

# Bicycle State Estimation with Extended Kalman Filter, GNSS and Wheel Speed Sensor Fusion

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## I. INTRODUCTION

## II. RELATED WORK

## III. PROBLEM STATEMENT

## IV. APPROACH

### 1. Dynamics Model

$$\vec{X} = [x, y, z, \theta, v_x, v_y, \omega_w, b_u]^T$$
$$\vec{u} = [\psi, \tau]^T$$

$$\dot{x} = v_x$$

$$\dot{y} = v_y$$

$$\dot{\theta} = V \tan \psi$$

$$\dot{v}_x = \dot{v} \cos \theta - v \sin \theta \dot{\theta}$$

$$\dot{v}_y = \dot{v} \sin \theta + v \cos \theta \dot{\theta}$$

$$\dot{\omega}_w = \frac{1}{I_w} (\tau - \dot{v} m r_w)$$

$$\dot{b}_u = 0$$

$$v = \sqrt{v_x^2 + v_y^2}$$

$$s = \frac{r \omega_w - v}{v}$$

$$\mu = \mu(s)$$

$$\dot{v} = \frac{\mu g l_1}{l_1 + l_2}$$

$$\psi \sim \mathcal{N} \left( 0, \left( \frac{\alpha}{v} \right)^2 \right)$$

$$\tau \sim \mathcal{N} \left( 0, (\sigma_\tau)^2 \right)$$

$$\begin{aligned}\vec{f}(x_k) &= \vec{X}_k + \Delta t \dot{\vec{X}}|_{x_k, u_k=0} \\ F_k &= \left. \frac{\partial \vec{f}}{\partial \vec{X}} \right|_{\vec{X}_k} = I + \Delta t \left. \frac{\partial \dot{\vec{X}}}{\partial \vec{X}} \right|_{\vec{X}_k} \\ B_k &= \left. \frac{\partial \vec{f}}{\partial \vec{u}} \right|_{\vec{X}_k} = \Delta t \left. \frac{\partial \dot{\vec{X}}}{\partial \vec{u}} \right|_{\vec{X}_k}\end{aligned}$$

$$\begin{aligned}h_\omega(\vec{X}) &= \omega \\ h_\rho^i(\vec{X}) &= \sqrt{(x^i-x)^2+(y^i-y)^2+(z^i-z)^2}+b_u-B^i \\ h_\rho^i(\vec{X}) &= (\vec{v}^i-\vec{v})^T\vec{1}^i+\dot{b}_u-\dot{B}^i\end{aligned}$$

$$Q_k = Q_{process} + B_k Q_u B_k^T$$

$$\begin{aligned}\hat{\vec{X}}_{k+1} &= \vec{f}(X_k) \\ \hat{P}_{k+1} &= F_k P_k F_k^T + Q_k\end{aligned}$$

$$\begin{aligned}\vec{v}_k &= \vec{z}_k - h(\hat{X}_k) \\ S_k &= H_k \hat{P}_{k+1} H_k^T + R_k \\ K_k &= \hat{P}_{k+1} H_k^T S_k^{-1} \\ \vec{X}_{k+1} &= \hat{\vec{X}}_{k+1} + K_k \vec{v} \\ P_{k+1} &= (I - K_k H_k) \hat{P}_{k+1}\end{aligned}$$

**V. RESULTS**

**VI. CONCLUSION**

**VII. FUTURE DIRECTIONS**