

KALMAN FILTER

It has two steps, prediction and updation.

PREDICTION:

It takes previous state of the model and predicts the current state using the following equation:

$$X(k) = A * X(k-1) + B * U$$

Where A is the state transition matrix and B is the control input.

U represents the acceleration.

State vector X is of the form $[[x],[y],[vx],[vy]]$ so A and B are chosen such that the new state is predicted according to kinematic equations..

$$x(k) = x(k-1) + vx * dt + 0.5 * dt^2 * ax$$

$$y(k) = y(k-1) + vy * dt + 0.5 * dt^2 * ay$$

$$vx(k) = vx(k-1) + ax * dt$$

$$vy(k) = vy(k-1) + ay * dt$$

from these equations, we get

$$A = \begin{bmatrix} 1 & 0 & dt & 0 \\ 0 & 1 & 0 & dt \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

$$\begin{bmatrix} 0 & 1 & 0 & dt \end{bmatrix},$$

$$\begin{bmatrix} 0 & 0 & 1 & 0 \end{bmatrix},$$

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

$$B = \begin{bmatrix} 0.5dt^2 & 0 \\ 0 & 0.5dt^2 \\ dt & 0 \\ 0 & dt \end{bmatrix}$$

$$\begin{bmatrix} 0 & 0.5dt^2 \end{bmatrix},$$

$$\begin{bmatrix} dt & 0 \end{bmatrix},$$

$$\begin{bmatrix} 0 & dt \end{bmatrix}$$

B*U term comes out to be zero as

Thus the prediction equation becomes $X(k) = A * X(k-1)$

The Kalman filter also predicts the covariance of the state estimation, which represents the uncertainty in the predicted state. It is given by the following equation:

$$P_k^- = A * P_{k-1} * A^T + Q$$

Where P_k^- is the predicted state covariance matrix of the current state ,

P_{k-1} is the state covariance matrix of the previous state and Q is the process noise covariance matrix.

$$Q = \begin{bmatrix} \text{var}(x), 0, \text{SD}(x)*\text{SD}(vx), 0 \\ 0, \text{var}(y), 0, \text{SD}(y)*\text{SD}(vy) \\ \text{SD}(x)*\text{SD}(vx), 0, \text{var}(vx), 0 \\ 0, \text{SD}(y)*\text{SD}(vy), 0, \text{var}(vy) \end{bmatrix}$$

Q matrix is taken such that it takes into account the independency of (x,vx) And (y,vy) pair and dependency of x and vx respectively and similarly y and vy.

$$Q = \begin{bmatrix} \text{var}(x), 0, \text{covariance}(x,vx), 0 \\ 0, \text{var}(y), 0, \text{covariance}(y,vy) \\ \text{covariance}(x,vx), 0, \text{var}(vx), 0 \\ 0, \text{covariance}(y,vy), 0, \text{var}(vy) \end{bmatrix}$$

Var=variance

sD=standard deviance

UPDATION:

Kalman gain is calculated as follows:

$$K_k = P_k^- * H^T * S^{-1}$$

Where

$$S = H * P_k^- * H^T + R$$

$$H = \text{transformation matrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \end{bmatrix}$$

$$R = \text{measurement noise covariance} = \begin{bmatrix} \text{var}(x), 0 \\ 0, \text{var}(y) \end{bmatrix}$$

R matrix is taken as a diagonal matrix because the measurement(x and y coordinates)are assumed to be independent. So we take the individual variances of x and y coordinates.

Var(x) and var(y) are the variances of the x and y gps coordinates given in the question respectively.

Updated estimate with measurement z_k :

$$X_k = X_k^- + K_k(z_k - H * X_k^-)$$

Where the term $(z_k - H * X_k^-)$ is the difference between gps coordinates and predicted coordinates.

Updated error covariance:

$$P_k = (I - K_k * H) P_k^-$$