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Indoor Altitude Estimation of Unmanned Aerial Vehicles Using a Bank of Kalman Filters

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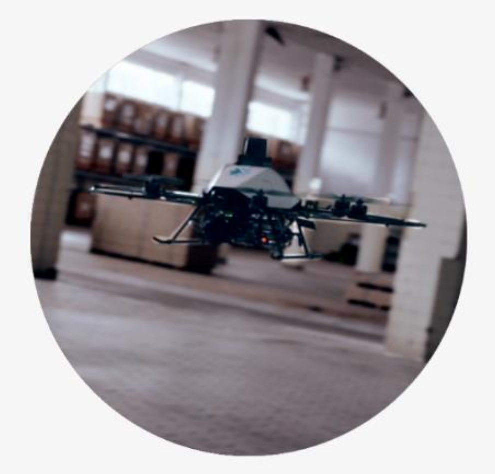
Overview

- ❖Motivation
- ❖Problem Description
- ❖State-space Formulation
- ❖Multiple Model Adaptive Estimation
- ❖Experiments
- ❖Conclusion

Motivation



Unmanned Aerial Vehicles (UAVs)

No GPS signals

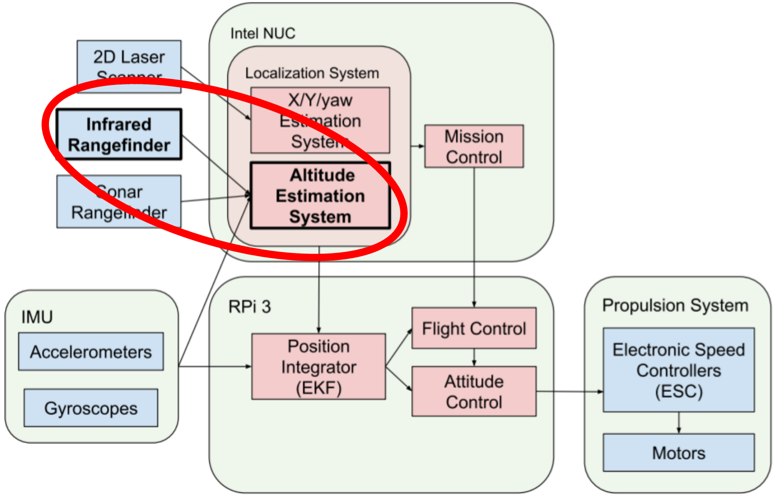
Tradeoff between accuracy, weight and cost

Irregular obstructions

*picture credit: Avansig S.L.

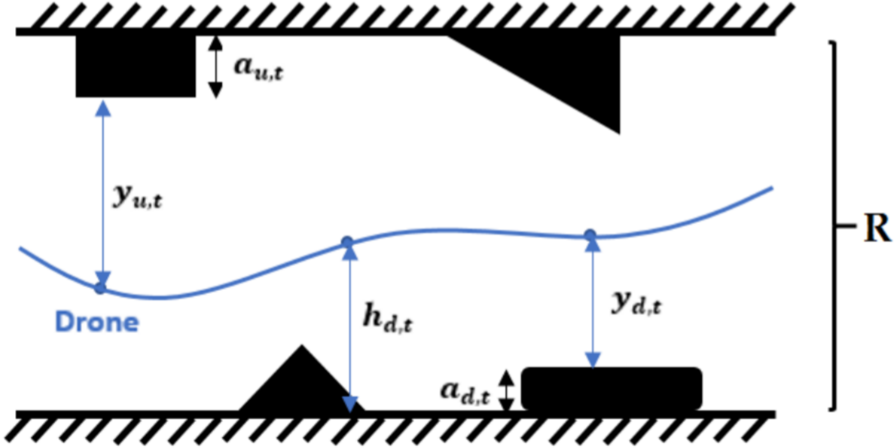
Problem Description

The UAV architecture



Problem Description

The altitude estimation scenario



Assumption:

1. Only access the data from two IR sensors
2. Two IR sensors are aligned in the same position.
3. The angle of tilt can be ignored.
4. The roof is level.

