Sensor-free Wind Velocity Estimate from Rotocopter Motion

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Introduction

- Accurate wind-velocity measurements are critical for research applications
  - Climate modeling
  - Dispersion modeling
  - Quantifying emission sources
  - Measuring Atmospheric Boundary Layer (very high altitudes)
- Drones can be outfitted with compact sonic anemometers (wind sensors)
  - High financial cost (one sensor per drone)
  - Susceptibility to measurement bias
  - Additional payload reduces flight time and aircraft compactness

Sensor-free methods

- Inertial Measurement Unit (IMU)
  - Provides flight data at high sampling rate (50 Hz)
  - This is in contrast to 1 Hz for sensor aboard drones
- Eliminates the need to purchase additional sensors or additional weight
  - Allows micro drones that otherwise could not carry sensors become sensors themselves
  - Deploy multiple drones at the same time without compounding cost
- Mitigates bias inherent to a mounted sensor

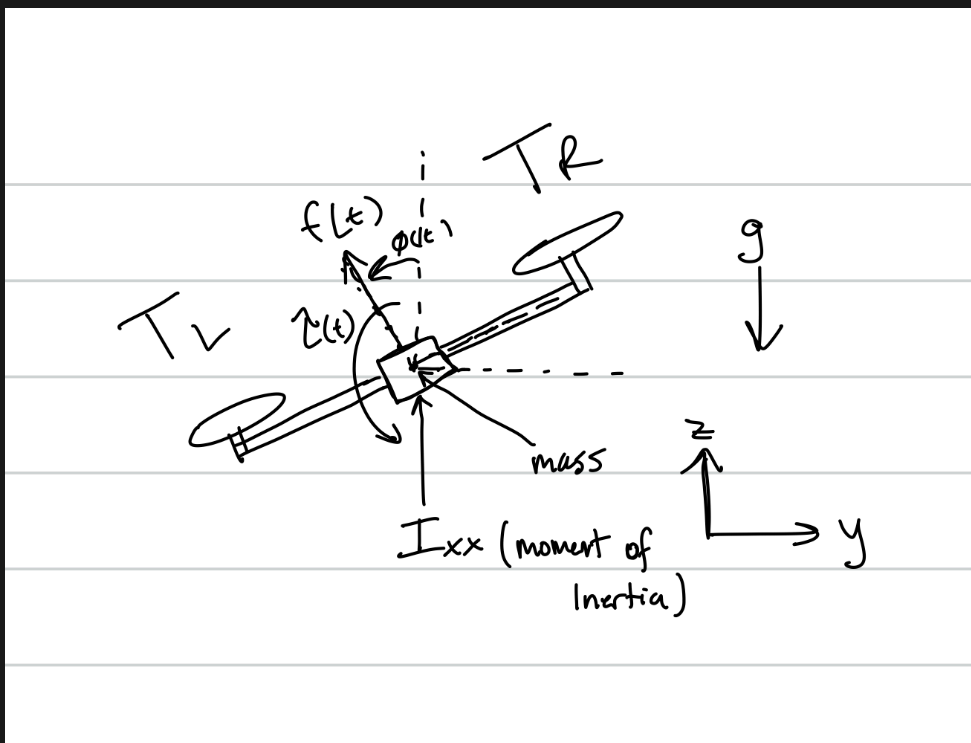
Considerations

- Variations in the mass moment of inertia effects the accuracy of the wind estimate
  - Increased sensitivity to perturbations by the wind

Limitations:

- Drones with smaller payload capacity may have reduced quality IMUs

2D drone toy model



Equations of motion:

$$-F(t)\sin\phi(t) = m\frac{d^2y}{dt^2}$$

$$F(t)\cos\phi(t) = mg + m\frac{d^2z}{dt^2}$$

$$\tau(t) = I_{xx}\frac{d^2\phi}{dt^2}$$

State space model

States:

$$x_1 = y(t)$$
$$x_2 = z(t)$$
$$x_3 = \phi(t)$$
$$x_4 = \dot{y}(t)$$
$$x_5 = \dot{z}(t)$$
$$x_6 = \dot{\phi}(t)$$

Inputs:

$$u_1 = F(t)$$
$$u_2 = \tau(t)$$

Outputs:

$$y_1 = y(t)$$
$$y_2 = z(t)$$
$$y_3 = \phi(t)$$

Non-linear model

$$\begin{bmatrix} \dot{x}_1 \\ \dot{x}_2 \\ \dot{x}_3 \\ \dot{x}_4 \\ \dot{x}_5 \\ \dot{x}_6 \end{bmatrix} = \begin{bmatrix} x_4 \\ x_5 \\ x_6 \\ -\frac{u_1}{m}\sin(x_3) \\ \frac{u_1}{m}\cos(x_3) - g \\ \frac{u_2}{I_{xx}} \end{bmatrix}$$

$$\begin{bmatrix} y_1 \\ y_2 \\ y_3 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \\ x_3 \end{bmatrix}$$

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Linearizing

Linearizing about small $\phi(t)$

Steady state dynamics

$$\begin{aligned} F_{eq}(t) &= mg \\ \tau_{eq}(t) &= 0 \\ \phi_{eq}(t) &= 0 \\ y_{eq}(t) &= y_0 \\ z_{eq}(t) &= z_0 \end{aligned}$$

First order Taylor expansion of non-linear terms for small angles of ϕ

$$\begin{aligned} \sin(\phi) &= \sin(0) + \cos(0)(\phi - 0) \\ &= \phi \\ \cos(\phi) &= \cos(0) - \sin(0)(\phi - 0) \\ &= 1 \end{aligned}$$

PD Controller

Three outputs (y, z, ϕ):

$$\begin{aligned}
\ddot{z}_{ctrl} &= \ddot{z}_d + K_{pz}(z_d - z) + K_{dz}(\dot{z}_d - \dot{z}) \\
\ddot{y}_{ctrl} &= \ddot{y}_d + K_{py}(y_d - y) + K_{dy}(\dot{y}_d - \dot{y}) \\
\ddot{\phi}_{ctrl} &= \ddot{\phi}_d + K_{p\phi}(\phi_d - \phi) + K_{d\phi}(\dot{\phi}_d - \dot{\phi})
\end{aligned}$$

Two inputs (F, τ):

$$\begin{aligned}
u_1 &= mg + m\ddot{z}_{ctrl} \\
u_2 &= I_{xx}\ddot{\phi}_{ctrl}
\end{aligned}$$

Simulating wind

We model the wind acting on the drone by propagating the following Stochastic DE in the integral solver:

Ornstein-Uhlenbeck process:

$$dx_t = \theta(\mu - x_t)dt + \sigma dW_t$$

Then produce a wind estimate by calculating component force produced in the direction of the wind by only looking at the outputs of the controller.

Project goals

- Benchmark wind estimates produced from Linear Quadratic Regulator vs PID controller
- Use different filtering (Kalman filter, partical filter) to produce a wind estimate
- Explore how changing the mass moment of inertia changes the certainty of the measurement
- Scale up the model to quad-copter and experimentally validate findings