

Data Fusion

An Intuitive Look

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- 1 Introduction
- 2 Graphical Solution
- 3 Mathematical Solution
- 4 Programmatical Solution

① Introduction

- Notation
- Problem Statement

② Graphical Solution

- Start
- Step 1
- Step 2
- Step 3

③ Mathematical Solution

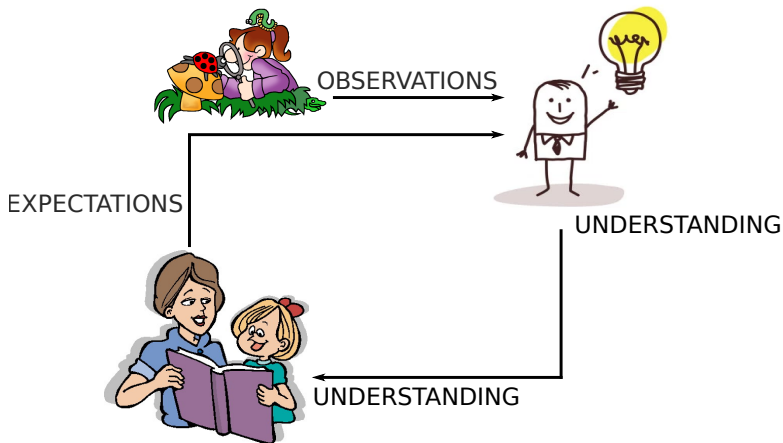
- Scalar Case
- Comparison With Vector Case

