On learning pseudo-sensors to improve egomotion estimation for mobile autonomy

by

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Abstract

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The ability to estimate *egomotion*, that is, to track one's own pose through an unknown environment, is at the heart of safe and reliable mobile autonomy. By inferring pose changes from sequential sensor measurements, egomotion estimation forms the basis of mapping and navigation pipelines, and permits mobile robots to self-localize within environments where external localization sources are intermittent or unavailable. Visual and inertial egomotion estimation, in particular, have become ubiquitous in mobile robotics due to the availability of high-quality, compact, and inexpensive sensors that capture rich representations of the world. To remain computationally tractable, 'classical' visual-inertial pipelines (like visual odometry and visual SLAM) make simplifying assumptions that, while permitting reliable operation in ideal conditions, often lead to systematic error. In this thesis, we present several data-driven learned *pseudo-sensors* that serve to augment conventional pipelines by inferring latent information from the same sensor data. Our approach retains much of the benefits of traditional pipelines, while leveraging high-capacity hyper-parametric models to extract complementary information that can be used to improve uncertainty quantification, correct for systematic bias, and improve robustness to difficult-to-model deleterious effects. We validate our pseudo-sensors on several kilometres of sensor data collected in sundry settings such as urban roads, indoor labs, and planetary analogue sites in the Canadian high arctic.

Epigraph

A little learning is a dangerous thing;
drink deep, or taste not the Pierian
spring: there shallow draughts
intoxicate the brain, and drinking
largely sobers us again.

Alexander Pope

The universe is no narrow thing and the order within it is not constrained by any latitude in its conception to repeat what exists in one part in any other part. Even in this world more things exist without our knowledge than with it and the order in creation which you see is that which you have put there, like a string in a maze, so that you shall not lose your way. For existence has its own order and that no man's mind can compass, that mind itself being but a fact among others.

Cormac McCarthy

Elephants don't play chess.

Rodney Brooks

To all those who encouraged (or, at least, *never discouraged*) my intellectual wanderlust.

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[2] especially the support and encouragement of Elyse
[3] in humouring my insatiable need for debate and banter (special thanks to Lee)

Contents

Notation

a	:	Symbols in this font are real scalars.
$\mathbf{a}$	:	Symbols in this font are real column vectors.
$\mathbf{A}$	:	Symbols in this font are real matrices.
$\mathcal{N}(\boldsymbol{\mu}, \mathbf{R})$	:	Normally distributed with mean $\boldsymbol{\mu}$ and covariance $\mathbf{R}$.
$E[\cdot]$	:	The expectation operator.
$\underrightarrow{\boldsymbol{\mathcal{F}}}_a$	:	A reference frame in three dimensions.
$(\cdot)^\wedge$	:	An operator associated with the Lie algebra for rotations and poses. It produces a matrix from a column vector.
$(\cdot)^\vee$	:	The inverse operation of $(\cdot)^\wedge$
$\mathbf{1}$	:	The identity matrix.
$\mathbf{0}$	:	The zero matrix.
$\mathbf{p}_a^{c,b}$	:	A vector from point b to point c (denoted by the superscript) and expressed in $\underrightarrow{\boldsymbol{\mathcal{F}}}_a$ (denoted by the subscript).
$\mathbf{C}_{a,b}$	:	The 3×3 rotation matrix that transforms vectors from $\underrightarrow{\boldsymbol{\mathcal{F}}}_b$ to $\underrightarrow{\boldsymbol{\mathcal{F}}}_a$: $\mathbf{p}_a^{c,b} = \mathbf{C}_{a,b}\mathbf{p}_b^{c,b}$.
$\mathbf{T}_{a,b}$	:	The 4×4 transformation matrix that transforms homogeneous points from $\underrightarrow{\boldsymbol{\mathcal{F}}}_b$ to $\underrightarrow{\boldsymbol{\mathcal{F}}}_a$: $\mathbf{p}_a^{c,a} = \mathbf{T}_{a,b}\mathbf{p}_b^{c,b}$.

