

# Application of the Kalman Filter to a Satellite Simulator to Predict Orbital Position

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$$\begin{bmatrix} a_{11} & a_{12} & a_{13} & a_{14} & a_{15} & a_{16} \\ a_{21} & a_{22} & a_{23} & a_{24} & a_{25} & a_{26} \\ a_{31} & a_{32} & a_{33} & a_{34} & a_{35} & a_{36} \\ a_{41} & a_{42} & a_{43} & a_{44} & a_{45} & a_{46} \\ a_{51} & a_{52} & a_{53} & a_{54} & a_{55} & a_{56} \\ a_{61} & a_{62} & a_{63} & a_{64} & a_{65} & a_{66} \end{bmatrix}$$

Symbol	Description	Dimensions	Role
$x$	State variable	$n \times 1$ column vector	Output
$P$	State covariance matrix	$n \times n$ matrix	Output
$z$	Measurement	$m \times 1$ column vector	Input
$A$	State transition matrix	$n \times n$ matrix	System Model
$H$	State-to-measurement matrix	$n \times n$ matrix	System Model
$R$	Measurement covariance matrix	$m \times m$ matrix	Input
$Q$	Process noise covariance matrix	$n \times n$ matrix	System Model
$K$	Kalman Gain	$n \times m$	Internal

Table 1: System variables, matrices, and their roles in the Kalman Filter

Symbol	Name	Description	Example
$x_k$	State Vector	The current estimate of the system's state at time $k$ .	$x_k = [px, py, pz, vx, vy, vz]$ , umn: position in m/s).
$\hat{x}_k$	Predicted State	The predicted state at time $k$ before incorporating sensor measurements.	Same 6x1 vector, but after predicting with $F$ .
$z_k$	Measurement Vector	The sensor's observation at time $k$ .	$z_k = [vx, vy, vz]$ from accel (e.g., [m/s]).
$F$	State Transition Matrix	Describes how the state evolves over time without external inputs. $\begin{bmatrix} 1 & 0 & 0 & \Delta t & 0 & 0 \\ 0 & 1 & 0 & 0 & \Delta t & 0 \\ 0 & 0 & 1 & 0 & 0 & \Delta t \\ 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	6x6 matrix:  (position grows with velocity)
$B$	Control Input Matrix	Maps the control input to the state. $\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ \Delta t & 0 & 0 \\ 0 & \Delta t & 0 \\ 0 & 0 & \Delta t \end{bmatrix}$	6x3 matrix:  (accel affects velocity)
$u_k$	Control Vector	The external input affecting the system at time $k$ .	$u_k = [ax, ay, az]$ from MPU6050 in m/s <sup>2</sup> .
$H$	Observation Matrix	Relates the state to the measurement. $\begin{bmatrix} 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix}$	3x6 matrix:  (picks velocities from state)
$P_k$	Covariance Matrix	Represents the uncertainty in the state estimate at time $k$ .	6x6 matrix, e.g., $\text{diag}(100, 100, 100, 0.01, 0.01, 0.01)$ (high uncertainty in position, low in velocity).
$Q$	Process Noise Covariance	Uncertainty added during prediction due to model imperfections.	6x6 matrix, e.g., $\text{diag}(0.01, 0.01, 0.01, 0.01, 0.01, 0.01)$ (noise for pos, vel, accel).
$R$	Measurement Noise Covariance	Uncertainty in the sensor measurements.	3x3 matrix, e.g., $\text{diag}(0.01, 0.01, 0.01)$ (noise in accel-decels).
$K$	Kalman Gain	Determines how much to trust the measurement vs. the prediction.	6x3 matrix, computed from $P_k, H, R$ , e.g., 0.5 means 50% trust in measurement.
$w_k$	Process Noise	Random errors in the system model (assumed Gaussian).	Handled by $Q$ , e.g., sensor drift, unmodeled effects.
$v_k$	Measurement Noise	Random errors in the sensor data (assumed Gaussian).	Handled by $R$ , e.g., sensor noise, accel readings.

Table 2: Kalman Filter Variables and Examples