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

Jacques Kaiser
Supervised by Dr. Agostino Martinelli

INRIA

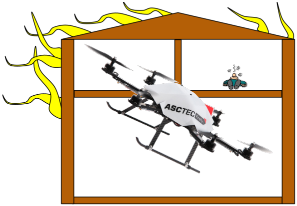
June 24, 2015

Micro aerial vehicles

Micro aerial vehicles

Micro aerial vehicles

Micro aerial vehicles



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

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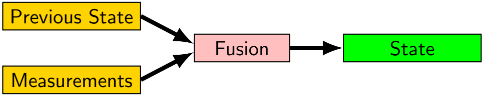
Localization in **various environments**

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

Visual-inertial sensor fusion

Filter based method



Visual-inertial sensor fusion

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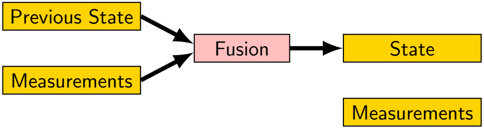

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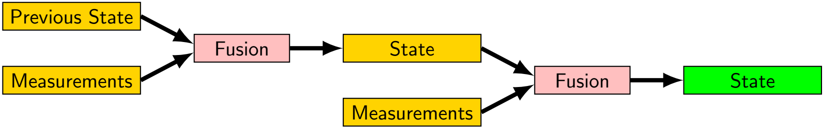

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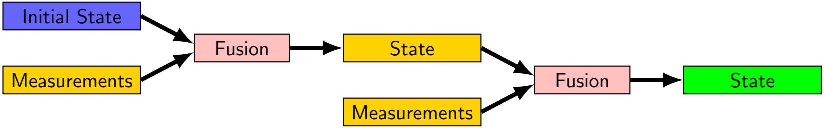
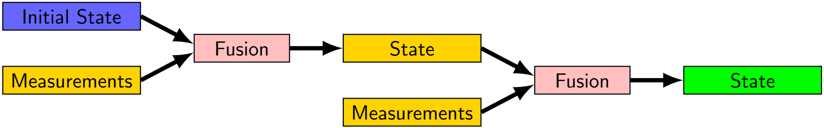


How to recover the **initial state**?

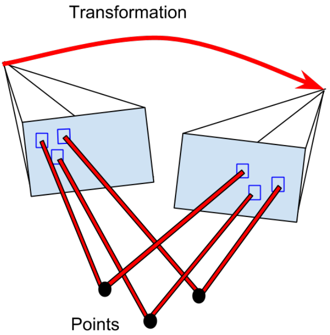
Visual-inertial sensor fusion

Filter based method

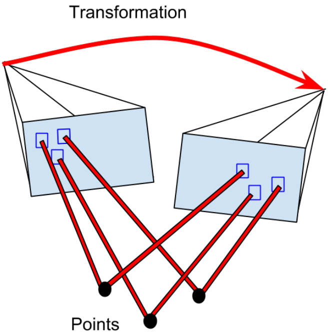


How to recover the **initial state**?
We need a **deterministic solution**

Deterministic solutions in Computer Vision



Deterministic solutions in Computer Vision



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

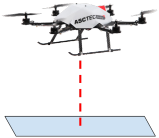
Absolute scale from visual measurements

How big is this building?

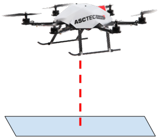
Absolute scale from visual measurements

Methods to recover the absolute scale

Methods to recover the absolute scale

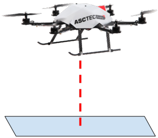


Methods to recover the absolute scale



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).

