Absolute scale velocity determination combining visual and inertial measurements for micro aerial vehicles

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INRIA

June 24, 2015

Section 1

Sensor fusion

Micro aerial vehicles

Micro aerial vehicles

Micro aerial vehicles

A basic state vector: $X = \begin{bmatrix} \textit{position} \\ \textit{velocity} \\ \textit{orientation} \end{bmatrix}$

Micro aerial vehicles

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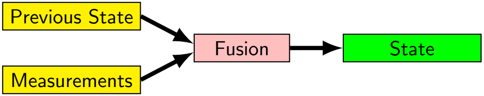
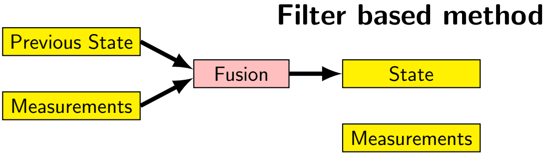
The goal of sensor fusion is to recover the state X

Visual-inertial sensor fusion

Filter based method



Visual-inertial sensor fusion



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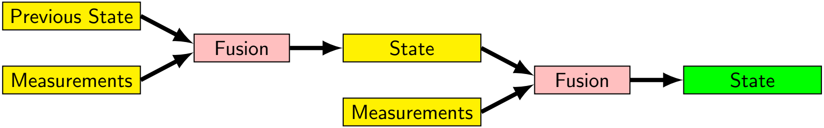

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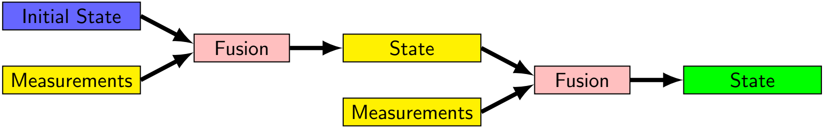
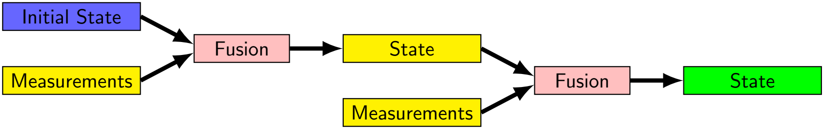


How to recover the **initial state**?

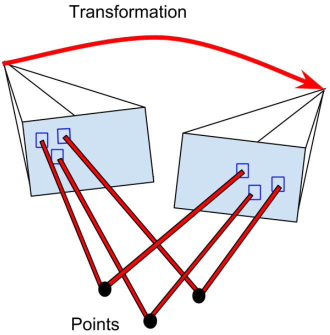
Visual-inertial sensor fusion

Filter based method

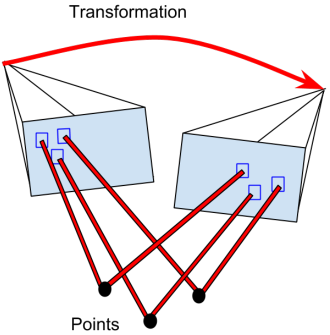


How to recover the **initial state**?
We need a **deterministic solution**

Deterministic solutions in Computer Vision



Deterministic solutions in Computer Vision



But the relative translation and distance to features are recovered only **up to scale**

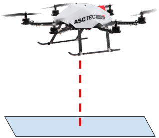
Absolute scale from visual measurements

How big is this building?

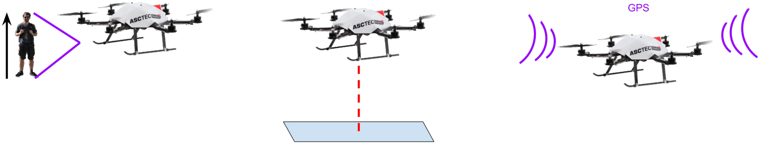
Absolute scale from visual measurements

Methods to recover the absolute scale

Methods to recover the absolute scale

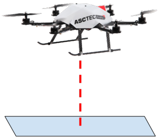


Methods to recover the absolute scale



Methods to recover the absolute scale

Not suited to unknown environments



Not precise, works only in hover

Does not work in GPS denied environments

Inertial Measurement Unit (IMU)

The IMU consists of two sensors providing **physical quantities**:

- Accelerometer: linear acceleration - gravity (m/s^2);
- Gyroscope: angular velocity (rad/s).

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Visual measurements

Inertial measurements

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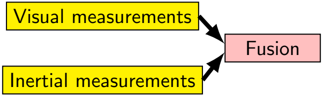

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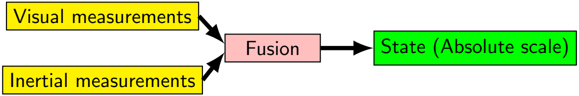

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Section 2

The closed-form solution

The Closed-Form Solution - 2014

Requires:

- Calibrated camera;
- Inertial Measurement Unit (IMU);
- External Camera IMU transformation.

Output:

- Initial velocity;
- Distance to point-features;
- Attitude.

