Localisation accuracy of semi-dense monocular SLAM

Kristiaan Schreve

Stellenbosch University

kschreve@sun.ac.za

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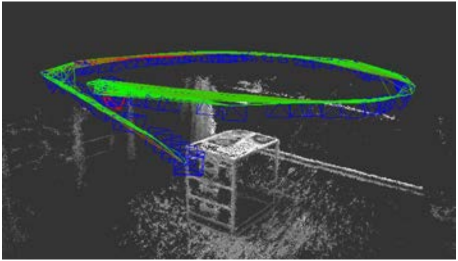
Overview I

Introduction I

- What is SLAM?
- What is monocular SLAM?
- Why semi-dense?
- Why monocular SLAM?
- Why is localisation accuracy important?



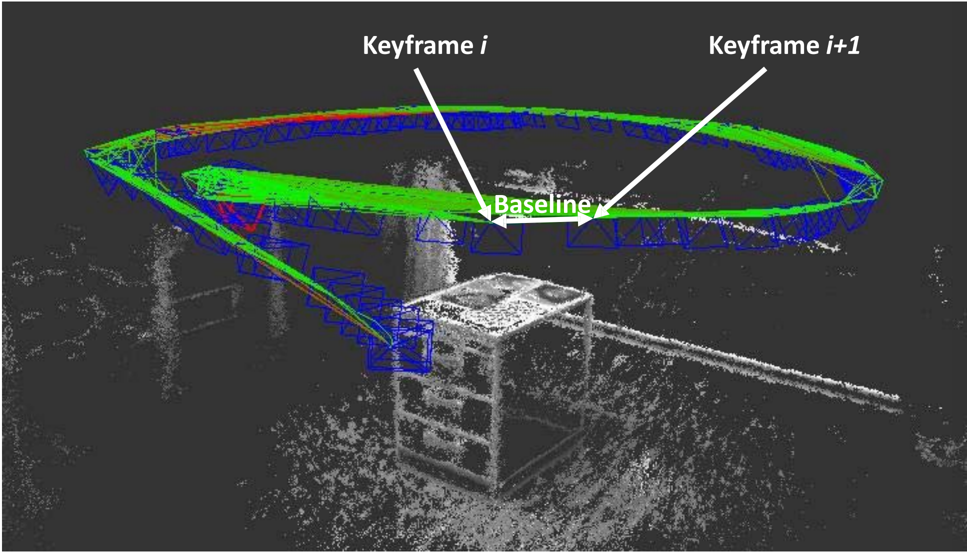
Introduction II

- Objective
  - Under ideal conditions, what is achievable?
- Method
  - Modelling and Simulation
  - Real world experiments

Modelling and Simulation I

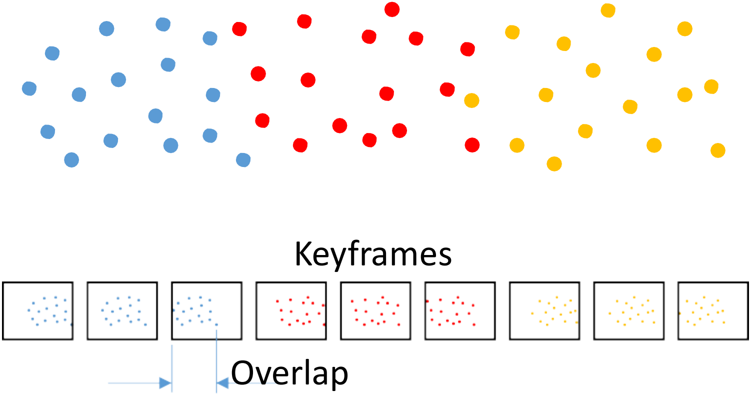
- Why simulation?
  - Reliable ground truth very difficult to obtain
  - Good control over system parameters Easier
  - to study effects of system parameters
- Assumptions:
  - Artificial Scene Points
  - Perfect point matching
  - No bias errors
  - No image distortion
  - Data scaled to real world coordinate system
  - Simulate 100 m straight line motion
- Based on ideas from LSD-SLAM and PTAM
- PTAM updates camera pose by doing a bundle adjustment on selected keyframes

Modelling and Simulation II



Modelling and Simulation III

Constant number of 3D scene points
(randomly distributed)