④ Programmatical Solution

Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Notation
Problem Statement

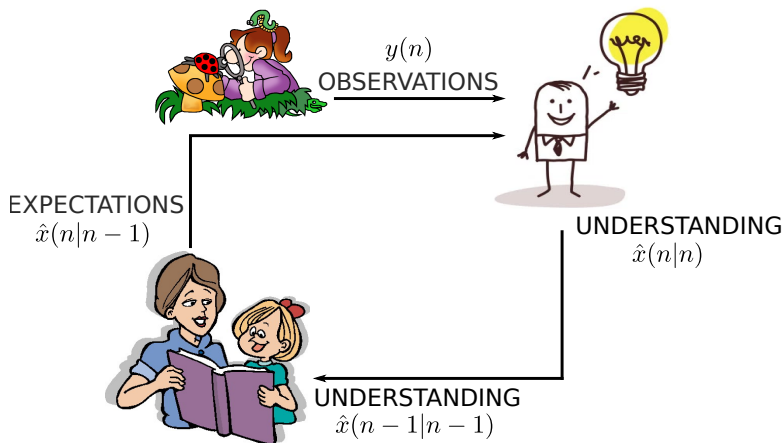
Overview



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Notation
Problem Statement

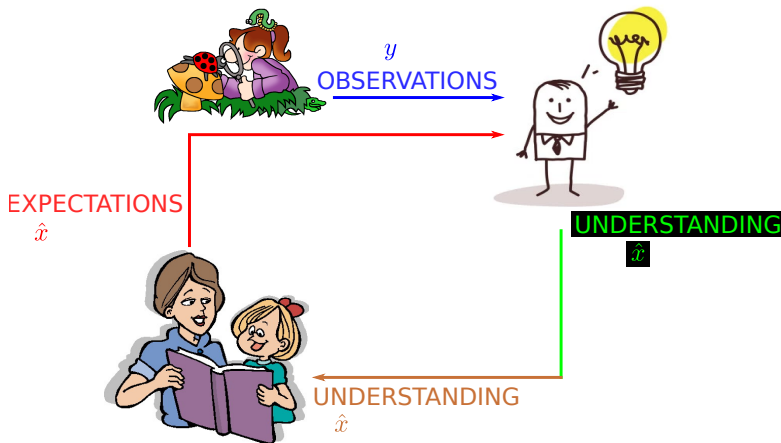
Overview



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Notation
Problem Statement

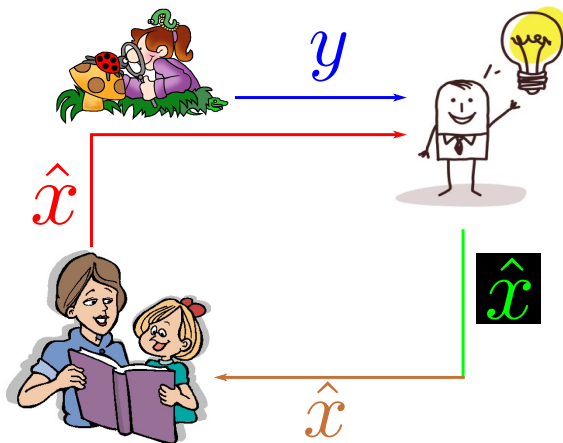
Overview



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Notation
Problem Statement

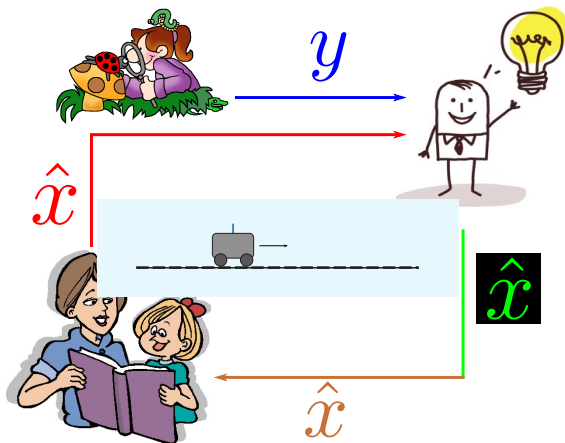
Overview



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Notation
Problem Statement

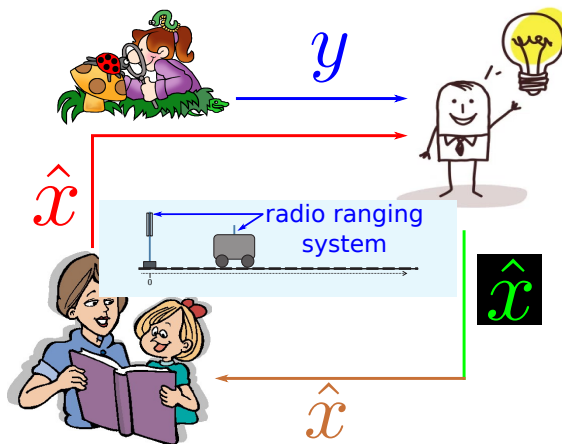
Overview



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Notation
Problem Statement

