2018 October Reading Reports

Colored Point Cloud Registration Revisited

The approach establishes correspondences in the physical three-dimensional space, but defines a joint optimization objective that integrates both geometric and photometric terms. It locks the alignment both along the tangent plane and (photometric term) the normal direction (geometric term).

RGB-D Image Alignment

Two objectives are introduced first, the photometric objective E_I and geometric objective E_G.

$$
\begin{gathered}
E_I(\mathbf{T}) = \sum_{\mathbf{x}} (I_i(\mathbf{x}') - I_j(\mathbf{x}))^2 \\
\mathbf{x}' = \mathbf{g}_{uv}(\mathbf{s}(\mathbf{h}(\mathbf{x}, D_j(\mathbf{x})), \mathbf{T})) \\
E_D(\mathbf{T}) = \sum_{\mathbf{x}} (D_i(\mathbf{x}') - \mathbf{g}_d(\mathbf{s}(\mathbf{h}(\mathbf{x}, D_j(\mathbf{x})), \mathbf{T})))^2
\end{gathered}
$$

Parametrization

For each colored point $\mathbf{p} \in \mathbf{P}$, the virtual orthogonal camera can provide two approximations of functions:

$$
\begin{gathered}
C_{\mathbf{p}}(\mathbf{u}) \approx C(\mathbf{p}) + {\mathbf{d}_{\mathbf{p}}}^\top \mathbf{u} \\
G_{\mathbf{p}} \approx (\mathbf{o}_{\mathbf{p}} - \mathbf{p})^\top \mathbf{n}_{\mathbf{p}}
\end{gathered}
$$

where $\mathbf{d}_{\mathbf{p}}$ is solved by least square fitting (constrained by the projection of the neighbor points and the normal direction), and the latter one is a constant function. The color parametrization requires to be **pre-computed**.

Objective

The final objective is $E(\mathbf{T}) = (1-\sigma)E_C(\mathbf{T}) + \sigma E_G(\mathbf{T})$, where E_C includes $C(\mathbf{q})$ and $C_{\mathbf{p}}(\mathbf{q}')$, $\mathbf{q}'$ on the tangent plane of $\mathbf{p}$, and E_G includes the transformed $\mathbf{q}$, $\mathbf{p}$ and $\mathbf{n}_{\mathbf{p}}$ (like point-to-plane distance, let $\mathbf{q}$ to be on the same plane where $\mathbf{p}$ is).

The optimization is coarse-to-fine (point cloud pyramid) with Gauss-Newton method.

StructVIO

It includes **line representation**, which integrates Atlanta world representation and structural features, **structural line parameterization** to recognize the local Manhattan world and vertical lines to help estimate orientation, **several improvements on the estimator and line tracking**, e.g. a novel marginalization method for long feature tracks and a line tracking method by sampling multiple points and delayed EKF update.

LSD line detector is used. The main pipeline is under **EKF** VIO (MSCKF). The main idea is to track the line and estimate the line parameters in the local frames. Residual are formed by the line residual r_k, which is related to the dot product of homogeneous coordinates of points and the predicted lines, and line prior (like EKF).

Information Sparsification in Visual-Inertial Odometry

Instead of marginalization, it uses sparsification by minimizing the KL divergence.

Sparse Iterative Closest Point

[Link]() and [Github]()

It formulates the registration optimization using sparsity inducing norms, which can deal with outliers and incomplete data.

It formulates the local alignment problem as recovering a rigid transformation that maximizes the number of zero distances between correspondences (l_p norms, where $p \in [0, 1]$). **Alternating Direction Method of Multipliers (ADMM)** is applied. Group sparsity vanish residual vector's x, y, z simultaneously.

This paper doesn't use the reweight approximation for the l_p norm, while it introduces a new set of variables Z and augmented Lagrangian function, which can be solved by ADMM. The ADMM decomposes the problem into three simple steps. ADMM is faster when using point-to-plane distance while not using point-to-point distance.

RaD-VIO

Not an interesting one. It uses planar assumption and homography constraints to estimate unscaled translation and use IMU orientation directly. The EKF is used to combine the range finder data to estimate the scale.

CNN for IMU Assisted Odometry Estimation using Velodyne LiDAR

Not an interesting one. It uses three channels' images from LiDAR as inputs and trains the model separately for translations and rotations.