

**MODULE 2 LESSON 4**

**AN IMPROVED EKF: THE**

# The Error-State EKF (ES-EKF)

By the end of this video, you will be able to

- Describe the error-state formulation of the Extended Kalman Filter
- Describe the advantages of the Error-state EKF over the vanilla EKF

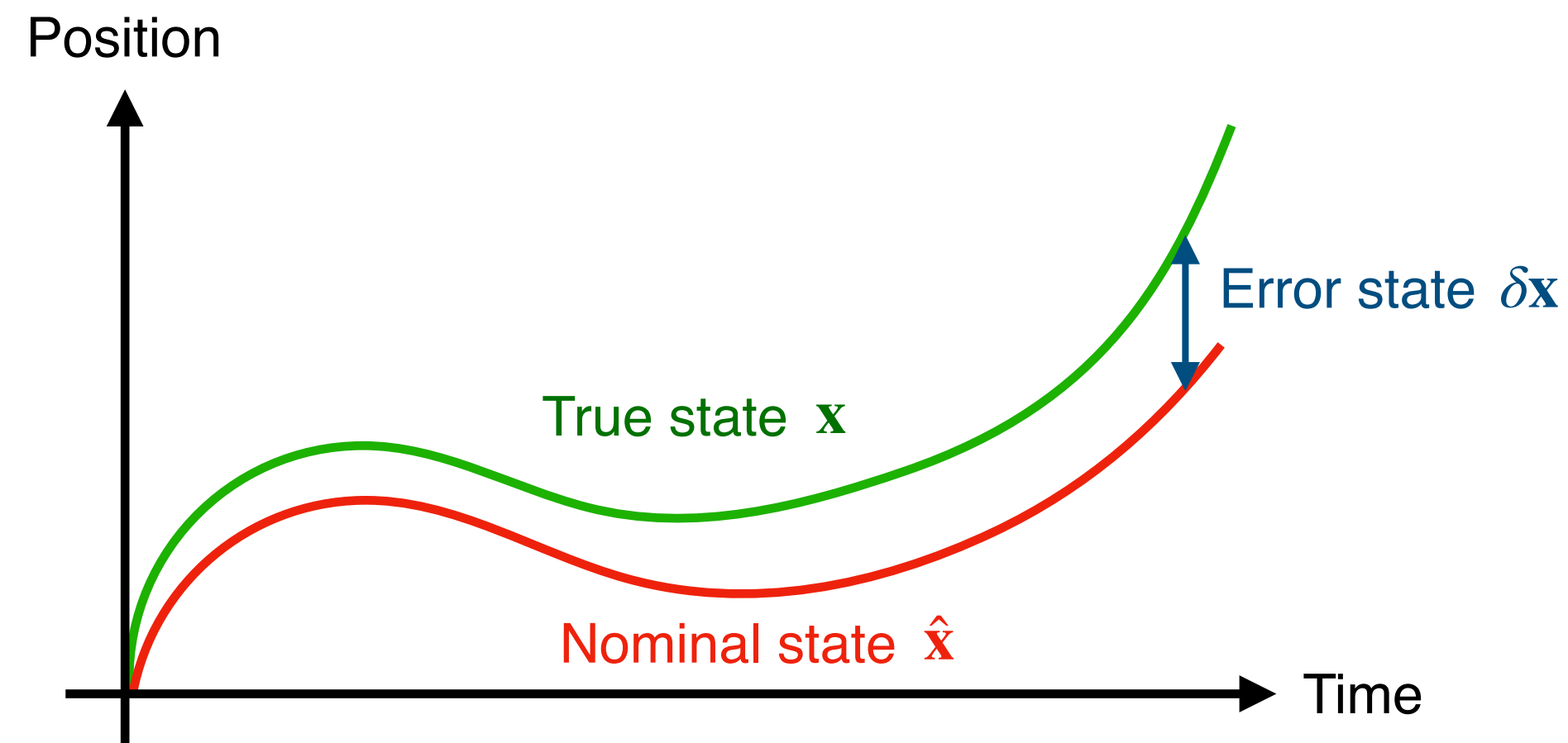
# What's in a State?

We can think of the vehicle state as composed of two parts:

$$\mathbf{x} = \hat{\mathbf{x}} + \delta\mathbf{x}$$

True State      Nominal State ("Large")      Error State ("Small")

The diagram shows the equation  $\mathbf{x} = \hat{\mathbf{x}} + \delta\mathbf{x}$  at the top. Below it, three labels are positioned: 'True State' on the left, 'Nominal State ("Large")' in the center, and 'Error State ("Small")' on the right. Arrows point from each label to its corresponding term in the equation: from 'True State' to  $\mathbf{x}$ , from 'Nominal State' to  $\hat{\mathbf{x}}$ , and from 'Error State' to  $\delta\mathbf{x}$ .



