2018 April Reading Reports

CamOdoCal

Monocular VO

Initial Estimate of Camera - Odometry Transform

Unified projection model proposed by Mei is used. Both of the intrinsic of the cameras and extrinsic parameters between cameras and odometry are calculated and SURF features are used.

Hand-eye problem for initialization:

$$q_{O_i}^{O_{i+1}} q_C^O = q_C^O q_{C_i}^{C_{i+1}} (1)$$
$$(R_{O_i}^{O_{i+1}} - I) t_C^O = s_j R_C^O t_{C_i}^{C_{i+1}} - t_{O_i}^{O_{i+1}} (2)$$
$$q_{C_i}^{O_{i+1}} = q_{C_i}^{O_{i+1}}$$
$$t_{O_i C_i}^{O_{i+1}} - t_{O_{i+1} C_{i+1}}^{O_{i+1}} = s_j t_{C_{i+1} C_i}^{O_{i+1}} - t_{O_{i+1} O_i}^{O_{i+1}}$$

Assume that $q_{O_i}^{O_{i+1}}$ has only rotation on z axis. Then q_z and $q_{O_i}^{O_{i+1}}$ are commutable, which can be solved by the planar hand eye calibration for initialization (https://github.com/hengli/camodocal/blob/master/src/calib/PlanarHandEyeCalibration.cc).

For q_{yx}, we have two constraints, $x_{q_{yx}} y_{q_{yx}} = -z_{q_{yx}} w_{q_{yx}}$ and $q_{yx}^T q_{yx} = 1$. These two equations will constraint the two least eigen vectors from SVD. $q_{yx} = \lambda_1 v_3 + \lambda_2 v_4$, in the program above, it is solved by the `solveQuadraticEquation` function, which solves $s = \frac{\lambda_1}{\lambda_2}, as^2 + bs + c = 0$ and $(sv_3 + v_4)^2 = t^2, \lambda_2 = 1/t, \lambda_1 = s/t$.

Use (2) to obtain the initial values of yaw (chose the the best hypothesis from the least square problem), 2D translations and scales.

3D Point Triangulation

to find feature correspondences and Ceres to optimize the image reprojection error (bundle adjustment) across all frames.

Finding Local Inter-Camera Feature Point Correspondences

Keep local frame history. The image pair is rectified on a common image plane which corresponds to the average rotation between the first camera's pose and the second camera's pose

Loop Closures

Most of the loops are last frame in one monocular VO segment for a particular camera, and the first frame in the next monocular VO segment for the same camera.

Full Bundle Adjustment

Optimizes all intrinsics, extrinsics, odometry poses, and 3D scene points.

MSCKF 2.0

MSCKF Brief Introduction

The effects of features for the linearization are avoided by multiply left nullspace of H_f. The feature in all the images are used for calculating the final position of the feature. The feature point is not in the state vector.

MSCKF 2.0, MSCKF, EKF-SLAM Comparison

It shows that MSCKF and EKF-SLAM has inconsistency.

Global parameterization of the rotation ${}^I_G R \approx {}^I_G \hat{R}(\mathbf{I}_3 - \lfloor \delta^G \tilde{\theta} \rfloor_\times)$, which removes the orientation error from the observable matrix. The authors also use first estimate Jacobian for not letting errors increase the rank of the observable matrix (a novel closed-form expression for the IMU error-state transition matrix and fixed linearization states).

Compare to the original MSCKF, it also includes extrinsic parameters.

The Monte-Carlo simulations part can be adapted for other tests.

Having a linearized system model with appropriate observability properties is more important than using re-linearization to better approximate the nonlinear measurement models.

The uncertainty of yaw and position are underestimated by MSCKF and FLS.

Probabilistic Surfel Fusion for Dense LiDAR Mapping

Main idea

Dual surfel maps are used, ellipsoid surfel map (ESM) is used to do localization, while disk surfel map (DSM) is used to fuse the map. Uncertainty model is used to represent the surfel.

Surfel uncertainty and fusion are the keys of the paper.

For ESM, the paper doesn't discuss a lot.

For DSM, the data association is done by first octree-based nearest neighbor search algorithm, then thresholds-based method to pick the correspondences. The position and normal of the surfel are updated by by Bayesian filtering, including the mean and covariance. Unstable surfels which are not observed for a certain period of time is removed when revisited.