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Visual

Measurements

Inertial

Back to the title

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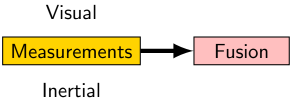

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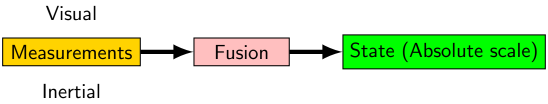

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The closed-form solution

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;
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Test setup

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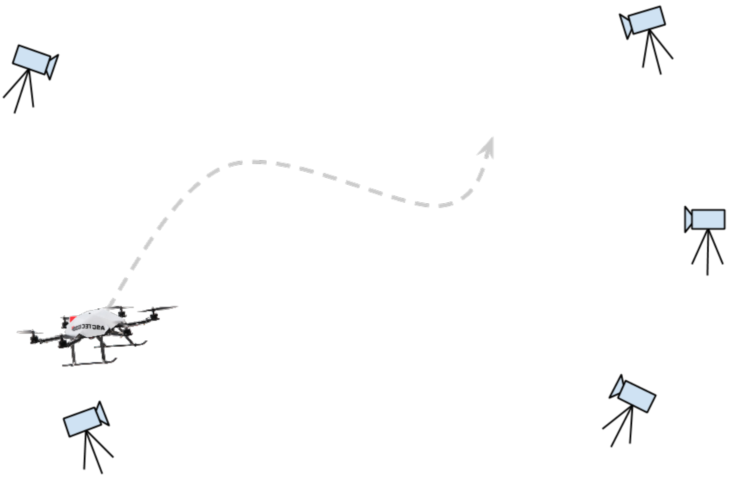

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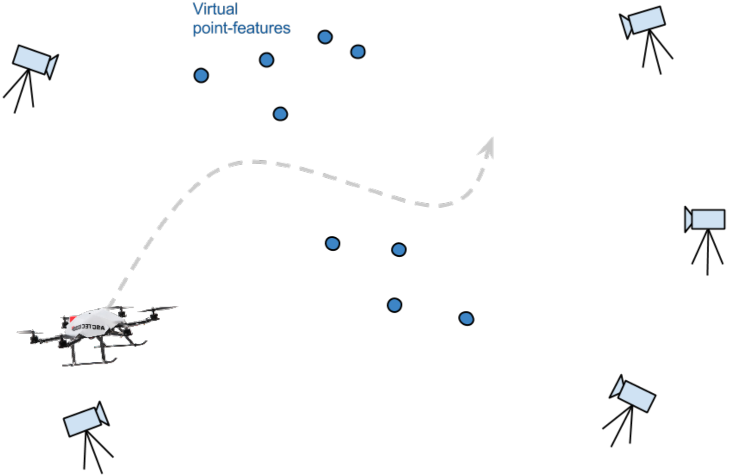

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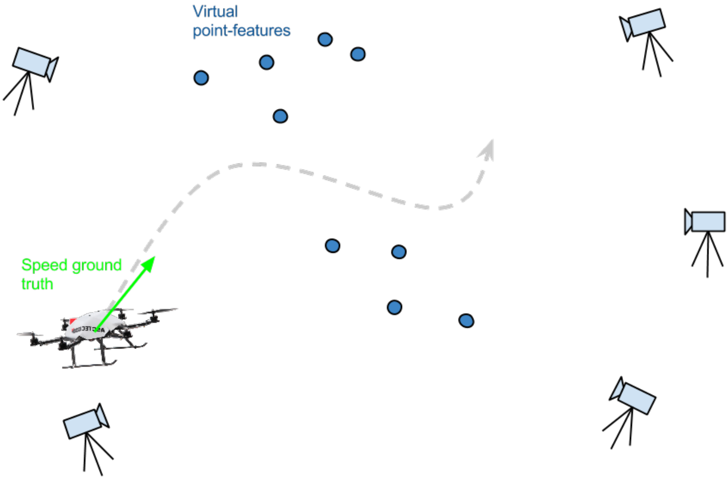