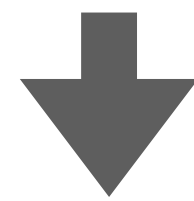
- We can continuously update the *nominal state* by integrating the motion model
- Modelling errors and process noise accumulate into the *error state*

# The Error-State Extended Kalman Filter

The Error-State Extended Kalman Filter estimates the error state directly and uses it as a correction to the nominal state:

Linearized motion model

$$\mathbf{x}_k = \mathbf{f}_{k-1}(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0}) + \mathbf{F}_{k-1} (\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1}) + \mathbf{L}_{k-1} \mathbf{w}_{k-1}$$

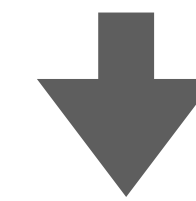


$$\underbrace{\mathbf{x}_k - \mathbf{f}_{k-1}(\hat{\mathbf{x}}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0})}_{\delta \mathbf{x}_k} = \mathbf{F}_{k-1} \underbrace{(\mathbf{x}_{k-1} - \hat{\mathbf{x}}_{k-1})}_{\delta \mathbf{x}_{k-1}} + \mathbf{L}_{k-1} \mathbf{w}_{k-1}$$

Error state

Linearized measurement model

$$\mathbf{y}_k = \mathbf{h}_k(\check{\mathbf{x}}_k, \mathbf{0}) + \mathbf{H}_k (\mathbf{x}_k - \check{\mathbf{x}}_k) + \mathbf{M}_k \mathbf{v}_k$$



$$\mathbf{y}_k = \mathbf{h}_k(\check{\mathbf{x}}_k, \mathbf{0}) + \mathbf{H}_k \underbrace{(\mathbf{x}_k - \check{\mathbf{x}}_k)}_{\delta \mathbf{x}_k} + \mathbf{M}_k \mathbf{v}_k$$

Error state

# The Error-State Extended Kalman Filter

## Loop:

1. Update nominal state with motion model

$$\check{\mathbf{x}}_k = \mathbf{f}_{k-1}(\mathbf{x}_{k-1}, \mathbf{u}_{k-1}, \mathbf{0})$$

↑  
This could be  
 $\check{\mathbf{x}}_{k-1}$  or  $\hat{\mathbf{x}}_{k-1}$

# The Error-State Extended Kalman Filter

## Loop:


1. Update nominal state with motion model
2. Propagate uncertainty

$$\check{\mathbf{P}}_k = \mathbf{F}_{k-1} \mathbf{P}_{k-1} \mathbf{F}_{k-1}^T + \mathbf{L}_{k-1} \mathbf{Q}_{k-1} \mathbf{L}_{k-1}^T$$

↑  
This could be  
 $\check{\mathbf{P}}_{k-1}$  or  $\hat{\mathbf{P}}_{k-1}$

# The Error-State Extended Kalman Filter

## Loop:

- 
1. Update nominal state with motion model
  2. Propagate uncertainty
  3. If a measurement is available:
    1. Compute Kalman Gain

$$\mathbf{K}_k = \check{\mathbf{P}}_k \mathbf{H}_k^T (\mathbf{H}_k \check{\mathbf{P}}_k \mathbf{H}_k^T + \mathbf{R})^{-1}$$

# The Error-State Extended Kalman Filter

## Loop:

1. Update nominal state with motion model
2. Propagate uncertainty
3. If a measurement is available:
  1. Compute Kalman Gain
  2. Compute error state

$$\delta \hat{\mathbf{x}}_k = \mathbf{K}_k(\mathbf{y}_k - \mathbf{h}_k(\check{\mathbf{x}}_k, \mathbf{0}))$$



# The Error-State Extended Kalman Filter

## Loop:

1. Update nominal state with motion model
2. Propagate uncertainty
3. If a measurement is available:
  1. Compute Kalman Gain
  2. Compute error state
  3. Correct nominal state

$$\hat{\mathbf{x}}_k = \check{\mathbf{x}}_k + \delta\hat{\mathbf{x}}_k$$

# The Error-State Extended Kalman Filter

## Loop:

1. Update nominal state with motion model
2. Propagate uncertainty
3. If a measurement is available:
  1. Compute Kalman Gain
  2. Compute error state
  3. Correct nominal state
4. Correct state covariance

$$\hat{\mathbf{P}}_k = (\mathbf{I} - \mathbf{K}_k \mathbf{H}_k) \check{\mathbf{P}}_k$$

# Why Use the ES-EKF?

## 1. Better performance compared to the vanilla EKF

The “small” error state is more amenable to linear filtering than the “large” nominal state, which can be integrated nonlinearly

## 2. Easy to work with constrained quantities (e.g., rotations in 3D)

We can also break down the state using a generalized composition operator

$$\mathbf{x} = \hat{\mathbf{x}} \oplus \delta\mathbf{x}$$

The diagram illustrates the decomposition of the True State  $\mathbf{x}$  into the Nominal State  $\hat{\mathbf{x}}$  and the Error State  $\delta\mathbf{x}$  using the composition operator  $\oplus$ . Arrows point from the labels below to the corresponding terms in the equation above.

True State      Nominal State  
(Overparametrized, constrained)

Error State  
(Minimal parametrization, unconstrained)

# Summary | The Error-State EKF (ES-EKF)

- The error-state formulation separates the state into a “large” nominal state and a “small” error state.
- The ES-EKF uses local linearization to estimate the error state and uses it to correct the nominal state.
- The ES-EKF can perform better than the vanilla EKF, and provides a natural way to handle constrained quantities like rotations in 3D.