Particle Filter SLAM with High Dimensional Vehicle Model

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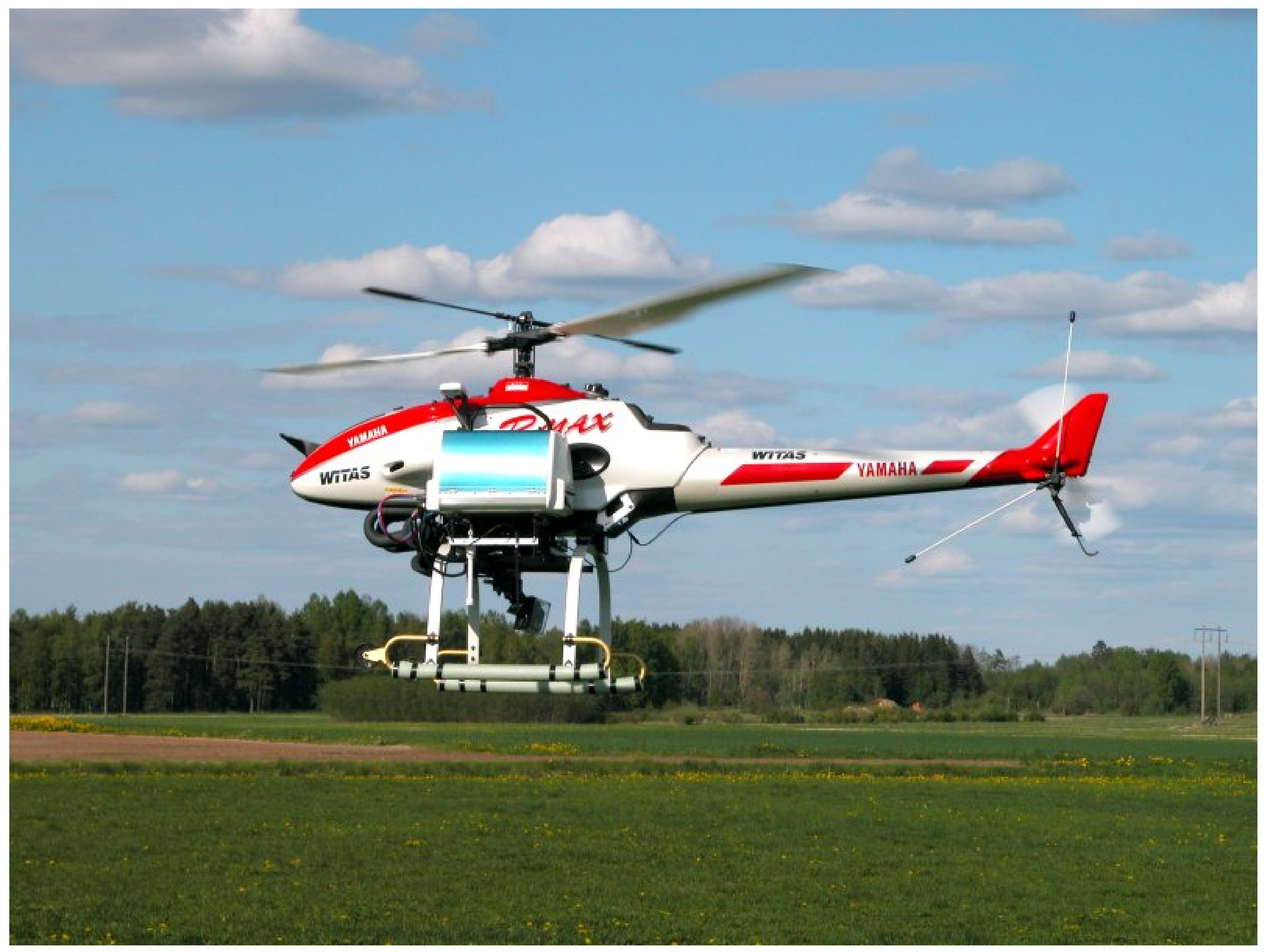
Contributions

The contributions of this work are to:

- Handle high dimensional vehicle models in the Particle Filter SLAM framework
- Unifying FastSLAM and Rao-Blackwellized Particle Filter
- Perform validation experiments using real data from a UAV

Test Platform

The derived algorithm is applied to experimental data from an autonomous aerial vehicle using the RMAX helicopter platform (see image below).