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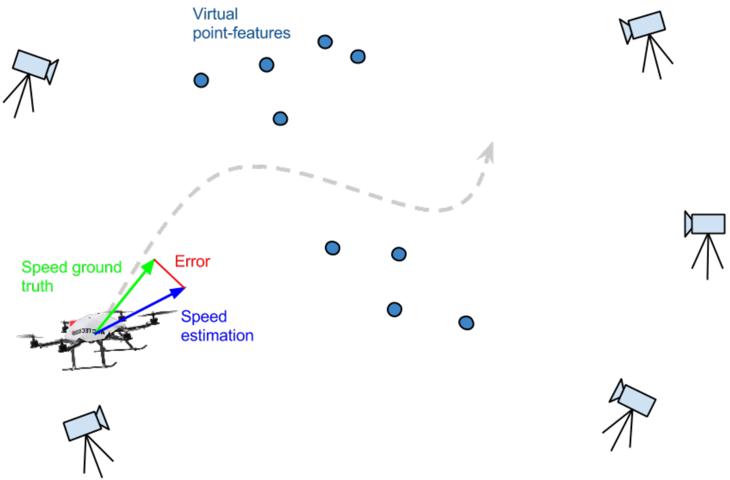
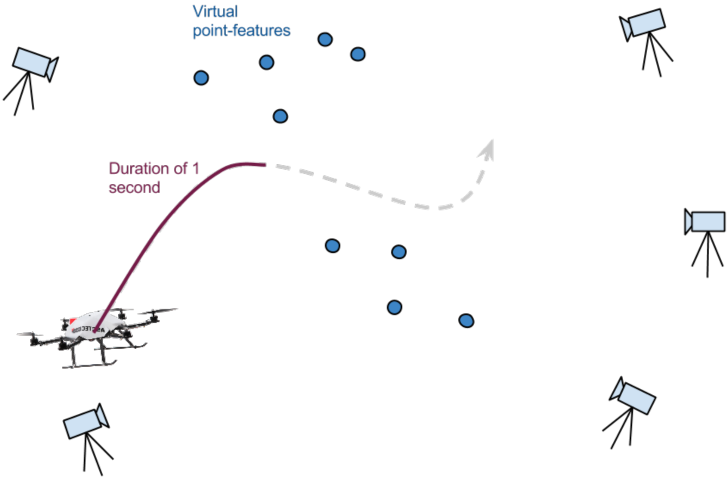


Virtual
point-features
Speed ground
truth
Error
Speed
estimation

Test setup



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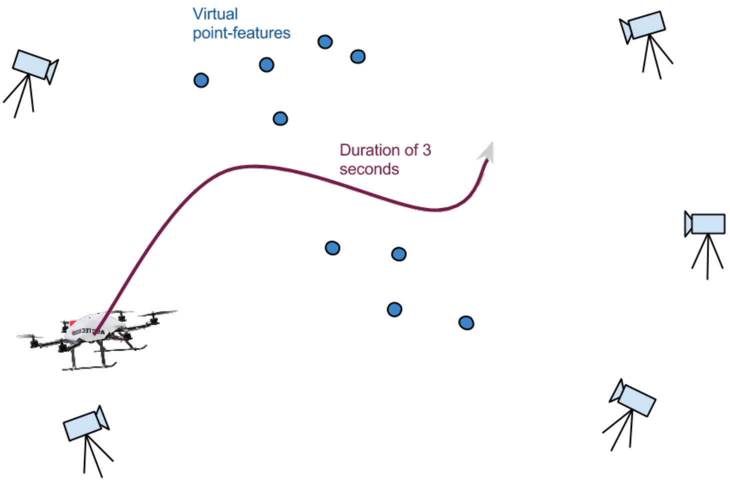

Problem: not robust in practice

> "**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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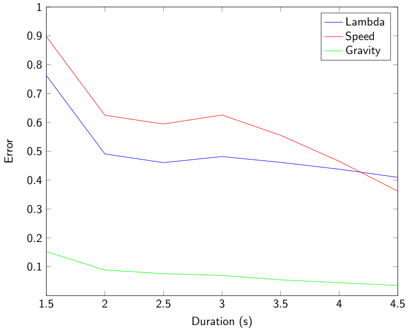

