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

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Supervised by Dr. Agostino Martinelli

INRIA

June 24, 2015

Micro aerial vehicles

Micro aerial vehicles

Micro aerial vehicles

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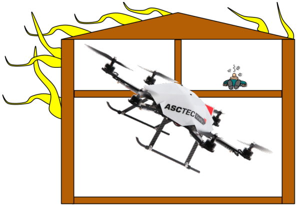

Micro aerial vehicles

Localization in **various environments**

Micro aerial vehicles

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Micro aerial vehicles

A basic state vector:

$$X = \begin{bmatrix} \textit{position} \\ \textit{velocity} \\ \textit{orientation} \end{bmatrix}$$

Localization in **various environments**

Micro aerial vehicles

Global Frame

A basic state vector:

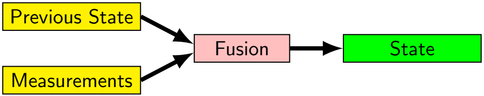
$$X = \begin{bmatrix} \textit{position} \\ \textit{velocity} \\ \textit{orientation} \end{bmatrix}$$

Localization in **various environments**

The goal of sensor fusion for state estimation is to **recover** X

Visual-inertial sensor fusion

Filter based method



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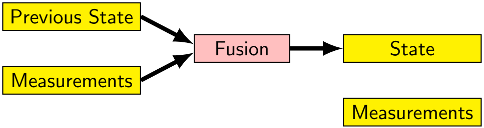

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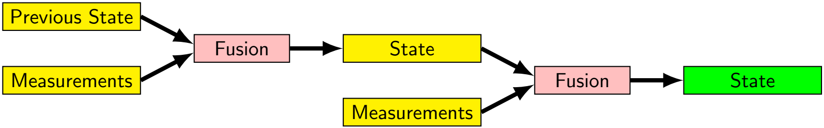

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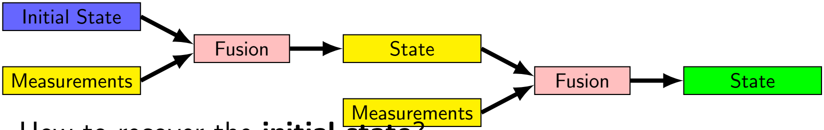
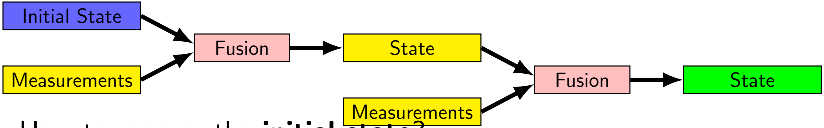


How to recover the **initial state**?

Visual-inertial sensor fusion

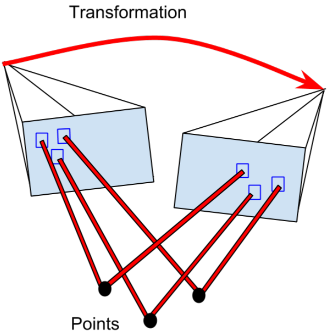
Filter based method



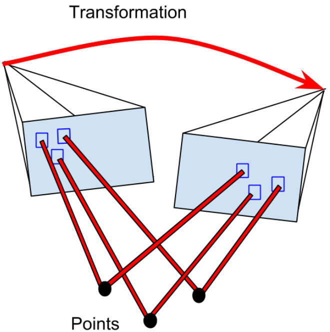
How to recover the **initial state**?

