RGB-Laser Odometry Under Interval Uncertainty for Guaranteed Localization

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Introduction

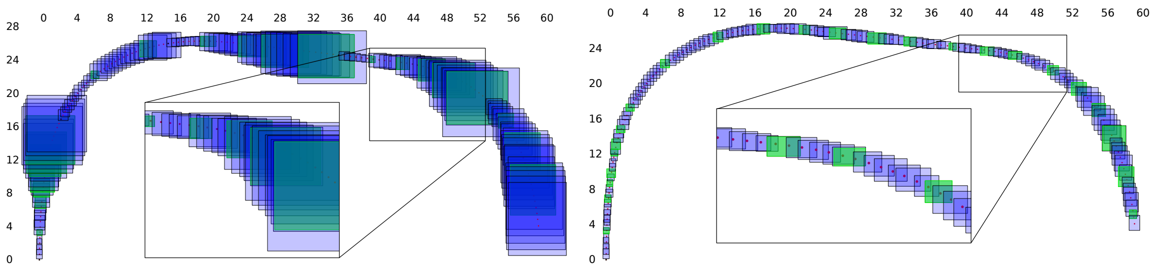
To navigate, robots have to localize themselves in the environment. Since GPS might not be available, robots need to estimate their egomotion gradually using different sensors such as cameras, laser scanners and/or inertial measurement units (IMUs). In the past, we developed a probabilistic approach to estimate the robot's odometry using a monocular camera and a depth sensor while simultaneously estimating the sensors' clock offsets [1]. Nevertheless, our approach and most other approaches [2] focus on computing a point-valued position for the robot only while neglecting the uncertainty of the pose estimation. However, due to the imperfections of every sensor, this point position might be erroneous. Further difficulties are the nonlinearity of the problem, which can lead to further deviations from the true position, and outliers, which can affect the result of these approaches since they tend to compute a solution that satisfies all observations. To overcome these issues, we propose an interval-based approach. Our method fuses camera, laser scanner and IMU information while taking the sensors' uncertainties into account to compute intervals for the robot's pose in 3D. Similar work was done by Kenmogne et al. [3], but they compute their robot's position relative to known landmarks, which we assume to be not available. Bethencourt and Jaulin [4] solve a similiar problem to ours, but apply it to 3D reconstruction instead of localization. While we do not believe that interval-based approaches will replace existing probabilistic approaches, our approach can be used to constrain the initial search space of probabilistic methods or to detect errors in the probabilistic solution.

Method

We estimate the robot's motion from one image frame to another. First, we find corresponding image features between image frames using SIFT [5]. Since depth (distance) information is needed to estimate the odometry from matched feature points, we use scan points from a laser scanner and find a guaranteed interval for a feature's depth. For this, we assume an unknown but bounded error for both sensors and for the transformation between the sensors. By projecting the laser scanner's scan boxes onto the image plane, we find all possible scan points for an image feature and calculate the depth as the union over all those scan boxes' depths. Our method is keyframe-based, which means that we estimate the motion from the current image frame relative to the most recently defined keyframe until we have to insert a new keyframe (e.g. if we cannot match enough features). To contract the intervals for the motion between two frames, we use a forward-backward contractor based on the rigid body transformation

$$\mathbf{X}_i^k = \mathbf{R}\mathbf{X}_i^c + \mathbf{T}, \tag{1}$$

where $\mathbf{X}_i^k$ and $\mathbf{X}_i^c$ are the 3D coordinates of the same feature i in the keyframe k and the current frame c, respectively. $\mathbf{R}$ and $\mathbf{T}$ are the rotation matrix and the translation vector, for which we want to contract the intervals. By reformulating the equation it is possible to also include features with depth information in one frame only or without any depth information. To find an initial enclosure for the rotation parameters, we use measurements from the IMU. Since some feature matches might be wrong, we use a relaxed intersection for the contractors to not only account for, but also identify outliers. Finally, if we have to insert a new keyframe, we use further constraints to



(a) GPS correction every three seconds. (b) GPS correction at new keyframe.

Figure 1: Odometry results.

contract the intervals for the motion to the previous keyframe (like bundle adjustment).

First results

To evaluate our approach we use small sequences from the KITTI data set [6]. After some time, we use GPS measurements to contract the intervals. Otherwise, the localization uncertainty grows infinitely large due to drift and the boxes convey no information anymore. For future work, we plan to build a map or use loop closure to prevent drift. In the first experiment (c.f. Figure 1(a)) we use GPS measurements every three seconds; in the second experiment (c.f. Figure 1(b)) we use GPS measurements whenever we have to insert a new keyframe. In both figures the red dots depict the true solution (GPS), the blue boxes depict our localization results and the green boxes depict a keyframe. It can be seen that the true solution is always enclosed in our intervals.

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