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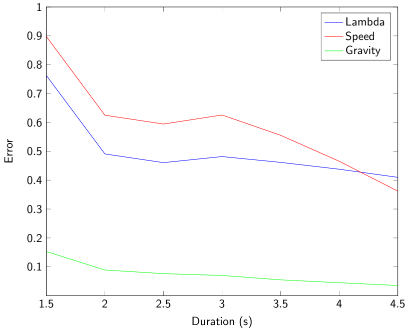

50% relative error on speed and distance estimation

Improving the performance

What makes the estimations so bad?

Possible bottlenecks

- Motion;

Improving the performance

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Sensors provide measurements affected by a Gaussian noise:

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

Improving the performance

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Possible bottlenecks

- Motion;
- Observed features;
- Noisy sensors.

Sensors provide measurements affected by a Gaussian noise:

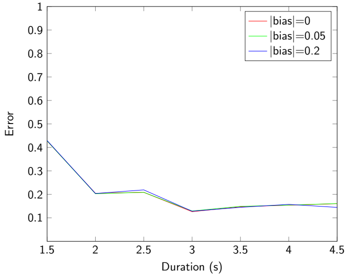
$$N(\mu + B, \sigma^2)$$

We considered:

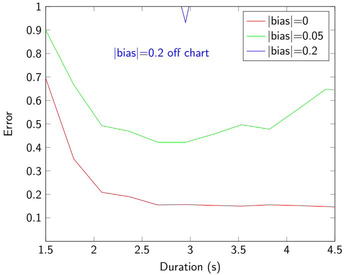
- Biased accelerometer;
- Biased gyroscope.

Biased inertial measurements

Speed estimation error



Varying accelerometer bias



Varying gyroscope bias

Estimating the gyroscope bias

Reminder: $\Xi X = S$

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- Insert the gyro bias B in X;

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- ~~Insert the gyro bias B in X;~~
- Alternative: non-linear minimization of the residual

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

With:
B the gyroscope bias,

Ξ and S computed with respect to B

Estimating the gyroscope bias

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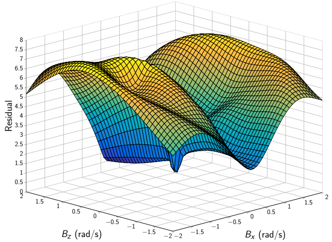

Cost function: residual with respect to gyroscope bias

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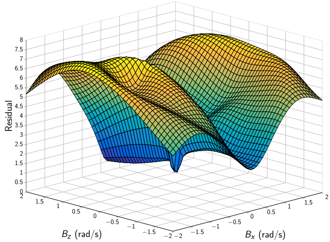
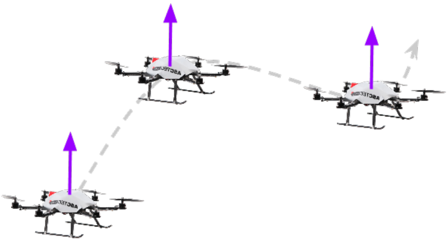


Cost function: residual with respect to gyroscope bias

Symmetry induced by the strong weight of the gravity

Dealing with the symmetry



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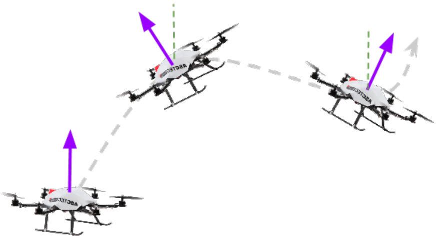