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$$S_j = \lambda_1^i \mu_1^i - V t_j - G \frac{t_j^2}{2} - \lambda_j^i \mu_j^i$$

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The Overconstrained Linear System

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Valid for every point-features i at any time t_j:

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The Overconstrained Linear System

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$$\Xi X = S$$

Problem: not robust in practice

"**A closed-form solution** *for state estimation with a visual-inertial system that does not require initialization was presented. However, this approach is* **not suitable for systems that rely on noisy sensor data**"

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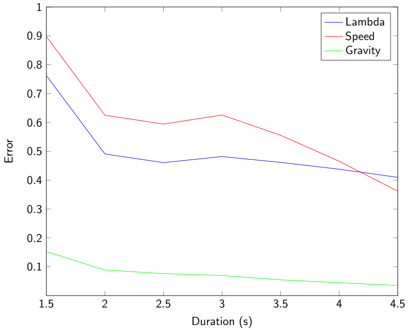

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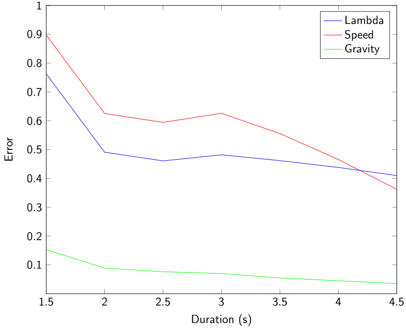

50% relative error on speed and distance estimation

Improving the performance

What makes the estimations so bad?

Possible bottlenecks

- Motion;

Improving the performance

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Improving the performance

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Possible bottlenecks

- Motion;
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Sensors provide measurements affected by a Gaussian noise:

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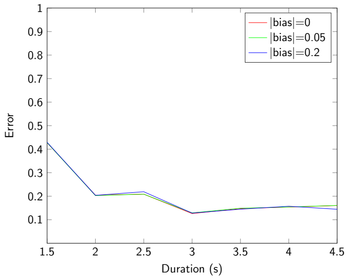
We considered:

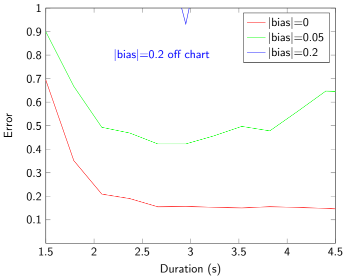
- Biased accelerometer;
- Biased gyroscope.

Biased inertial measurements

Speed estimation error



Varying accelerometer bias



Varying gyroscope bias

Estimating the gyroscope bias

- When solving $\Xi X = S$, we are solving $\operatorname{argmin}_X ||\Xi X - S||^2$;

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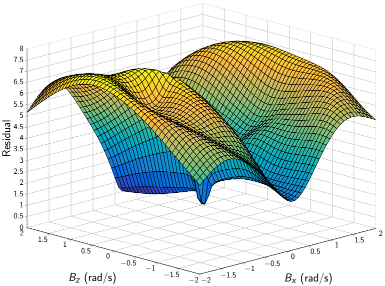
- Alternative: non-linear minimization

$$\underset{{\color{red}B},X}{\mathrm{argmin}} \, ||\Xi X - S||^2$$

With B the gyroscope bias, Ξ and S computed with respect to B



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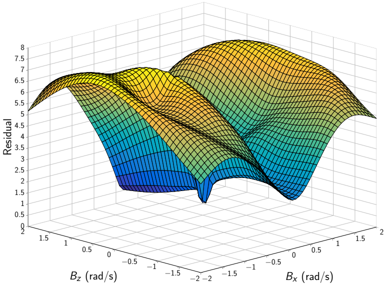

Symmetry induced by the strong weight of the gravity

Estimating the gyroscope bias

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- Unfortunately, we can not express the gyroscope bias linearly;
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$$\underset{B,X}{\mathrm{argmin}} \, ||\Xi X - S||^2 + \lambda \times |B|$$

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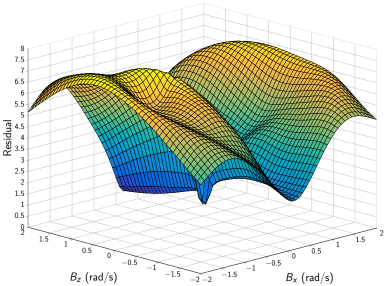

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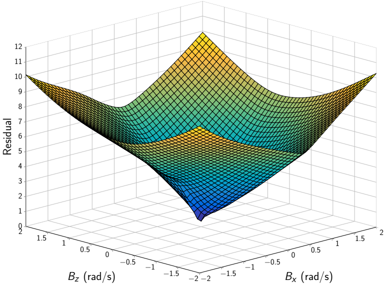
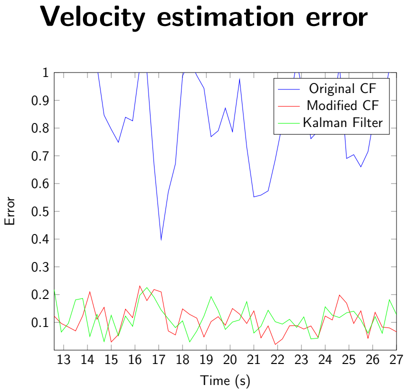


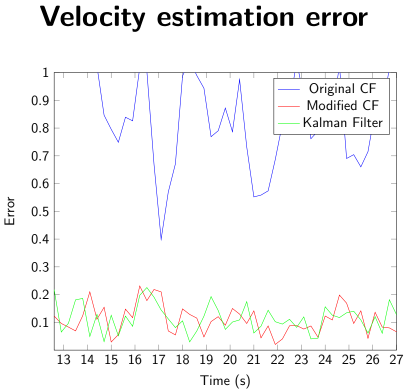
With regularization $\lambda = 3$

Results



Velocity estimation error
Error
Time (s)
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
13 14 15 16 17 18 19 20 21 22 23 24 25 26 27
Original CF
Modified CF
Kalman Filter

Results



Moreover, our technique also provides the gyroscope bias

Section 3

Conclusion

Conclusion

Potential PhD

Thank you for your attention,
Any question?