Chapter 3

Classical Visual Odometry

> Eventually, my eyes were opened, and I really understood nature.
>
> — Claude Monet

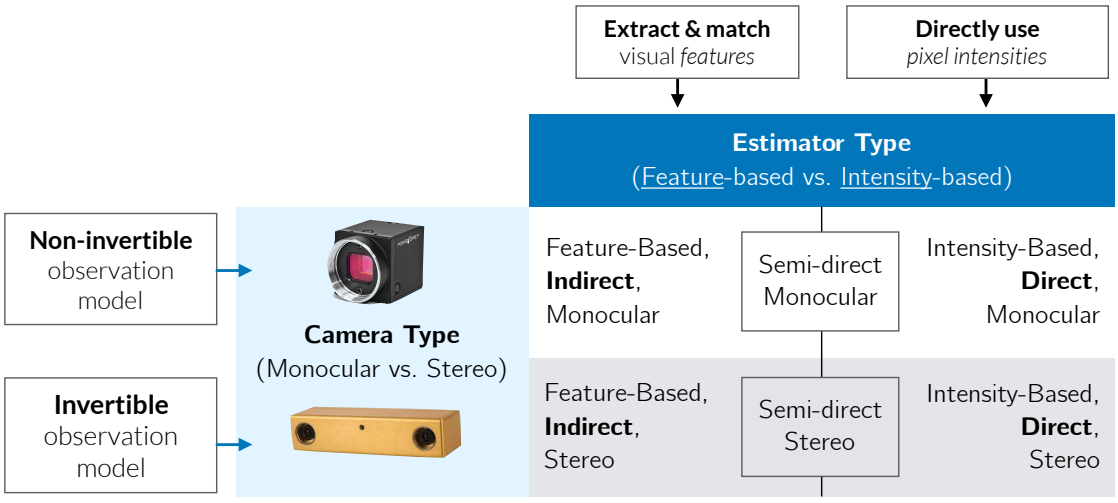


Figure 3.1: A taxonomy of different types of visual odometry.

Visual odometry (VO) has a rich history in mobile robotics and computer vision. As this dissertation largely deals with the improvement of a baseline visual odometry pipeline, we first outline the components of what we have chosen to be a canonical VO system. For a seminal tutorial on visual odometry and its more general cousin, visual SLAM, we refer the reader to two seminal papers: Scaramuzza and Fraundorfer (2011) and Cadena et al. (2016).

3.1 A taxonomy of VO

VO can be largely divided along two dimensions (Figure 3.1): (1) the type of camera used to capture images (monocular vs. stereo) and (2) the type of data association used to compute motion estimates (indirect, or feature-based vs. direct, or pixel intensity-based).

Monocular vs. Stereo: Monocular VO methods use a single camera to infer motion and can use a single compact, low-power vision sensor. They do not require any extrinsic calibration but must rely on known visual cues or external information (e.g., wheel odometry, inertial measurements) to provide metric egomotion estimates. Conversely, stereo VO methods use a stereo camera to triangulate objects with metric scale. This allows stereo VO to provide metrically-acurate egomotion estimates. However, stereo methods rely on accurate extrinsic calibration, and their ability to resolve depth is limited by the baseline distance between the stereo pair and by the quality of stereo matches (which can be degraded by self-similar textures, occlusions, and foreshortening effects).

Direct vs. Indirect: The second distinction is based on the type of data association used to match sequential images and infer motion. Direct methods make the assumption of brightness constancy, and attempt to *directly* maximize the similarity of pixel intensities. Indirect methods, however, rely on image features detectors to extract a set of salient landmarks, and then match these landmarks across images (typically through some sort of invariant descriptor).

3.2 A classical VO pipeline

In this thesis, we apply our learned pseudo-sensors to a baseline stereo, indirect visual odometry pipeline (Figure 3.2 largely based on the work of Furgale (2011). We choose this baseline system for its computational efficiency and robustness. We briefly summarize the main components of the pipeline here.

3.2.1 Preprocessing

During preprocessing, we use a lens model (assumed to be known apriori) to undistort each stereo image. Further, using the camera extrinsic parameters (also assumed to be known), we *rectify* the stereo pair such that the images can be assumed to come from two cameras whose principal axes are parallel (Figure 3.3). Finally, we also assume that the stereo camera intrinsics are known a priori or compute them through a calibration process (Furgale et al., 2013).

