2018 November Reading Reports

On Degeneracy of Optimization-based State Estimation Problems

The problem is only solved in well-conditioned directions, and the best guess is used in degenerate directions. The method checks the rows in $||Ax - b||$.

Degeneracy of a linearized system is defined by $(\mathbf{c}^T\mathbf{A}^T\mathbf{A}\mathbf{c} + 1)^{-1}$, which can be solved by

$$\arg\min_{\mathbf{c}} \frac{\mathbf{c}^T\mathbf{A}^T\mathbf{A}\mathbf{c}}{\mathbf{c}^T\mathbf{c}}$$

with the minimum eigenvalue of $\mathbf{A}^T\mathbf{A}$.

Solution remapping is used to handle degeneracy $x_f \leftarrow \mathbf{V}_f^{-1}\mathbf{V}_u\Delta x_u$, or $x_f \leftarrow \mathbf{V}_u^T\mathbf{V}_f^{-T}\Delta x_u$ (in my implementation $\mathbf{V}^T$ is the matrix of eigenvectors).

Single View Point Omnidirectional Camera Calibration from Planar Grids

A method to calibrate sphere projection model is proposed (MEI). The model can used for many kinds of camera with catadioptric lenses. The camera and lens are modeled together. It projects the points in $\mathbb{R}^3$ to a unit sphere and then projects from another point (can be different from the origin point) to an image plane.

Colourising Point Clouds Using Independent Cameras

This letter first synchronizes the mapping device data and camera data using optical flow information (yaw rate, cross-correlation). **Visible analysis** based on exponential kernel function is introduced, followed by memory-efficient coloring (mean of weighted Gaussian distribution).

Result dataset

3D LIDAR–camera intrinsic and extrinsic calibration: Identifiability and analytical least-squares-based initialization

This paper introduces a method use calibration plane. It assumes the normal direction is known, and solve a problem in the form of

$$\alpha_i(\rho_{ijk} + \rho_{oi})^C \bar{n}_j^T {}_{Li}^C C \bar{p}_{ijk} + {}^C \bar{n}_j^T {}_{Li}^C t - d_{ijk}$$

where $\alpha_i, \rho_{oi}, {}_{Li}^C C, {}_{Li}^C t$ are the parameters to be estimated, others are the measurements containing errors (the plane coefficients are provide by stereo system).

At the beginning, it is solve in a two-step linear estimation, first $\rho_{oi}, {}_{Li}^C C$ (polynomial system solver is used, the multiplication matrix, monomial, Gröbner basis, ideal etc.), then $\alpha_i, {}_{Li}^C t$. Then a non-linear optimization iteratively uses a minimal parameterization of the unknowns with some of the initial values in the linear solver part.

Identifiability conditions are also discussed in the paper. It shows that **three planes** with linearly independent normal vectors are observed, we can determine all of the unknowns.

Intrinsic and extrinsic parameters are estimated. The evaluation can be referred.

REMODE: Probabilistic, Monocular Dense Reconstruction in Real Time

A probabilistic depth map containing Gamma and Gaussian. A fast smoothing method smoothes the noisy depth.

Link

Video-based, real-time multi-view stereo

The probabilistic model with Gamma and Gaussian is proposed as the same as the one in REMODE. It is in the form of

$$q(Z;\pi|a_n;b_n;\mu_n;\sigma_n) := Beta(\pi|a_n,b_n)N(Z|\mu_n;\sigma_n^2)$$

It is updated with the new measurement with mean and second moment approximation (ref: supplementary material and PRML 10.1.1). Then pruning of seeds is used to keep seeds as constant.

Voxblox

It uses Truncated Signed Distance Fields (TSDFs) to build Euclidean Signed Distance Fields (ESDFs). For the TSDF, it uses a behind-surface drop-off and grouped raycasting. For building ESDF, it uses the distance stored in the TSDF map (wavefronts, waves that propagate from a start voxel to its neighbors, priority queue, quasi-Euclidean Distance). The error of ESDF is discussed to be used to inflate the model.

Real-Time Camera Tracking and 3D Reconstruction Using Signed Distance Functions

Similar with KinectFusion, the main difference is on the camera pose tracking, which uses the gradient from SDF instead of ICP.

Integrating Deep Semantic Segmentation Into 3-D Point Cloud Registration

Integrate semantic information to the point cloud registration (GICP and NDT).

Camera and LIDAR Fusion for Mapping of Actively Illuminated Subterranean Voids

It uses Markov Random Field (MRF) [1] among illuminated HDR image and lidar points.

The polar estimates (θ_{nl}, from corrected illumination intensity $E_{unbiased}$ and the the albedo values ρ_{est}) are combined with azimuth estimates (ϕ) from the range image and converted to **gradients** for integration in the MRF. In my opinion, it combines the surface normal and light direction to get the gradient direction, which can be used in the MRF.

It focuses on **a continuously rotating planar LIDAR scanner and an (iluminated HDR) 8 megapixel DSLR camera from a single view point** (or odometry/ICP with evenly spaced intervals roughly 3 meters apart).

The results are displayed using a hole-filling method.

[1] Diebel, J., & Thrun, S. (2006). An application of markov random fields to range sensing. In *Advances in neural information processing systems* (pp. 291-298).

An Application of Markov Random Fields to Range Sensing

This paper applies **graphical models** to the problem of fusing low-res depth images with high-res camera images.

It **increases the resolution** of our depth sensor by an order of magnitude while **improves local accuracy**.

Two layers depth measurement potential and depth smoothness prior are used to form $p(y|x, z)$. The weights are based on smoothing occur across edges in the image. The gradient (CG) algorithms are used to iteratively solve the mode of the posterior from bilinear interpolation of z (laser range measurement).