Goal:

Estimate the true altitude of the UAV $h_{d,t}$

by measuring the biased ranges from the upward and downward IR sensors

State-space Formulation

- The range measurements from two IR sensors:

$$y_{u,t} = R - h_{d,t} - a_{u,t} + \epsilon_{u,t},$$
$$y_{d,t} = h_{d,t} - a_{d,t} + \epsilon_{d,t},$$

- Independent measurement errors:

$$\epsilon_{u,t}, \epsilon_{d,t} \sim \mathcal{N}(0, \sigma_y^2)$$

- The observation equation in matrix form:

$$\mathbf{y}_t = \mathbf{H}\mathbf{x}_t + \boldsymbol{\epsilon}_t,$$

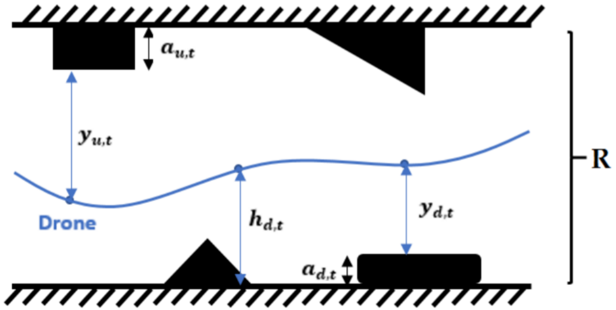
Observation vector: $\mathbf{y}_t = [y_{u,t} - R, y_{d,t}]^\top$

State vector: $\mathbf{x}_t = [h_{d,t}, v_t, a_{u,t}, a_{d,t}]^\top$

Error vector: $\boldsymbol{\epsilon}_t \sim \mathcal{N}(\mathbf{0}, \sigma_y^2\mathbf{I}_2)$

The matrix $\mathbf{H}$ is

$$\mathbf{H} = \begin{bmatrix} -1 & 0 & -1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}$$



State-space Formulation

- State transition equations:

$$h_{d,t} = h_{d,t-1} + T_s v_{t-1} + 0.5T_s^2 u_{v,t-1},$$
$$v_t = v_{t-1} + T_s u_{v,t-1},$$
$$a_{u,t} \sim \mathcal{N}(0, \sigma_a^2),$$
$$a_{d,t} \sim \mathcal{N}(0, \sigma_a^2),$$

Vertical velocity: v_t

Sampling interval: T_s

Vertical acceleration: $u_{v,t-1} \sim \mathcal{N}(0, \sigma_v^2)$

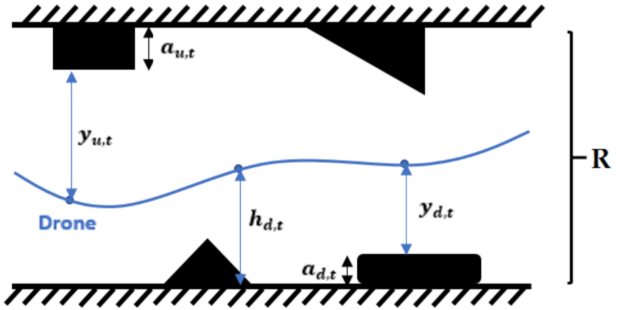
- The transition equation in matrix form:

$$\mathbf{x}_t = \mathbf{F}\mathbf{x}_{t-1} + \mathbf{u}_{t-1}$$

The state error: $\mathbf{u}_{t-1} \sim \mathcal{N}(\mathbf{0}, \mathbf{Q})$

The covariance matrix is $\mathbf{Q} = \begin{bmatrix} 0.25T_s^4\sigma_v^2 & 0.5T_s^4\sigma_v^2 & 0 & 0 \\ 0.5T_s^4\sigma_v^2 & T_s^4\sigma_v^2 & 0 & 0 \\ 0 & 0 & \sigma_a^2 & 0 \\ 0 & 0 & 0 & \sigma_a^2 \end{bmatrix}$,

The matrix $\mathbf{F}$ is $\begin{bmatrix} 1 & T_s & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$.



