Efficient Visual-Inertial Navigation using IMU Pre-integration

Liyang Liu

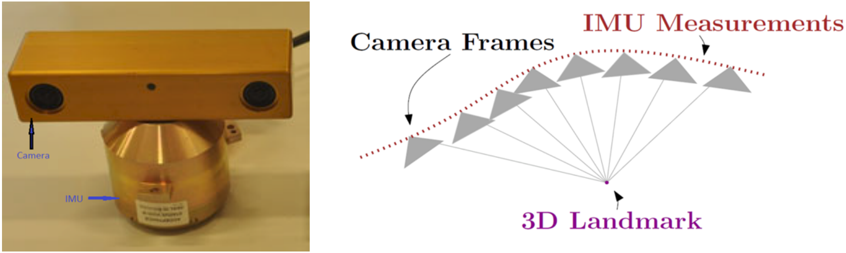
Centre for Autonomous Systems

University of Technology Sydney

May 23, 2016

Visual Inertial SLAM

Introduction



(a) (b)

Figure: *a*) Sensors: Camera+IMU ?, *b*) Sensor information ?

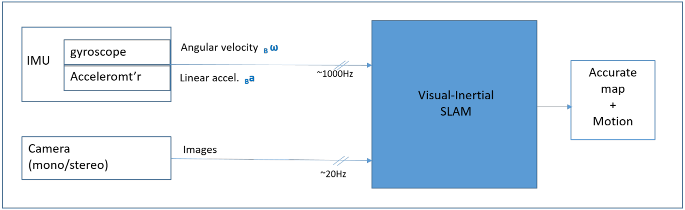


Figure: VIN data flow

The Vin problem

UTS:CAS
CENTRE FOR AUTONOMOUS SYSTEMS

Gauss-Newton Framework

Needs to linearize f(**x**), given:
- Parameterization of **x**, **z**
- f(**x**)
- *Jacobian(* f(**x**) *)*
- $\boldsymbol{\Sigma}_z$

A constrained optimization problem: assuming Gaussian observation

$$\min(\|\boldsymbol{z} - f(\boldsymbol{x})\|^2_{\boldsymbol{\Sigma}_z})$$

ML (maximum likelihood) of state space

$$\boldsymbol{x}_{1:T}, \boldsymbol{m} = \underset{\boldsymbol{x}_{1:T},\ \boldsymbol{m}}{\operatorname{argmax}} (p(\boldsymbol{z}_{1:T} \mid \boldsymbol{x}_{1:T}, \boldsymbol{m}, \boldsymbol{u}_{1:T}, \boldsymbol{x}_0))$$

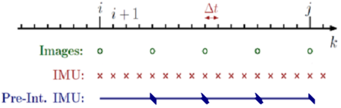


Fig. : Different rates for IMU and camera.

- Nave parameterization:
  - $\boldsymbol{x}$: pose, orientation, velocity $\{R_t, {}_{\mathrm{W}}\boldsymbol{p}_t, {}_{\mathrm{W}}\boldsymbol{v}_t\}, t \in [0, T_{total}]$ for IMU smpls
  - $\boldsymbol{z}$: all IMU data points $\{{}_{\mathrm{B}}\boldsymbol{\omega}_t, {}_{\mathrm{B}}\boldsymbol{a}_t\}$ feature observations $\{\boldsymbol{z}_{il}\}, i \in I_{total}, l \in C_i$

    I_{total} : all images, C_l : correspondences in frm body frame
  - $\Sigma_{\boldsymbol{z}}$: η^g - angular rate noise, η^a - lin noise, η^i - image uv noise
- Infeasible:
  - Too much observation data
  - Re-compute integration at each new linearization (e.g. rotation R_t).

Example

- example 1
- example 2

Title

normal block – colors can be changed easily

$$\sum \log(x_i) \tag{1}$$

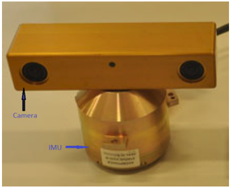


Figure: Sensors: Camera + IMU