

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

Jacques Kaiser

Supervised by Dr. Agostino Martinelli

INRIA



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Micro aerial vehicles



Micro aerial vehicles



Micro aerial vehicles



Micro aerial vehicles



Micro aerial vehicles



Localisation in various environments

Micro aerial vehicles



Global Frame

Localisation in various environments

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

Micro aerial vehicles



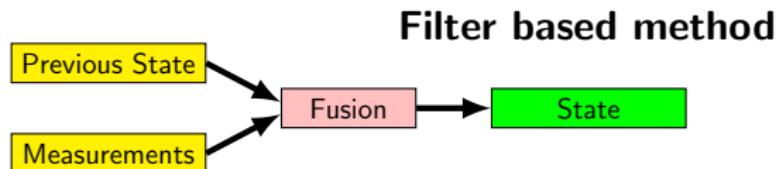
Global Frame

Localisation in various environments

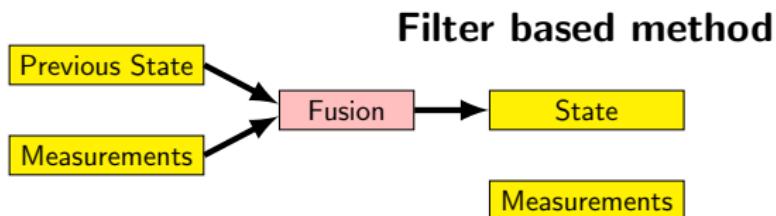
A basic state vector: $X = \begin{bmatrix} \textit{position} \\ \textit{velocity} \\ \textit{orientation} \end{bmatrix}$

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

Visual-inertial sensor fusion

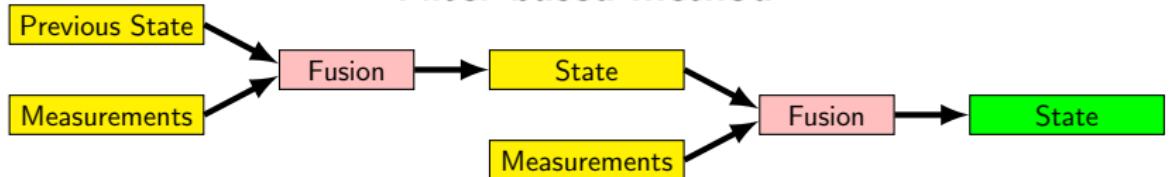


Visual-inertial sensor fusion

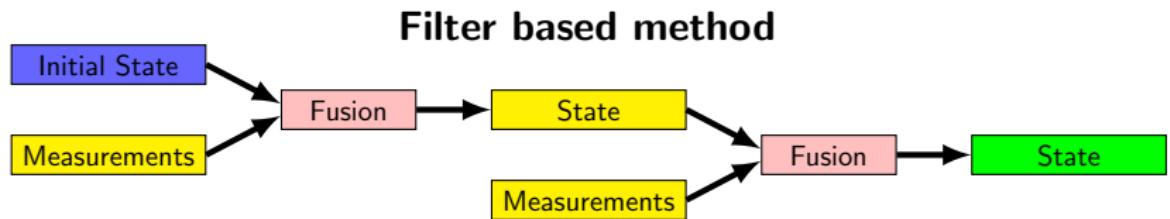


Visual-inertial sensor fusion

Filter based method

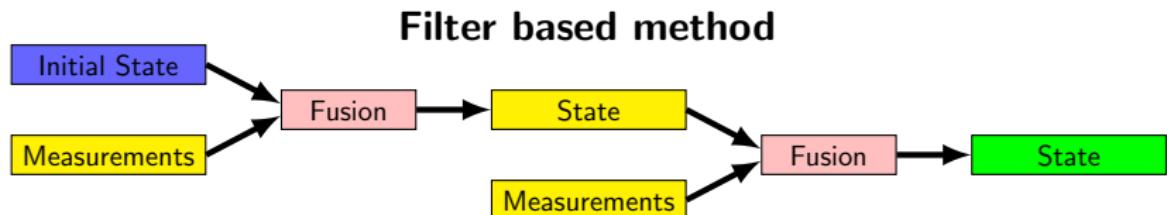


Visual-inertial sensor fusion



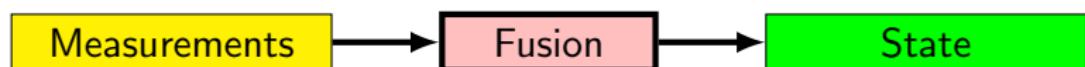
How to recover the **initial state**?