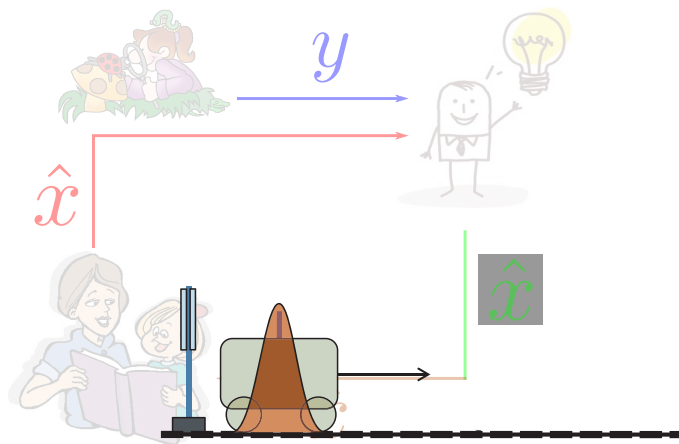
Overview



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Start
Step 1
Step 2
Step 3

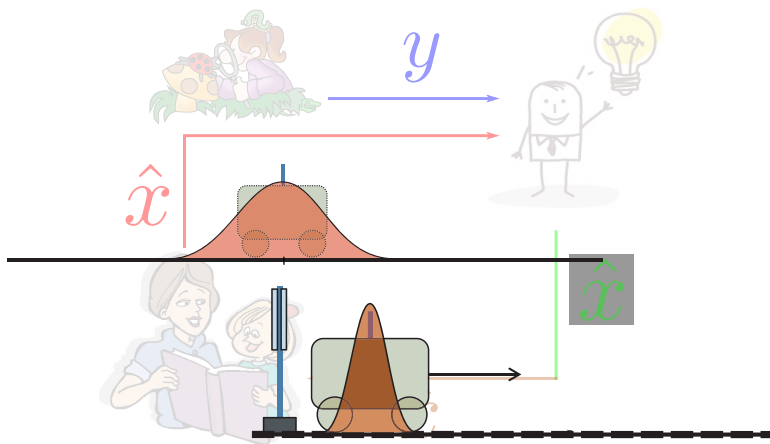
Old Understanding



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Start
Step 1
Step 2
Step 3

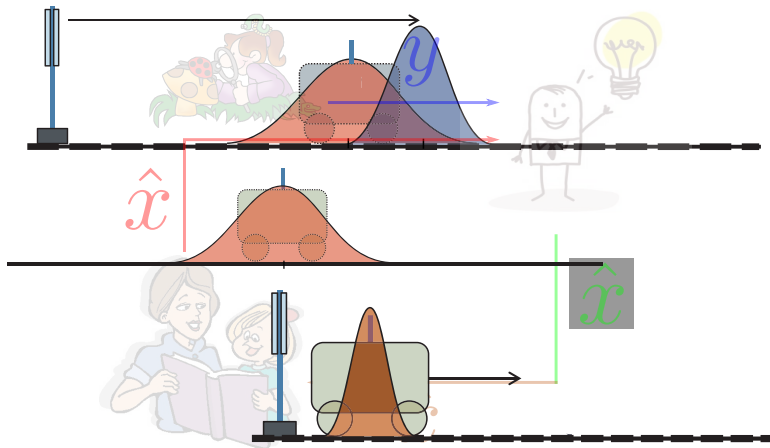
Expectations



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Start
Step 1
Step 2
Step 3

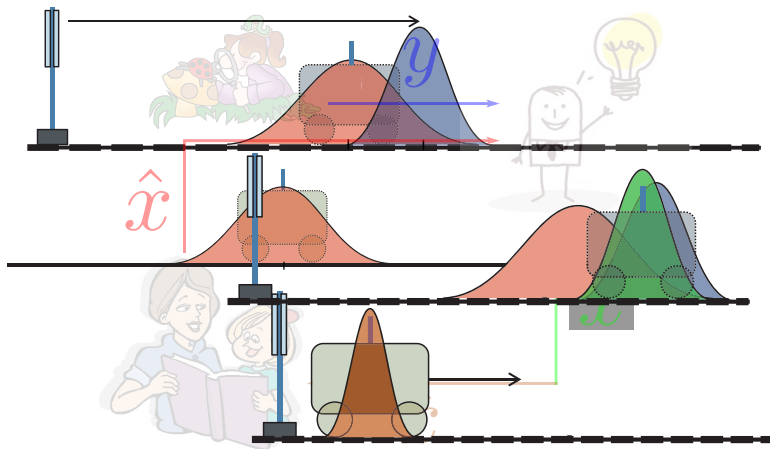
Observations



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Start
Step 1
Step 2
Step 3

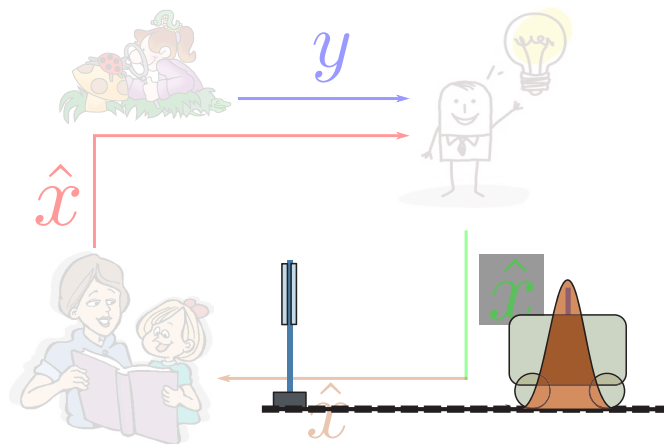
New Understanding



Introduction
Graphical Solution
Mathematical Solution
Programmatical Solution

Start
Step 1
Step 2
Step 3

New Understanding



Derivation of Scalar Case

Let p_1 and p_2 be two Gaussian pdfs:

$$p_1(x; \mu_1, \sigma_1) = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}}$$
$$p_2(x; \mu_2, \sigma_2) = \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}$$

Their product is:

$$p_1 p_2 = \frac{1}{\sqrt{2\pi\sigma_1^2}} e^{-\frac{(x-\mu_1)^2}{2\sigma_1^2}} \frac{1}{\sqrt{2\pi\sigma_2^2}} e^{-\frac{(x-\mu_2)^2}{2\sigma_2^2}}$$

Derivation of Scalar Case

$p_1 p_2$ will be a Gaussian function with mean

$$\begin{aligned}
 \mu_{fused} &= \frac{\mu_1 \sigma_2^2 + \mu_2 \sigma_1^2}{\sigma_1^2 + \sigma_2^2} \\
 &= \frac{\mu_1 \sigma_2^2 + \mu_2 C \sigma_1^2}{C^2 \sigma_1^2 + \sigma_2^2} \\
 &= \mu_1 + \frac{\sigma_1^2 (C \mu_2 - C^2 \mu_1)}{C^2 \sigma_1^2 + \sigma_2^2} \\
 &= \mu_1 + \frac{C \sigma_1^2 (\mu_2 - C \mu_1)}{C^2 \sigma_1^2 + \sigma_2^2} = \mu_1 + K(\mu_2 - C \mu_1)
 \end{aligned}$$

Derivation of Scalar Case

And variance

$$\begin{aligned}
 \sigma_{fused}^2 &= \frac{\sigma_1^2 \sigma_2^2}{\sigma_1^2 + \sigma_2^2} \\
 &= \frac{\sigma_1^2 \sigma_2^2}{C^2 \sigma_1^2 + \sigma_2^2} \\
 &= \sigma_1^2 - \frac{C^2 \sigma_1^4}{C^2 \sigma_1^2 + \sigma_2^2} \\
 &= \sigma_1^2 - \frac{C \sigma_1^2}{C^2 \sigma_1^2 + \sigma_2^2} C \sigma_1^2 \\
 &= (1 - K C) \sigma_1^2
 \end{aligned}$$

where K is the same as defined in the previous slide

One-to-one Correspondence

I. PREDICTION

1. state
2. state variance/covariance

II. UPDATE

3. state
4. state variance/covariance

■ prediction
■ measurement
■ update

single state

from previous time

$$\begin{aligned}\mu_1 &= A\mu_{fused} + Bu \\ \sigma_1^2 &= A\sigma_{fused}^2 A + Q \\ &= A^2\sigma_{fused}^2 + Q\end{aligned}$$

$$\begin{aligned}\mu_{fused} &= \mu_1 + K(\mu_2 - C\mu_1) \\ &= \mu_1 + \frac{\sigma_1^2 C (C\sigma_1^2 C + \sigma_2^2)^{-1}}{C^2 \sigma_1^2 + \sigma_2^2} (\mu_2 - C\mu_1) \\ &= \frac{C\sigma_1^2}{C^2 \sigma_1^2 + \sigma_2^2} \mu_2 + \frac{\sigma_2^2}{C^2 \sigma_1^2 + \sigma_2^2} \mu_1\end{aligned}$$

$$\sigma_{fused}^2 = (1 - KC)\sigma_1^2$$

multiple states

from previous time

$$\begin{aligned}\hat{\mathbf{x}}_{k|k-1} &= A\hat{\mathbf{x}}_{k-1|k-1} + B\mathbf{u}_{k-1} \\ \mathbf{P}_{k|k-1} &= A\mathbf{P}_{k-1|k-1}A^T + \mathbf{Q}_k\end{aligned}$$