Multiple Model Adaptive Estimation

- Candidate models:

No obstacles
$$\mathbf{H}_1 = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

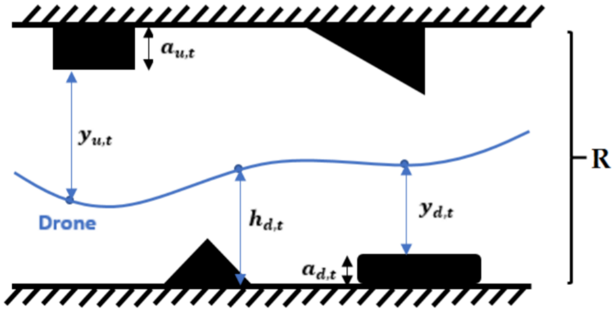
Obstacle above
$$\mathbf{H}_2 = \begin{bmatrix} -1 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 \end{bmatrix}$$

Obstacles below
$$\mathbf{H}_3 = \begin{bmatrix} -1 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}$$

Obstacles above and below
$$\mathbf{H}_4 = \begin{bmatrix} -1 & 0 & -1 & 0 \\ 1 & 0 & 0 & -1 \end{bmatrix}$$

- We use the same state variable x_t and transition equation in all candidate models.

$$y_{u,t} = R - h_{d,t} - a_{u,t} + \epsilon_{u,t},$$
$$y_{d,t} = h_{d,t} - a_{d,t} + \epsilon_{d,t},$$
$$\mathbf{y}_t = [y_{u,t} - R, y_{d,t}]^\top$$
$$\mathbf{x}_t = [h_{d,t}, v_t, a_{u,t}, a_{d,t}]^\top$$



Multiple Model Adaptive Estimation

- MMAE for UAV altitude estimation:

Initialize
$\boldsymbol{x}_0, \mathbf{P}_0$

a. Predict the prior estimate $\boldsymbol{x}^{(m)}_{t|t-1}$ and its covariance $\mathbf{P}^{(m)}_{t|t-1}$

b. Calculate the innovation $\boldsymbol{z}^{(m)}$ and its covariance $\mathbf{S}^{(m)}$

c. Compute the optimal Kalman gain $\mathbf{K}^{(m)}$

d. Up… r estimate $\boldsymbol{x}^{(m)}_{t|t}$ and covariance $\mathbf{P}^{(m)}_{t|t}$

Kalman Filter

Forgetting factor [0,1]

e. Up… lihood of model

$$l^{(m)}_{log} = \alpha \times l^{(m)}_{log} - \frac{1}{2}\left[\boldsymbol{z}^{(m)T}\{\mathbf{S}^{(m)}\}^{-1}\boldsymbol{z}^{(m)} + \log(|\mathbf{S}^{(m)}|) + 2\log(2\pi)\right]$$

Marginal likelihood

$$p(\boldsymbol{y}_{1:t}) = p(\boldsymbol{y}_{1:t-1})p(\boldsymbol{y}_t|\boldsymbol{y}_{1:t-1})$$
$$= p(\boldsymbol{y}_{1:t-1})\int p(\boldsymbol{y}_t|\boldsymbol{x}_t)p(\boldsymbol{x}_t|\boldsymbol{y}_{1:t-1})d\boldsymbol{x}_t$$
$$= p(\boldsymbol{y}_{1:t-1})\mathcal{N}(\boldsymbol{y}_t|\mathbf{H}\boldsymbol{x}_{t|t-1}, \mathbf{S})$$

Convert the log-likelihood to likelihood and normalize it as $w^{(m)}$

Weighted sum the estimate $\boldsymbol{x}_t$ and covariance $\mathbf{P}_t$

$$x_t = \sum_{m=1}^{M} w^{(m)}\, \boldsymbol{x}^{(m)}_{t|t},$$

$$P_t = \sum_{m=1}^{M} w^{(m)} \left[\mathbf{P}^{(m)}_{t|t} + (\boldsymbol{x}^{(m)}_{t|t} - x_t)(\boldsymbol{x}^{(m)}_{t|t} - x_t)^T\right]$$