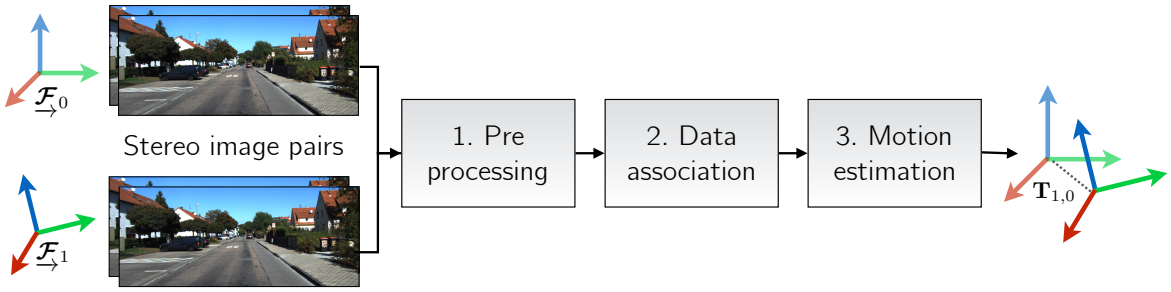
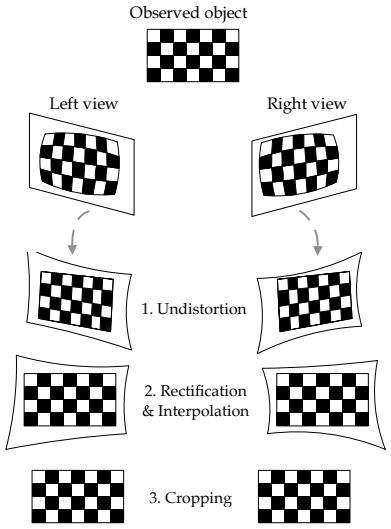
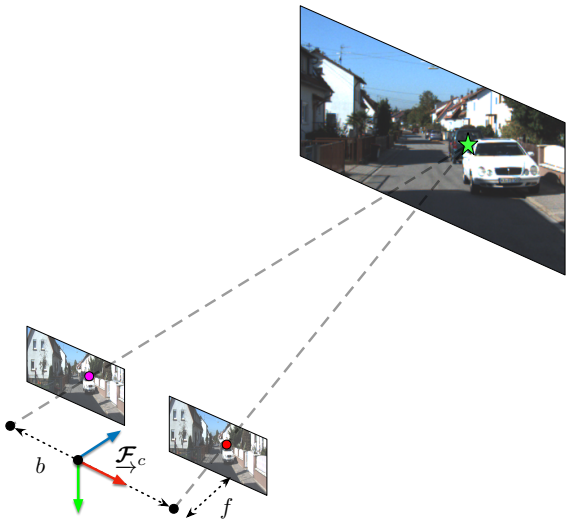


Figure 3.2: A 'classical' stereo visual odometry pipeline consists of several distinct components that have interpretable inputs and outputs.



(a) Rectification and undistortion process. Figure adapted from Florez (2010).



(b) Ideal stereo camera.

Figure 3.3: We pre-process stereo images (left) to simulate an ideal stereo camera (right).

3.2.2 Data Association

Feature Extraction and Matching

In this thesis, we focus on indirect stereo visual odometry for its computational efficiency. Although a number of different types of indirect feature extraction and matching methods can be used towards this end, we choose to use the `viso2` (Geiger et al., 2011) image feature extraction and matching algorithm as it is especially designed for sequential feature matching. In `viso2`, features are extracted using blob and corner masks with non-minimum and non-maximum suppression. Unlike other features detectors that do not assume a particular camera motion, `viso2` assumes a smooth camera trajectory that permits fast matching through a

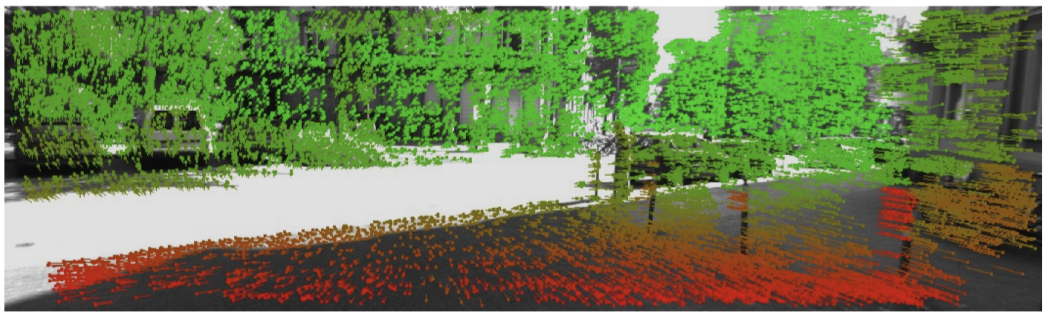


Figure 3.4: Feature tracking using `libviso2`, taken from Geiger et al. (2011). Colours correspond to depth.

simple sum-of-absolute-difference error metric based on Sobel filter responses. Features are matched across a stereo-pair and forward in time to ensure that a single feature exists across two consecutive stereo camera poses.

