k-1} + B_{k-1}u_{k-1} + w_{k-1}$$

$$A = \begin{bmatrix} -\frac{1}{T_1} & 0 & \frac{A_3}{A_1 T_3} & 0 \\ 0 & -\frac{1}{T_2} & 0 & \frac{A_4}{A_2 T_4} \\ 0 & 0 & -\frac{1}{T_3} & 0 \\ 0 & 0 & 0 & -\frac{1}{T_4} \end{bmatrix} \quad B = \begin{bmatrix} \frac{\gamma_1 k_1}{A_1} & 0 \\ 0 & \frac{\gamma_2 k_2}{A_2} \\ 0 & \frac{(1-\gamma_2)k_2}{A_3} \\ \frac{(1-\gamma_1)k_1}{A_4} & 0 \end{bmatrix}$$

where the time constants are

$$T_i = \frac{A_i}{a_i} \sqrt{\frac{2h_i^0}{g}}, \quad i = 1, \dots, 4,$$

$$z_k = H_k x_k + D_k u_k + v_k \quad H = \begin{bmatrix} k_c & 0 & 0 & 0 \\ 0 & k_c & 0 & 0 \end{bmatrix}$$