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Experiments
(Synthetic Data)

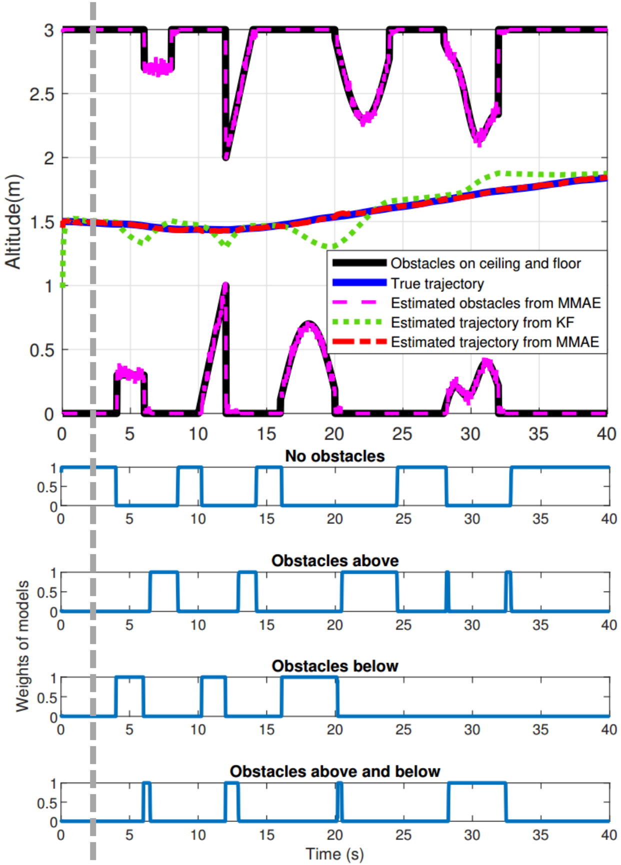
- Scenario

Height of room $R = 3\text{m}$	Sampling interval $T_s = 0.02\text{s}$
Process noise $\sigma_v^2 = 0.001\text{m}^2/\text{s}^4$	Observation noise $\sigma_y^2 = 0.001\text{m}^2$
Time length $T = 2000$	Initial states $h_{d,0} = 1.5\text{m}$ $v_0 = 0\text{m/s}$

- Mean squared errors (MSEs) of altitude estimation

in 1000 Monte Carlo simulations

σ_y^2	0.001			0.01		
σ_a^2 \ σ_v^2	0.01	0.1	1	0.01	0.1	1
0.01	2.8e-3	4.8e-3	1.3e-2	4.6e-3	6.6e-3	1.4e-2
0.1	1.4e-3	2.4e-4	5.1e-4	1.9e-3	7.3e-4	7.7e-4
1	1.4e-3	**2.3e-4**	2.9e-4	2.1e-3	1.4e-3	2.9e-2