Visual-inertial sensor fusion

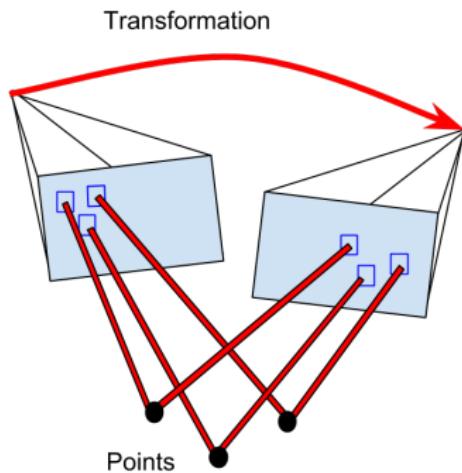


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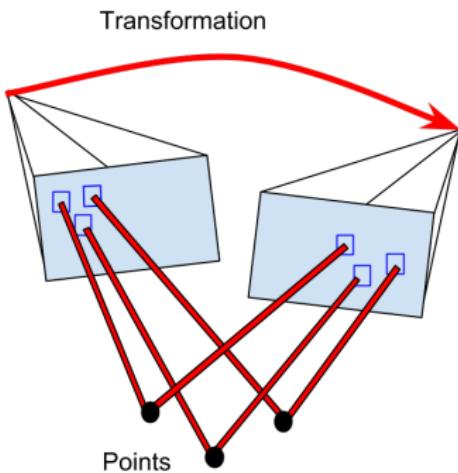
We need a **deterministic solution**



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

[Back to the title](#)

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[Back to the title](#)

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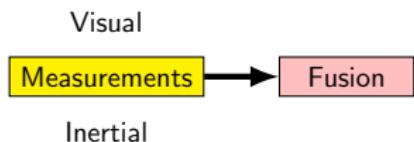
Visual

Measurements

Inertial

Back to the title

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Back to the title

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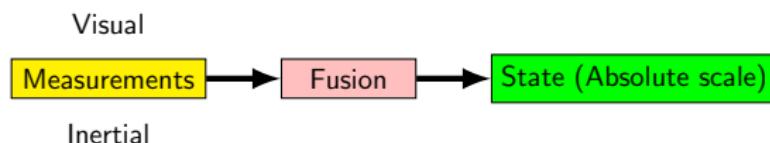


Table of Contents

Sensor fusion

- Filter based fusion

- Deterministic solution

- Absolute scale

The closed-form solution

- Linear system

- Identifying performance bottlenecks

- Estimating the gyroscope bias

- Validation

Conclusion

The closed-form solution

Transactions on Robotics (T-RO) 2012

International Journal of Computer Vision (IJCV) 2014

The Closed-Form Solution - 2014

Requires:

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

Output:

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

The Closed-Form Solution - 2014

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$$\begin{bmatrix} S_2 = \lambda_1^1 \mu_1^1 - V t_2 - G \frac{t_2^2}{2} - \lambda_2^1 \mu_2^1 \\ S_2 = \lambda_1^2 \mu_1^2 - V t_2 - G \frac{t_2^2}{2} - \lambda_2^2 \mu_2^2 \\ \vdots \\ S_3 = \lambda_1^1 \mu_1^1 - V t_3 - G \frac{t_3^2}{2} - \lambda_3^1 \mu_3^1 \\ \vdots \\ S_N = \lambda_1^{n_i} \mu_1^{n_i} - V t_N - G \frac{t_N^2}{2} - \lambda_N^{n_i} \mu_N^{n_i} \end{bmatrix}$$

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$$\Xi X = S$$

Problem: not robust in practice

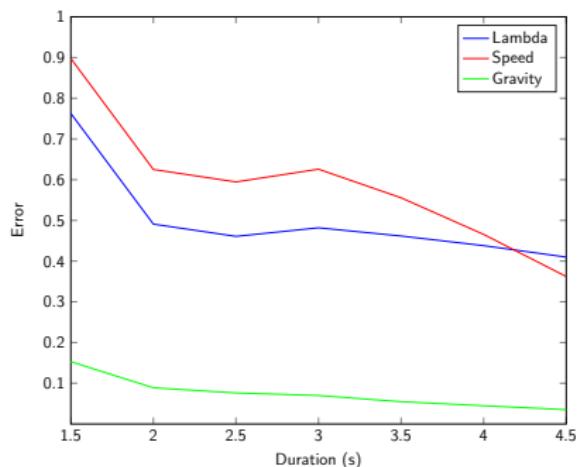
"A closed-form solution for state estimation with a visual-inertial system that does not require initialization was presented. However, this approach is not suitable for systems that rely on noisy sensor data"

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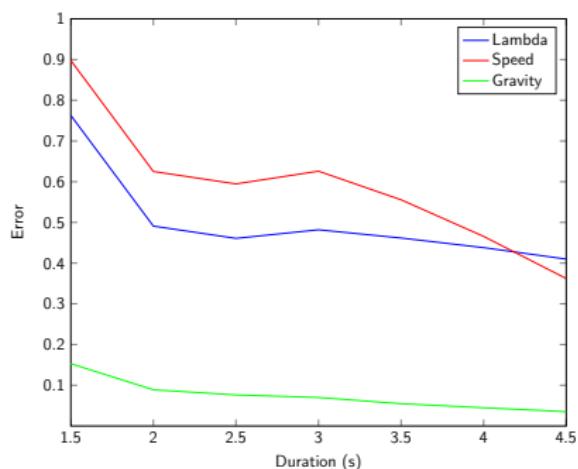
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50% relative error on speed and distance estimation

Improving the performance

What makes the estimations so bad?