Each extract feature corresponds to a point in space, expressed in homogeneous coordinates in the camera frame as $\boldsymbol{p}_{i,c} := \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \end{bmatrix}^T \in \mathbb{P}^3$. Given our intrinsics and extrinsic calibration parameters, our idealized stereo-camera model, $\mathbf{f}$, projects a landmark expressed in homogeneous coordinates into image space, so that $\mathbf{y}_{i,c}$, the stereo pixel coordinates of landmark i in the camera frame, is given by

$$\mathbf{y}_{i,c} = \begin{bmatrix} u_l \\ v_l \\ u_r \\ v_r \end{bmatrix} = \mathbf{f}(\boldsymbol{p}_{i,c}) = \mathbf{M}\frac{1}{p_3}\boldsymbol{p}_{i,c}, \tag{3.1}$$

where

$$\mathbf{M} = \begin{bmatrix} f & 0 & c_u & f\frac{b}{2} \\ 0 & f & c_v & 0 \\ f & 0 & c_u & -f\frac{b}{2} \\ 0 & f & c_v & 0 \end{bmatrix}. \tag{3.2}$$

Here, $\{c_u, c_v\}$, $\{f_u, f_v\}$, and b are the principal points, focal lengths and baseline of the stereo camera respectively (computed through intrinsic calibration). Note that in this formulation, the stereo camera frame is centred between the two individual cameras.

Outlier Rejection

To filter out any residual outlier matches, we use a three-point random sample consensus algorithm (RANSAC, Fischler and Bolles (1981)) based on an analytic solution to the six degree-of-freedom motion (Umeyama, 1991).

3.2.3 Maximum Likelihood Motion Solution

Finally, we compute the rigid-body transform between to stereo camera frames using maximum likelihood estimation. We define the rigid-body transform, $\mathbf{T}_t \in \mathrm{SE}(3)$, to be the rigid-body transform between two subsequent stereo camera poses, $\underrightarrow{\mathcal{F}}_{c_0}$ and $\underrightarrow{\mathcal{F}}_{c_1}$. In other words,

$$\mathbf{T}_t = \mathbf{T}_{c_1 w} \mathbf{T}_{c_0 w}^{-1}, \tag{3.3}$$

where $\underrightarrow{\mathcal{F}}_w$ is a privileged world frame. After data association, we assume we have a set of N_t matches, $\{\mathbf{y}_{i,c_0}, \mathbf{y}_{i,c_1}\}_{i=1}^{N_t}$, between visual landmarks in the subsequent camera frames. For each match, we define an error function, $\mathbf{e}_i(\mathbf{T}_t)$, that relates the rigid transform to these stereo feature matches. Throughout this dissertation, we assume that these errors are corrupted by zero-mean independent Gaussian noise with the (potentially heteroscedastic) covariance, $\mathbf{\Sigma}_{i,t}$;

$$\mathbf{e}_i(\mathbf{T}_t) \sim \mathcal{N}\left(\mathbf{0}, \mathbf{\Sigma}_{i,t}\right). \tag{3.4}$$

Under this noise model, the maximum likelihood transform, $\mathbf{T}_t^*$, is given by

$$\mathbf{T}_t^* = \underset{\mathbf{T} \in \mathrm{SE}(3)}{\operatorname{argmax}} \prod_{i=1}^{N_t} p(\mathbf{e}_i(\mathbf{T}_t)) = \underset{\mathbf{T} \in \mathrm{SE}(3)}{\operatorname{argmin}} \sum_{i=1}^{N_t} \mathbf{e}_i(\mathbf{T}_t)^T \mathbf{\Sigma}_{i,t}^{-1} \mathbf{e}_i(\mathbf{T}_t). \tag{3.5}$$

We will define the error function in two different ways.