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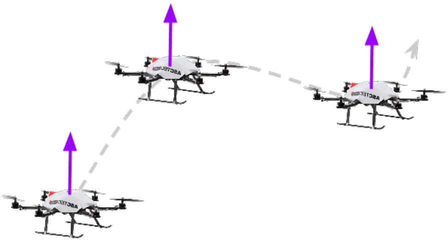

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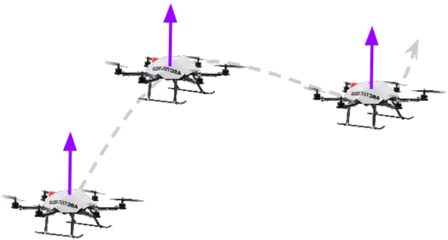
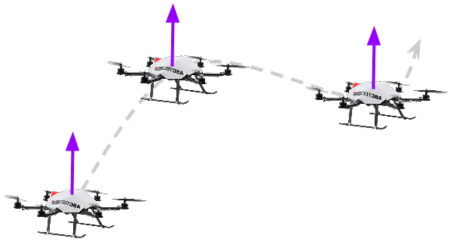


We tweak the cost function:

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

Dealing with the symmetry



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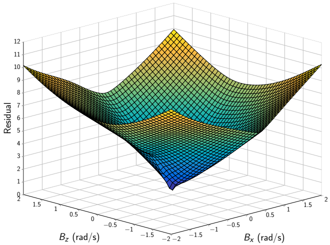
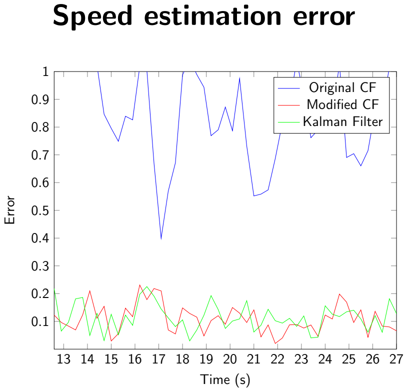
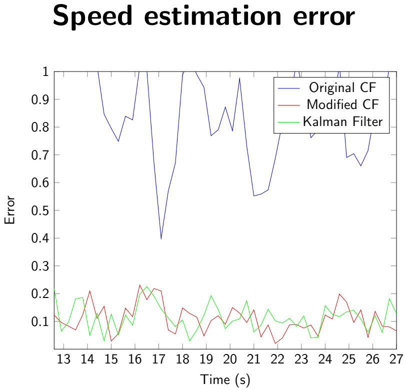


Regularized cost function with $\lambda = 3$

Results


Speed estimation error
Original CF
Modified CF
Kalman Filter
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

Results



Moreover, our technique:

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

Conclusion

Conclusion

Before:

- Method for state estimation without initialization;
- Does not work well in practice.

After:

- Gyroscope bias is the bottleneck;
- Method to factor it out.

Future work

Implementation on a real platform

Thank you for your attention,
Any question?

The Closed-Form Solution

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- Calibrated camera;
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Requires:

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

The Closed-Form Solution

Requires:

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

The Overconstrained Linear System

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

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

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

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

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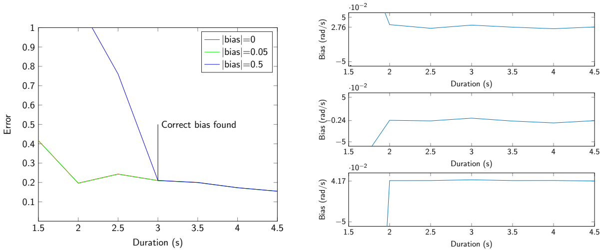
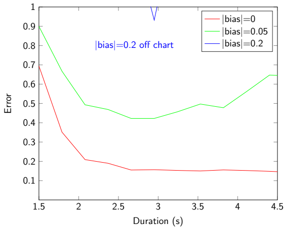
$$\Xi X = S$$

Gyroscope bias estimation

Optimized Closed-form solution



Original Closed-form solution



Numerical stability

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

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