Framework

- The vehicle states are: position, velocity, acceleration, quaternions (orientation), angular velocity and biases for accelerometer and gyro. The features in the map also have one state per feature consisting of its 3D position.
- The states are divided into three parts, position and orientation in x_t^p, the rest of the vehicle states in x_t^k and the map in m_t.

$$x_t = \left((x_t^p)^T \; (x_t^k)^T \; m_t^T\right)^T$$

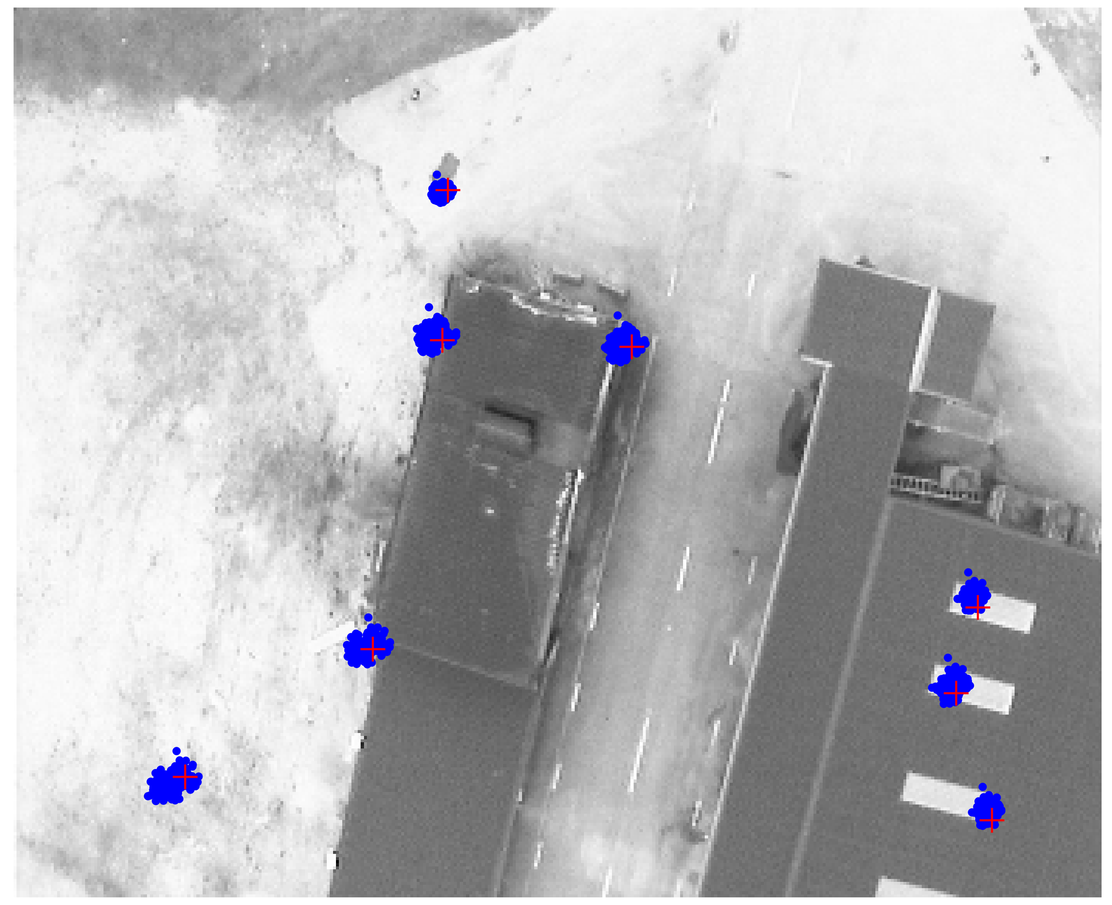
The state partitioning makes the following key factorization possible

$$p(x_{1:t}^p, x_t^k, m_t | y_{1:t}) = \prod_{j=1}^{M_t} \underbrace{p(m_{j,t}|x_{1:t}^p, x_t^k, y_{1:t}) p(x_t^k|x_{1:t}^p, y_{1:t})}_{\text{(extended) Kalman filter}} \underbrace{p(x_{1:t}^p|y_{1:t})}_{\text{particle filter}}.$$

- The navigation sensors are three accelerometers, three gyros, a pressure sensor, and a camera. GPS is used only for evaluation purposes.

Results

The camera view from the helicopter. The blue particle clouds represent the features and the red crosses are the measured feature positions.



Since SLAM, without closing the loop, is dead-reckoning there will be some drift. This is greatly reduced by the vision measurements.