Possible bottlenecks

- ▶ Motion;

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

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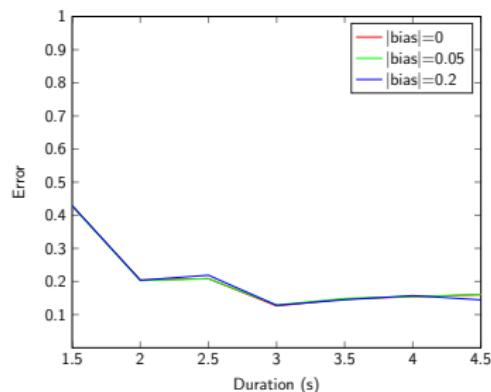
$$N(\mu + B, \sigma^2)$$

We considered:

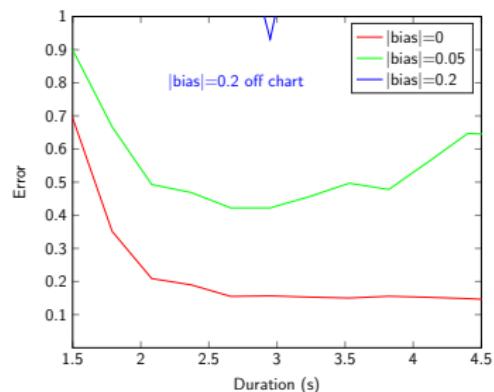
- ▶ Biased accelerometer;
- ▶ Biased gyroscope.

Biased inertial measurements

Speed estimation error



Varying accelerometer bias



Varying gyroscope bias

Estimating the gyroscope bias

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- ▶ Alternative: non-linear minimization

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

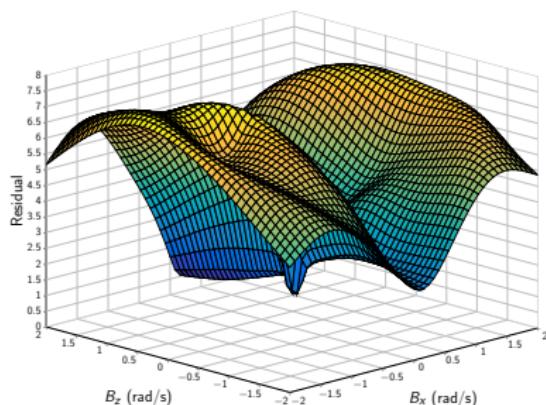
With B the gyroscope bias, Ξ and S computed with respect to B

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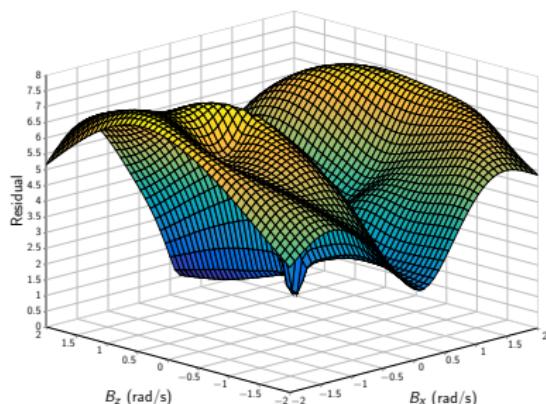


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$$\text{cost}(B) = \operatorname{argmin}_X \|\Xi X - S\|^2 + \lambda \times |B|$$

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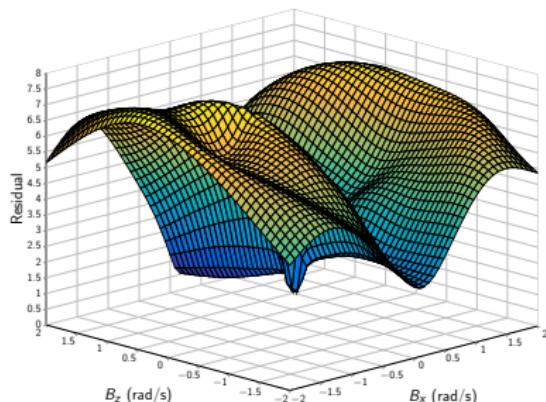
Symmetry induced by the strong weight of the gravity