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

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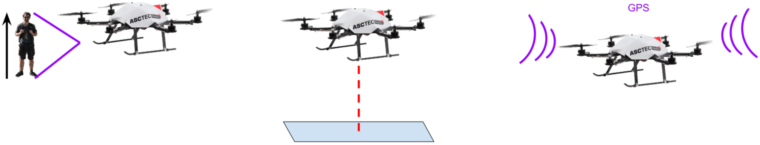
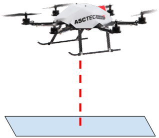


Methods to recover the absolute scale

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

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Visual

Measurements

Inertial

Back to the title

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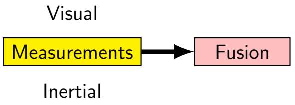

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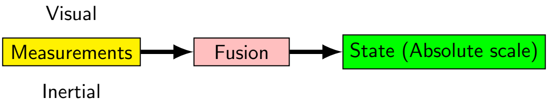

Table of Contents

The closed-form solution

Transactions on Robotics (T-RO) 2012
International Journal of Computer Vision (IJCV) 2014

The Closed-Form Solution

Requires:

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

Output:

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

The Closed-Form Solution

Requires:

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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-feature i at any time t_j:

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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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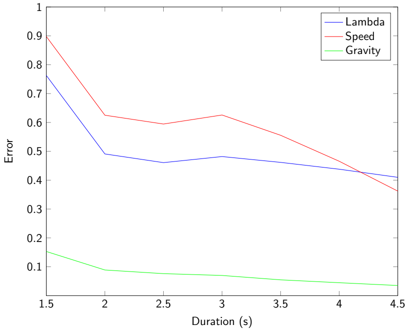

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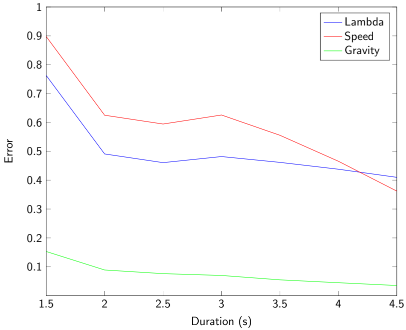

50% relative error on speed and distance estimation

Improving the performance

What makes the estimations so bad?

Possible bottlenecks

- Motion;

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Sensors provide measurements affected by a Gaussian noise:

$$N(\mu + B, \sigma^2)$$

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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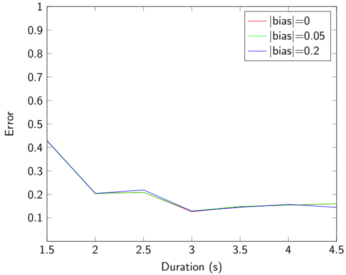
We considered:

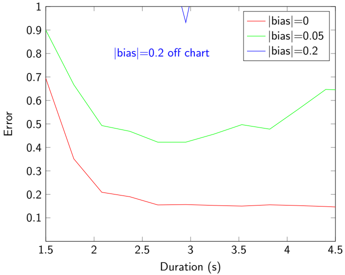
- Biased accelerometer;
- Biased gyroscope.

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

$$cost(B) = \underset{X}{\text{argmin}} \, ||\Xi X - S||^2$$

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

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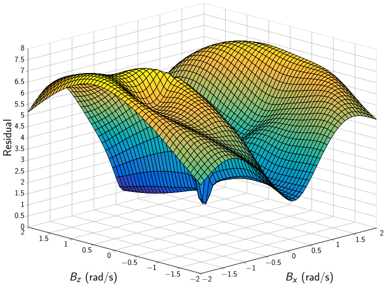

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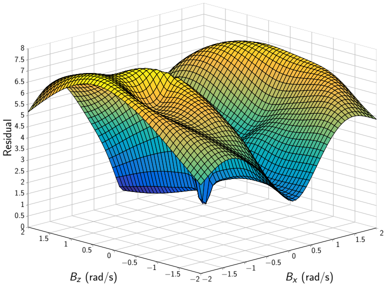

Symmetry induced by the strong weight of the gravity

Estimating the gyroscope bias

- When solving $\Xi X = S$, we are solving $\mathrm{argmin}_X \, ||\Xi X - S||^2$;
- Unfortunately, we can not express the gyroscope bias linearly;
- Alternative: non-linear minimization

$$cost(B) = \underset{X}{\mathrm{argmin}} \, ||\Xi X - S||^2 + \lambda \times |B|$$

