
Kalman Filter Theory and Applications

Equation Drilldown

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Part 1

Equation Drilldown

Topics

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- Mathematical Formulation of the Problem

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- Drilldown on State Dynamics and Covariance Extrapolation Equations

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where $R(k)$ is the measurement noise covariance matrix (to be defined later) governing the white measurement noise $v(k)$ in the measurement model:

$$z(k) = H(k)x(k) + v(k)$$

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