Scene 1

Scene 2

Scene 3

Keyframes

Overlap

Modelling and Simulation IV

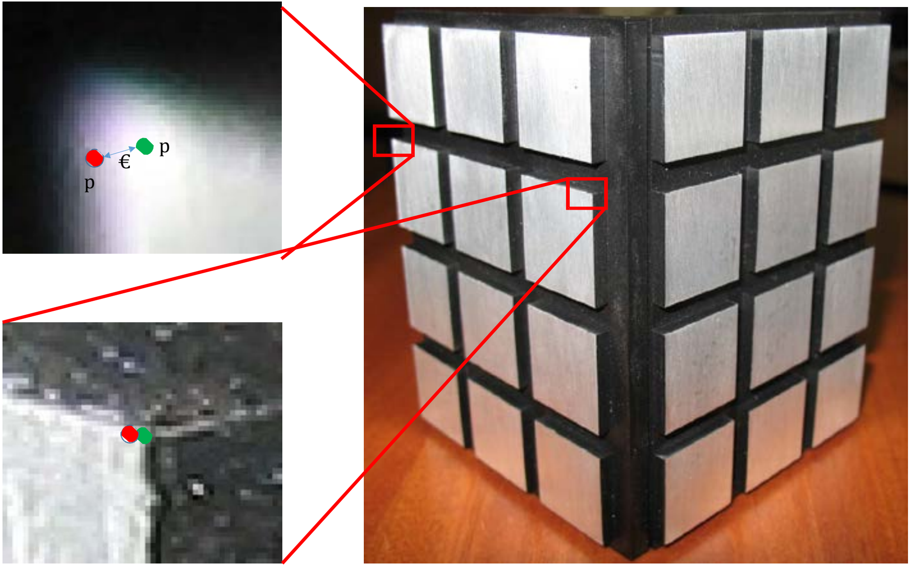
- Minimise

$$S = \sum_{i=0}^{2m-1} (E_i)^2$$

$$E_i = (p_{u_i} - \tilde{p}_{u_i}) \qquad i \in 0 \ldots m-1$$
$$E_i = (p_{v_i} - \tilde{p}_{v_i}) \qquad i \in m \ldots 2m-1$$

- Where
  - m is the number of scene points
  - where $(p_{u_i}, p_{v_i})^T$ is the originally identified image point
  - $(\tilde{p}_{u_i}, \tilde{p}_{v_i})^T$ is the back projected point

Modelling and Simulation V

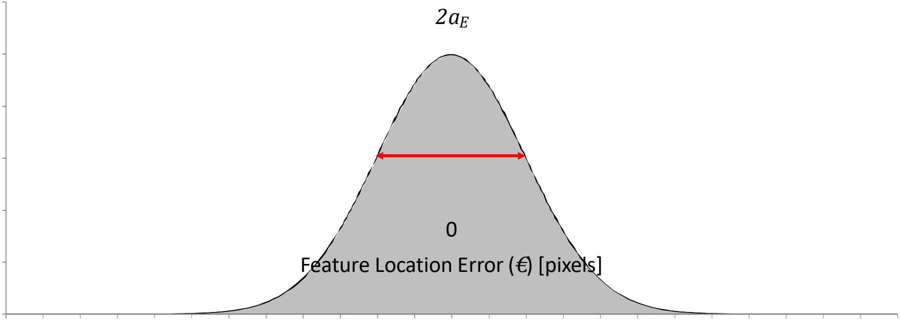


Modelling and Simulation VI

- Localisation uncertainty represented by measurement noise covariance R_t
- R_t influenced by bundle adjustment step (function of camera pose).
- Use Law of Error Propagation to estimate R_t. For least squares problems, this is

$$R_t = \frac{2S}{n-p}H^{-1}$$

- H is the Hessian of the cost function $S = \sum_{i=0}^{2m-1}(E_i)^2$ (Hessian of S with respect to camera pose parameters)
- n is the number of system equations, i.e. $n = 2m$
- p is the number of variables to be solved.
- We need a value for S



$$\sigma_E^2 = \frac{\sum_{i=0}^{2m-1}(E_i - \overline{E})^2}{2m} = \frac{S}{2m}$$

Modelling and Simulation VIII

- Using the Law of Error Propagation, it is known that

$$\sigma_E^2 = J_s \Lambda J_s^T$$

- Where
  - J_s is the Jacobian of S

$$J_s = \left[\frac{\partial S}{\partial \lambda}, \frac{\partial S}{\partial f}, \frac{\partial S}{\partial x}, \frac{\partial S}{\partial y}, \frac{\partial S}{\partial z}, \frac{\partial S}{\partial \varphi}, \frac{\partial S}{\partial \vartheta}, \frac{\partial S}{\partial \psi}, \frac{\partial S}{\partial u_1}, \frac{\partial S}{\partial v_1}, \ldots, \frac{\partial S}{\partial u_m}, \frac{\partial S}{\partial v_m} \right]$$

  - Λ is the covariance matrix of the input variables (focal length, scale factor, camera pose, image points)