Point Cloud Error

First, we can follow classical approach (Maimone et al., 2007) and define $\mathbf{e}_i(\mathbf{T}_t)$ based on a three-dimensional point cloud error. To do this, we invert our stereo camera model to triangulate pairs of points in each frame, $\boldsymbol{p}_{i,c_0} = \mathbf{f}^{-1}(\mathbf{y}_{i,c_0})$ and $\boldsymbol{p}_{i,c_1} = \mathbf{f}^{-1}(\mathbf{y}_{i,c_1})$,

$$\mathbf{e}_i(\mathbf{T}_t) = \mathbf{D}(\boldsymbol{p}_{i,c_1} - \mathbf{T}_t \boldsymbol{p}_{i,c_0}), \tag{3.6}$$

where $\mathbf{D} = \begin{bmatrix} \mathbf{1}_{3\times 3} & \mathbf{0} \end{bmatrix} \in \mathbb{R}^{3\times 4}$ converts homogenous coordinates into Euclidian coordinates. We can then follow Maimone et al. (2007) and assume each stereo projection is corrupted by

additive Gaussian noise,

$$\mathbf{y}_{i,c} \sim \mathcal{N}\left(\bar{\mathbf{y}}_{i,c}, \mathbf{R}_{i,c}\right), \tag{3.7}$$

then we can compute a density on the error function itself through first order noise propagation as

$$\mathbf{e}_i(\mathbf{T}_t) \sim \mathcal{N}\left(\mathbf{0}, \mathbf{\Sigma}_{i,t}\right), \tag{3.8}$$

where

$$\mathbf{\Sigma}_{i,t} = \mathbf{D}\mathbf{G}_{i,c_1}\mathbf{R}_{i,c_1}\mathbf{G}_{i,c_1}^T\mathbf{D}^T + \mathbf{D}\mathbf{T}_t\mathbf{G}_{i,c_0}\mathbf{R}_{i,c_0}\mathbf{G}_{i,c_0}^T\mathbf{T}_t^T\mathbf{D}^T \tag{3.9}$$

with $\mathbf{G}_{i,c} = \left.\dfrac{\partial \mathbf{f}^{-1}}{\partial \mathbf{y}}\right|_{\mathbf{y}_{i,c}}$.

Reprojection Error

Alternatively, we can represent reprojection errors in the second frame directly as

$$\mathbf{e}_i(\mathbf{T}_t) = \mathbf{y}_{i,c_1} - \mathbf{f}(\mathbf{T}_t\mathbf{f}^{-1}(\mathbf{y}_{i,c_0})), \tag{3.10}$$

and assume the following simple noise model

$$\mathbf{e}_i(\mathbf{T}_t) \sim \mathcal{N}\left(\mathbf{0}, \mathbf{\Sigma}_{i,t}\right) = \mathcal{N}\left(\mathbf{0}, \mathbf{R}_{i,t}\right), \tag{3.11}$$

where we abuse notation (slightly) and replace the index for the camera frames c_0 or c_1 with t to indicate that this covariance refers to the reprojection error that involves both sets of features.

Importantly, Sibley et al. (2007) show that using reprojection error (as compared to 3D point cloud error) results in less biased estimates for long-range stereo triangulation. Consequently, we favour this latter formulation in the large majority of our work (the one exception being the initial work on isotropic PROBE described in Appendix A).

Solution via Gauss-Newton Optimization

In either case, we have now defined a weighted nonlinear least squares problem which can be solved iteratively using standard techniques. For our purposes, we opt to use Gauss-Newton optimization and follow Barfoot (2017) to optimize constrained poses.

Namely, at a given iteration n, we linearize the error function $\mathbf{e}_i(\mathbf{T}_t)$, about an operating point $\mathbf{T}_t^{(n)} \in \mathrm{SE}(3)$, which results in a quadratic approximation to Equation (A.3). To

linearize, we consider the left perturbations $\delta\boldsymbol{\xi} \in \mathbb{R}^6$ represented in exponential coordinates:

$$\mathbf{T}_t = \operatorname{Exp}(\delta\boldsymbol{\xi})\,\mathbf{T}_t^{(n)} \approx (\mathbf{1} + \delta\boldsymbol{\xi}^{\wedge})\mathbf{T}_t^{(n)}. \tag{3.12}$$