$$\begin{aligned}\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k \left(\mathbf{y}_k - C\hat{\mathbf{x}}_{k|k-1} \right) \\ &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{P}_{k|k-1} C^T \left(C\mathbf{P}_{k|k-1} C^T + \mathbf{R}_k \right)^{-1} (\mathbf{y}_k - C\hat{\mathbf{x}}_{k|k-1}) \\ &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{P}_{k|k-1} C^T \left(C\mathbf{P}_{k|k-1} C^T + \mathbf{R}_k \right)^{-1} (\mathbf{y}_k - C\hat{\mathbf{x}}_{k|k-1})\end{aligned}$$

innovation: measurement
 innovation: covariance

$$\mathbf{P}_{k|k} = (\mathbf{I} - \mathbf{K}_k C) \mathbf{P}_{k|k-1}$$

Introduction

Graphical Solution

Mathematical Solution

Programmatical Solution

Matlab Code I

The code below implements 2 time steps for the train:

```
clear; clc; clf;
%initialization
x = -5:0.1:25; %x axis
A = 2; %state transition matrix
B = 5; %control input matrix
C = 1; %transformation matrix
u = 1; %control input
Q = 1.2; %process noise variance, adds uncertainty to prediction
mu_2 = [7 14]; %the output of the radio ranging system at next two times
var_2 = 1; %the variance of the radio ranging system given by manufacturer
mu_f = 0; %the estimated location of the train at current time, k=0
var_f = 1; %the estimated variance of our estimate at current time, k=0
pdf_0 = (1/sqrt(2*pi*var_f))*exp(-(0.5/var_f)*(x-mu_f).^2);

%=====
%run Kalman Filter
%=====
for k=1:2
    %predict
    mu_1 = A*mu_f + B*u;
    var_1 = A^2*var_f + Q;
    %update
    K = (C*var_1)/(C^2*var_1 + var_2);
    mu_f = mu_1 + K*(mu_2(k)-C*mu_1);
    var_f = (1-K*C)*var_1;
    pred = (1/sqrt(2*pi*var_1))*exp(-(0.5/var_1)*(x-mu_1).^2);
    meas = (1/sqrt(2*pi*var_2))*exp(-(0.5/var_2)*(x-mu_2(k)).^2);
    fused = (1/sqrt(2*pi*var_f))*exp(-(0.5/var_f)*(x-mu_f).^2);
```

Matlab Code II

```
axis([-5 25 0 0.5]);  
grid on;  
hold on;  
plot(x, pred, 'r—x');  
plot(x, meas, 'b—o');  
plot(x, fused, 'g—');  
plot(x, pdf_0, 'g—');  
end  
legend('predicted', 'measured', 'fused')  
xlabel('railway_track_(meters),_direction_along_which_train_is_traveling_→')  
ylabel('belief_in_fused/predicted/measured_position_of_train')  
title('Data_fusion_using_the_Kalman_Filter')
```

Introduction

Graphical Solution

Mathematical Solution

Programmatical Solution

Results

The code on the previous slide produces this output:

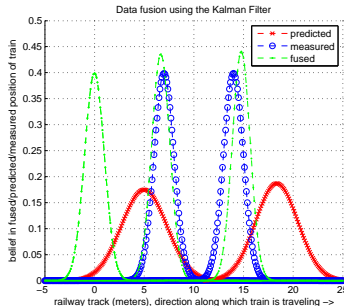


Figure: In this example, a train is moving along the x-axis. The problem begins at time $kT = 0$ sec when our initial estimate of the train is that it is standing at $x = 0$ meters. The prediction and measurements for the next two time instants, $kT = 1$ sec and $kT = 2$ sec are shown. We assume for simplicity but without loss of generality, that $T = 1$ sec, and therefore we use k (in sec) to depict time. It may be mentioned that the version of the Kalman filter for continuous time is called the Kalman-Bucy filter.

Questions