The tests are performed under synthetic and real environments. It shows that the method have less noise in the fused map.

Continuous 3D Scan-Matching with a Spinning 2D Laser

Main idea

This paper uses 3D spinning lidar sensor on a skid-steer loader vehicle to produce quality map of outdoor scenes and estimate the vehicle trajectory.

The shape parameters are from mean and covariance and eigenvalues. Matching is based on ICP with first compute correspondences (centroid, smallest eigenvector and largest eigenvector), then estimate the trajectories with three constraints: match constraints, smoothness constraints and initial constraints.

The industrial environment test is compared to 2D laser SLAM system, while off-road environment test is compared to closed-loop results (appearance-based methods). Box plots are used to visualize the translational and rotational errors.

Generalized-ICP

This can be thought of as 'plane-to-plane'. Outperform both standard ICP and point-to-plane and to be more robust to incorrect correspondences. More expressive probabilistic models. Addition of outlier terms, measurement noise, and other probabilistic techniques to increase robustness.

G-ICP aims to take into account structure.

ICP

1. Compute correspondences between the two scans.
2. Compute a transformation which minimizes distance between corresponding points.

Point-to-plane

1. ICP improves performance by taking advantage of surface normal information

Generalized-ICP

1. Standard Euclidean distance to find correspondences. Kd-trees in the look up of closest

points. Outliers are removed.
2. Probabilistic model models the covariance matrices associated with the measured points.

Transform a to b.

$$\begin{aligned} d_i^{(\mathbf{T})} &\sim \mathcal{N}(\hat{b_i} - (\mathbf{T}^*)\hat{a_i}, C_i^B + (\mathbf{T}^*)C_i^A(\mathbf{T}^*)^T) \\ &= \mathcal{N}(0, C_i^B + (\mathbf{T}^*)C_i^A(\mathbf{T}^*)^T)) \end{aligned}$$

$$\mathbf{T} = \mathrm{argmax}_{\mathbf{T}} \prod_i p(d_i^{(\mathbf{T})}) = \mathrm{argmax}_{\mathbf{T}} \sum_i \log(p(d_i^{(\mathbf{T})}))$$

$$\mathbf{T} = \mathrm{argmin}_{\mathbf{T}} \sum_i (d_i^{(\mathbf{T})^T}(C_i^B + (\mathbf{T})C_i^A(\mathbf{T})^T))^{-1} d_i^{(\mathbf{T})}), \text{(from multi-gaussian)}$$

Standard ICP can be seen as $C_i^A = 0, C_i^B = I$, while point-to-plane as $C_i^A = 0, C_i^B = P_i^{-1}$, where $P_i = A(A^T A)^{-1} A^T$ and $A = v_i$ is the direction of the normal.

Since P_i is non-invertible, we need to approximate it with an invertible Q_i.

Locally planar assumption.

Plane-to-plane: Increase the symmetry of the model, constraint along its surface normal, but not exact correspondence. High covariance along its local plane, and very low covariance in the surface normal direction.

$$\begin{bmatrix} \epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

$$C_i^A = R_{\nu_i} \begin{bmatrix} \epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} R_{\nu_i}^T$$

$$C_i^B = R_{\mu_i} \begin{bmatrix} \epsilon & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} R_{\mu_i}^T$$

The incorrect correspondences form very weak and uninformative constraints. PCA (20 closest points) is used to recover surface normals from point clouds. The rotation matrices in the above equations are replaced by eigen decomposition $\hat{\Sigma} = UDU^T$, where D is replaced with $\mathrm{diag}(\epsilon, 1, 1)$.

Standard ICP was used in the pairwise matching to generate the ground truth. The testing were extracted with much higher spacing.

The proposed method is less sensitive to d_{max} and give equal consideration to both scans (removed local minima in point-tp-plane).

But how the normal in source scans to be extracted will still be a problem.

Visual–inertial navigation, mapping and localization: A scalable real-time causal approach

Explains why extrinsic parameters are observable. It is related to identifiability given the measurements.

Motion model

Under constant dynamic model, or trivial dynamics (constant, slowly varying, or random walk).

Observability

The author proves that under that motion model the model (4)–(5) and T_{bi}, R_{bi}, γ(gravity vector) added to the state with constant dynamics, is locally observable, so long as motion is sufficiently exciting and the global reference frame is fixed (equivalently the initial conditions ($R(0)$, $T(0)$)).