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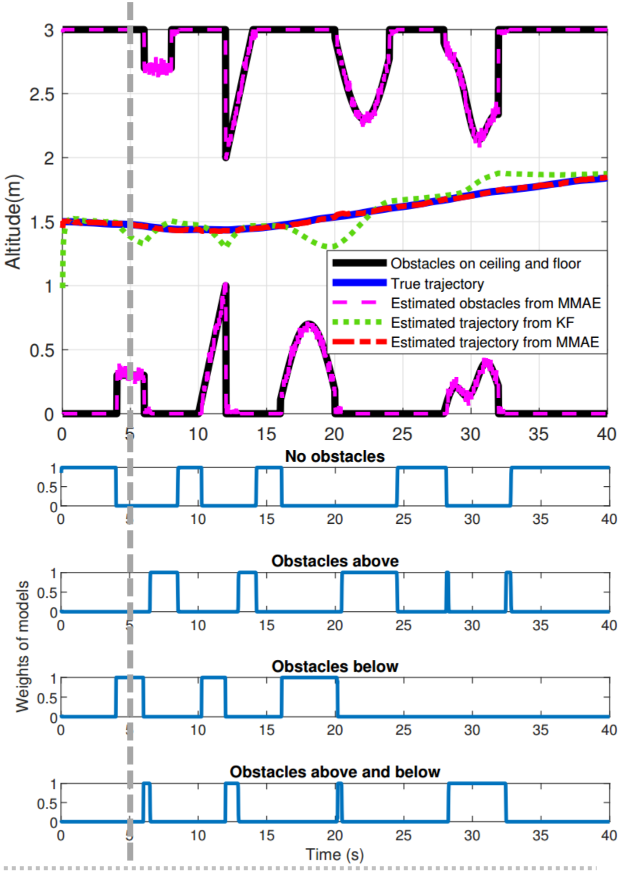
1	1.4e-3	**2.3e-4**	2.9e-4	2.1e-3	1.4e-3	2.9e-2



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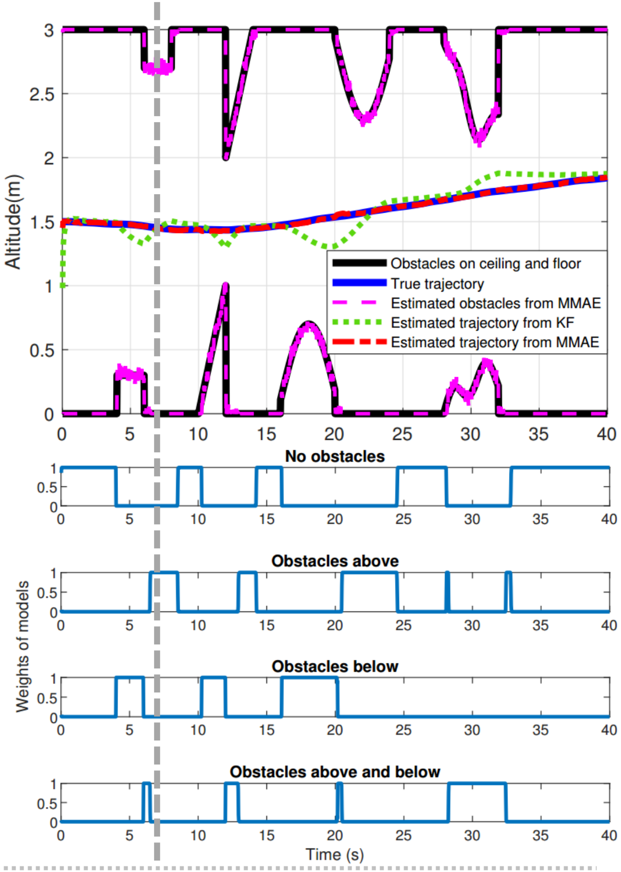

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(Synthetic Data)

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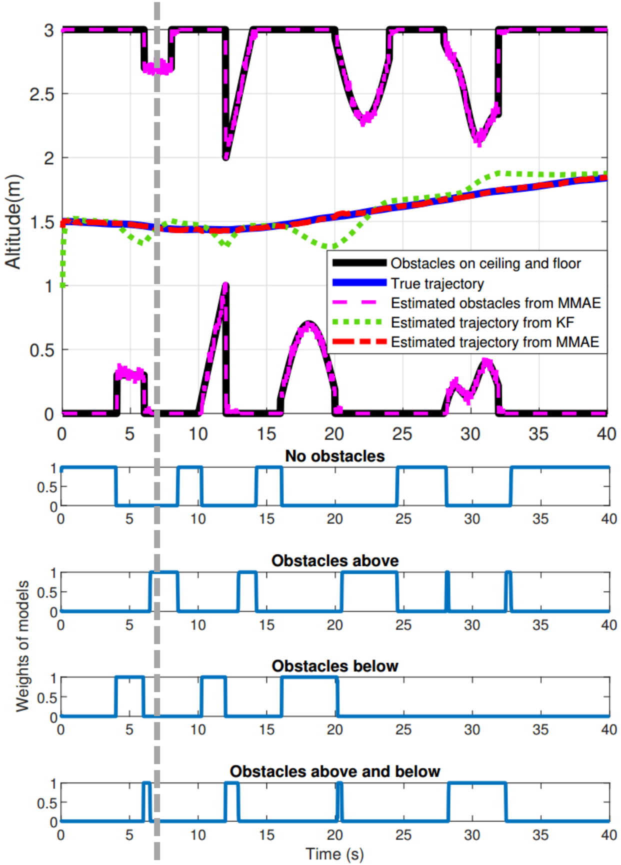