Experiments - Simulation I

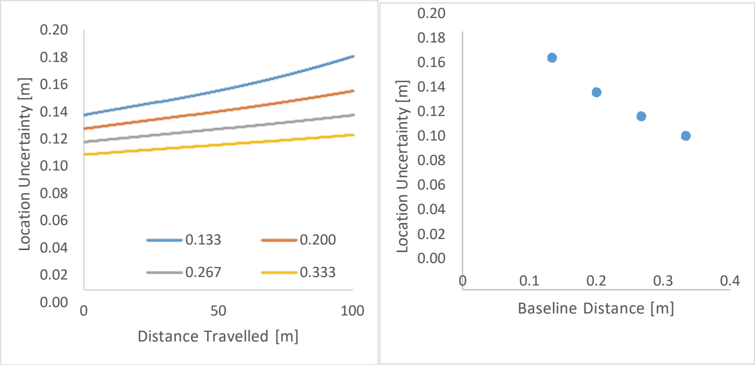


Figure: Camera uncertainty when varying the effective baseline.

Experiments - Simulation II

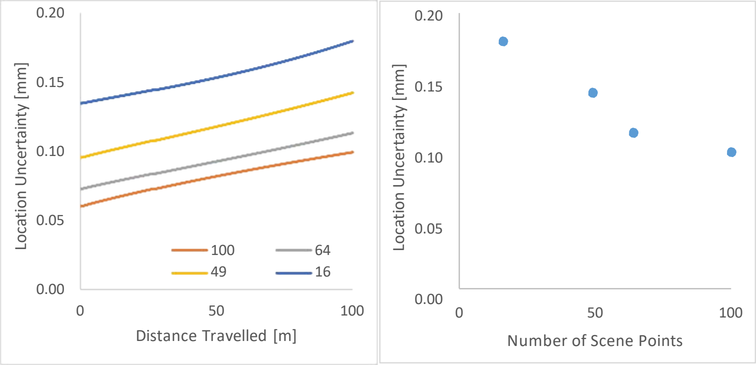


Figure: Camera uncertainty when varying the number of scene points.

Experiments - Simulation III

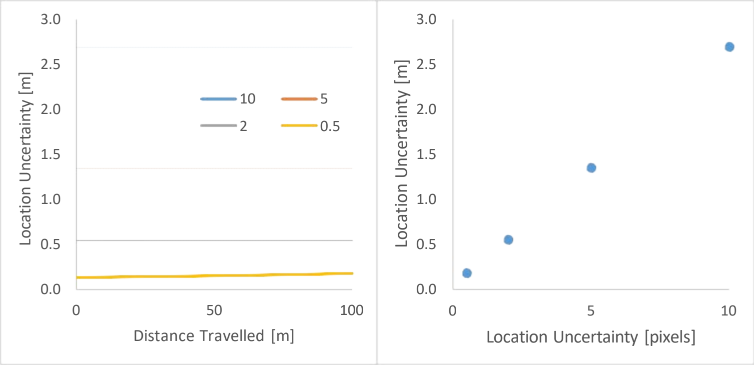


Figure: Camera uncertainty when varying the image point location uncertainty.

1. USB webcam (Logitech c170 with 640x480 resolution)
2. Measurement wheel (GRIP GT9050)
3. GoPro Hero 3 (used for distance scaling)
4. Tape
5. Laptop running LSD-SLAM

Experiments - Real world I

Figure 1: Experiment hardware setup.

Figure: Experiment hardware setup. 1) USB webcam (Logitech c170 with 640x480 resolution) 2) Measurement wheel 3) GoPro Hero 3 (used for distance scaling) 4) Tape 5) Laptop running LSD-SLAM

Experiments - Real world II

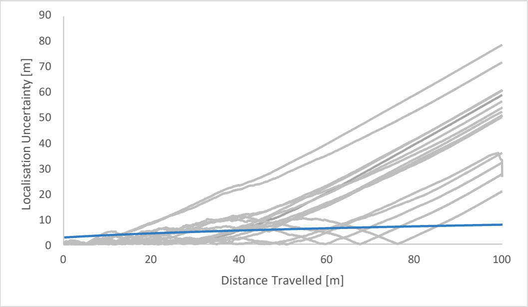


Figure: Experimental results compared with simulation results. The grey curves are the experimental results scaled after a distance of 5 m. The blue curve is a comparable simulation result.

Conclusions I

- Simulation showed influence of systems parameters
  - Increasing baseline reduces localisation uncertainty
  - Effect of number of scene points decreases asymptotically
  - Linear dependence on feature location accuracy
- Real world experiments
  - Large errors associated with monocular SLAM

Thank You