Kalman FIlter Explained

Matt Snyder, Mason Satnik

New Predicted State

$X^P = A*X_{t-1} + B*u_t + w_t$

The state transition matrix is applied to the previous state, $B*u_t$ applies acceleration which provides values to update the position and velocity of A*X, and then w_t is applied to it, which is a zero mean multivariate distribution using zero as its mean and standard deviation.

$P^P = A*P_{t-1}*A^T + Q_t$

The process covariance matrix is updated with the state transition matrix, and then the system noise Q_t, the covariance of the process noise is applied.

Kalman Gain

$K = P^P*H^T / (H*P^P*H^T + R)$

To calculate the Kalman Gain, K, we compare the error in the estimate to the combined errors in the estimate as well as the covariance of the observation noise(R). H is used to get the desired dimension for output of K.

$Y_t = C*Y_t + R_t$

Observational data about what had just occurred,Y_t , is found by using C as the identity matrix in which we choose which variables we decide to look at on the most recent state matrix, and the measurement noise is applied, R_t .

Updating

$P_t = (I - K*H)*P^P$

To get the new process covariance matrix we take the identity matrix minus the kalman gain, K. and apply it to the previous covariance matrix. H is used to get the desired dimensions again.

$X_t = X^P + K[Y-HX^P]$

Update state matrix by adding the kalman gain onto the measurement gain between now, Y, and the previous example