Experiments
(Real Data*)

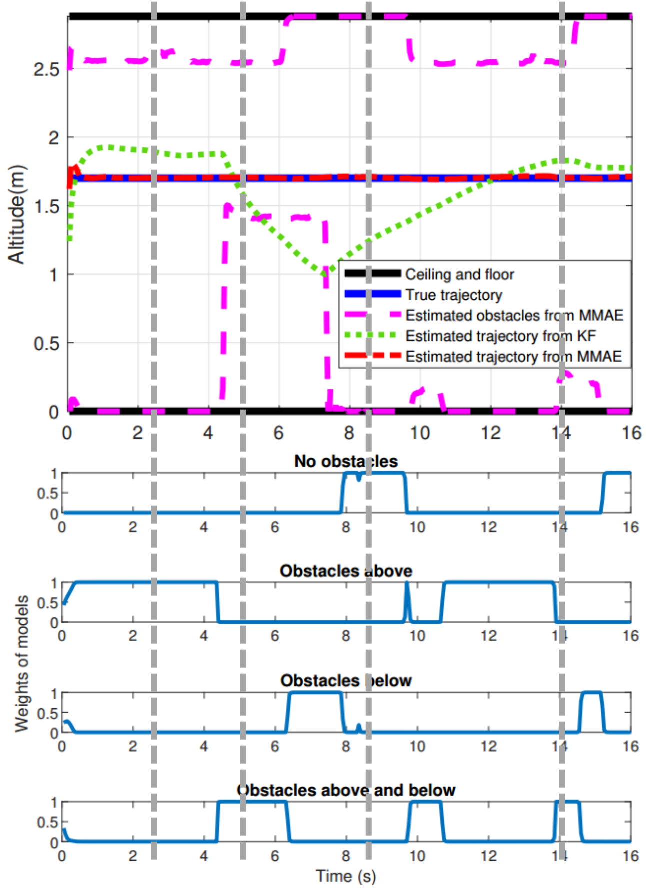
- Scenario

Height of room $R = 2.88\text{m}$
Process noise $\sigma_v^2 = 0.2\text{m}^2/\text{s}^4$
Real altitude $h_{d,t} = 1.7\text{m}$

Sampling interval $T_s = 0.05\text{s}$
Observation noise $\sigma_y^2 = 0.001\text{m}^2$
Uncertainty of obstacles $\sigma_a^2 = 1\text{m}^2$

- MSEs of altitude estimation in different arrangements of the obstacles

Ceiling \ Floor	None	Regular Parallel	Regular Inclined	Irregular
None	1.36e-4	3.57e-5	9.42e-5	1.49e-4
Regular	2.53e-4	3.61e-4	3.58e-4	4.25e-4
Irregular	4.51e-4	5.93e-4	9.50e-4	5.14e-4



*provided by Avansig S.L.

Conclusion

- Addressed the problem of altitude estimation for UAVs in indoor setting only using infrared sensor data
- Tackled the problem by formulating four candidate state-space models and applying multiple model adaptive estimation with a bank of Kalman filters
- Experiments using both synthetic data and real data show the promise

Thank you very much for your attention!

Contacts

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