This allows us to transform Equation (A.3) into a linear least squares objective in $\delta\boldsymbol{\xi}$:

$$\mathcal{L}(\delta\boldsymbol{\xi}) = \frac{1}{2}\sum_{i=1}^{N_t} (\mathbf{e}_i - \mathbf{J}_i\delta\boldsymbol{\xi})^T \boldsymbol{\Sigma}_i^{-1} (\mathbf{e}_i - \mathbf{J}_i\delta\boldsymbol{\xi}) \tag{3.13}$$

where $\mathbf{J}_i = \left.\dfrac{\partial \mathbf{e}_i}{\partial \delta\boldsymbol{\xi}}\right|_{\mathbf{T}_t^{(n)}}$, $\mathbf{e}_i = \mathbf{e}_i(\mathbf{T}_t^{(n)})$, and $\boldsymbol{\Sigma}_i = \boldsymbol{\Sigma}_{i,t}(\mathbf{T}_t^{(n)})$. The minimum to this objective can be solved for analytically by solving the normal equations. This results in the optimal parameters,

$$\delta\boldsymbol{\xi}^{\star} = \left(\sum_{i=1}^{N_t} \mathbf{J}_i^T \boldsymbol{\Sigma}_i^{-1}\mathbf{J}_i\right)^{-1} \sum_{i=1}^{N_t} \mathbf{J}_i^T \boldsymbol{\Sigma}_i^{-1}\mathbf{e}_i. \tag{3.14}$$

Given $\delta\boldsymbol{\xi}^{\star}$, we can update the operating point using the constraint-sensitive update

$$\mathbf{T}^{(n+1)} = \operatorname{Exp}(\delta\boldsymbol{\xi}^{\star})\,\mathbf{T}^{(n)}, \tag{3.15}$$

and iterate until convergence.

There are many reasonable choices for both the initial transform $\mathbf{T}^{(0)}$ and for the conditions under which we terminate iteration. For most visual odometry applications, it suffices to initialize the estimated transform to identity, and iteratively perform the update given by eq. (3.15) until we see a relative change in the squared error of less than one percent after an update.

3.3 Robust Estimation

Since Equation (3.13) assigns cost values that grow quadratically with measurement error, it is very sensitive to outlier measurements. A common solution to this problem is to replace the L_2 cost function with one that is less sensitive to large measurement errors (MacTavish and Barfoot, 2015). These robust cost functions are collectively known as M-estimators, and many variants exist. Each uses a re-weighting function, $\rho(\cdot)$,

$$\mathbf{T}^{*} = \underset{\mathbf{T}\in \mathrm{SE}(3)}{\operatorname{argmin}} \sum_{i=1}^{N_t} \rho\left(\mathbf{e}_i{}^T \boldsymbol{\Sigma}_{i,t}^{-1}\mathbf{e}_i\right) = \underset{\mathbf{T}\in \mathrm{SE}(3)}{\operatorname{argmin}} \sum_{i=1}^{N_t} \rho(\epsilon_i), \tag{3.16}$$

where. given a parameter c, some common examples include:

$$\rho(\epsilon) = \begin{cases} \frac{c^2}{2} \log\left(1 + \frac{\epsilon^2}{c^2}\right) & \text{Cauchy,} \\ \frac{1}{2} \frac{\epsilon^2}{c^2 + \epsilon^2} & \text{Geman-McClure (Geman et al., 1992),} \\ \begin{cases} \frac{\epsilon^2}{2} & \text{if } \|\epsilon\| < c \\ c \|\epsilon\| - \frac{c^2}{2} & \text{if } \|\epsilon\| \geq c \end{cases} & \text{Huber (Huber, 1964).} \end{cases} \tag{3.17}$$

3.4 Outstanding Issues

There are several outstanding limitations of classical visual odometry pipelines that we can address with learned pseudo-sensors.

Table 3.1: **Data efficiency vs. computational efficiency**

Synopsis	Addressed by
Classical VO pipelines face a difficult-to-optimize trade-off between using all of the information contained within image and while still remaining computationally tractable.	PROBE, DPC-Net, Sun-BCNN, HydraNet

Table 3.2: **Systematic bias**

Synopsis	Addressed by
Stereo visual odometry can incur systematic bias through poor extrinsic or intrinsic calibration, stereo triangulation errors, poor feature *spread* (i.e., concentration of features on one side of an image), and poor data association due self-similar textures.	DPC-Net

Table 3.3: **Homoscedastic uncertainty**

Synopsis	Addressed by
Stationary, homoscedastic noise in observation models can often reduce the consistency and accuracy of state estimates. This is especially true for complex, inferred measurement models.	PROBE, Sun-BCNN, HydraNet

Appendices

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