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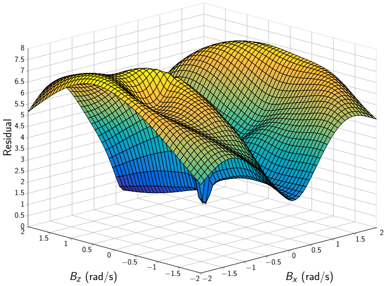

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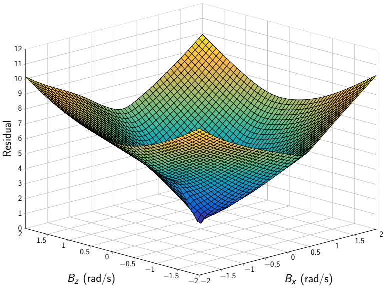
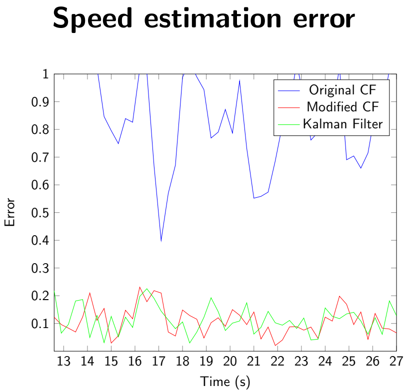


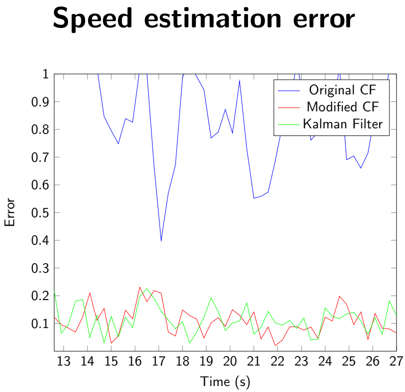
With regularization $\lambda = 3$

Results



Speed 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:

- Does not require initialization;
- Provides the gyroscope bias.

Conclusion

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   - No initialization required;
   - Recovers the absolute scale.

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4. **Method to estimate this bias**;

Conclusion

1. Closed-form solution for visual-inertial fusion;
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4. **Method to estimate this bias**;
5. Works well in practice;

Conclusion

1. Closed-form solution for visual-inertial fusion;
   - No initialization required;
   - Recovers the absolute scale.
2. Does not work well in practice;
3. Gyroscope bias is a performance bottleneck;
4. **Method to estimate this bias**;
5. Works well in practice;
6. Also provides the gyroscope bias.

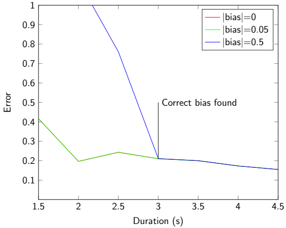
Future work

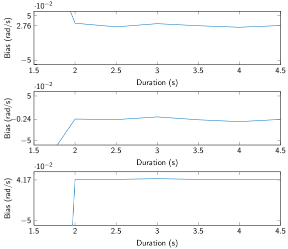
Implementation on a real platform

Thank you for your attention,
Any question?

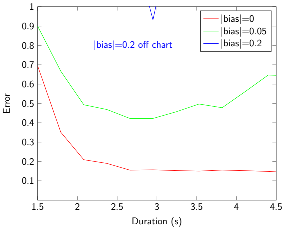
Gyroscope bias estimation

Optimized Closed-form solution





Original Closed-form
solution



Numerical stability

$$\left[\begin{array}{rcl} S_j & = & \lambda_1^1\mu_1^1 - Vt_j - G\,\frac{t_j^2}{2} - \lambda_j^1\mu_j^1 \\ 0_3 & = & \lambda_1^1\mu_1^1 - \lambda_j^1\mu_j^1 - \lambda_1^i\mu_1^i + \lambda_j^i\mu_j^i \end{array}\right.$$

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