Estimating the gyroscope bias

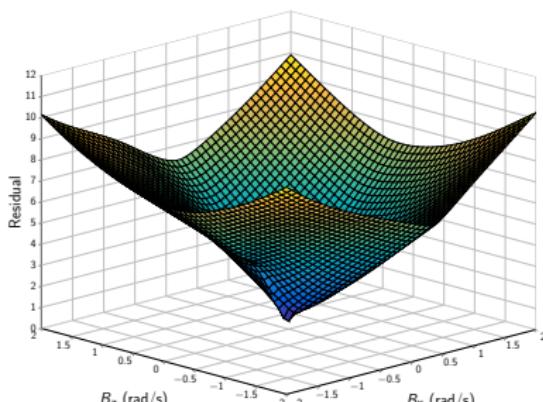
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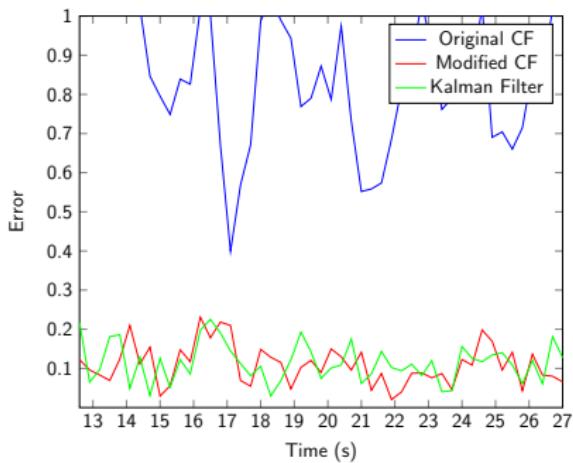
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With regularization $\lambda = 3$

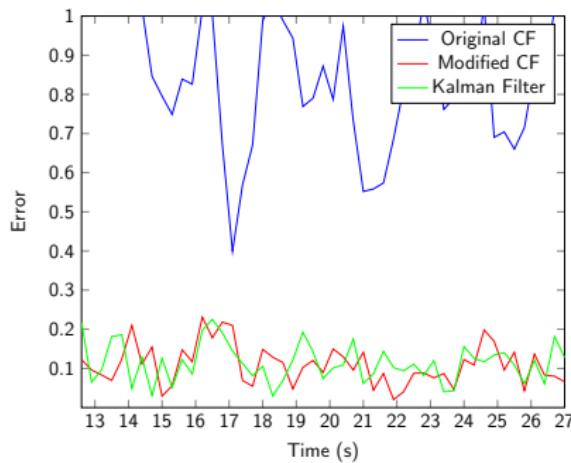
Results

Speed estimation error



Results

Speed estimation error



Moreover, our technique:

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

Conclusion

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 - ▶ No initialization required;
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1. Closed-form solution for visual-inertial fusion;
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4. **Method to estimate this bias;**

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1. Closed-form solution for visual-inertial fusion;
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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

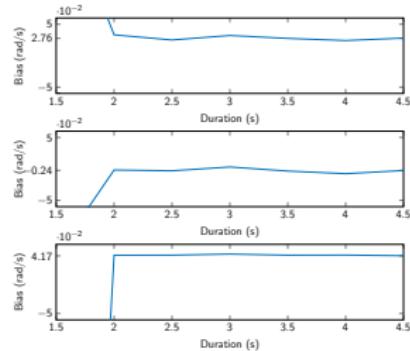
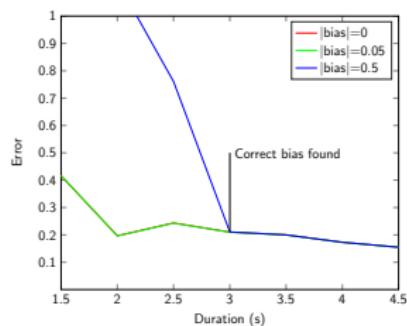
Implementation on a real platform



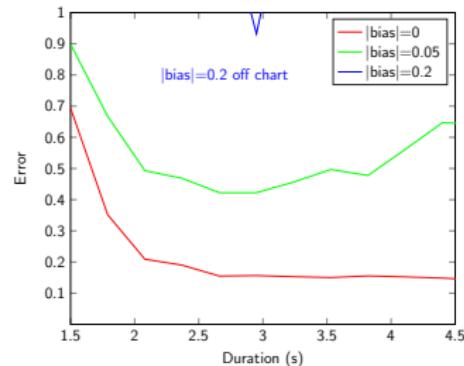
Thank you for your attention,
Any question?

Gyroscope bias estimation

Optimized Closed-form solution



Original Closed-form solution



Numerical stability

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

