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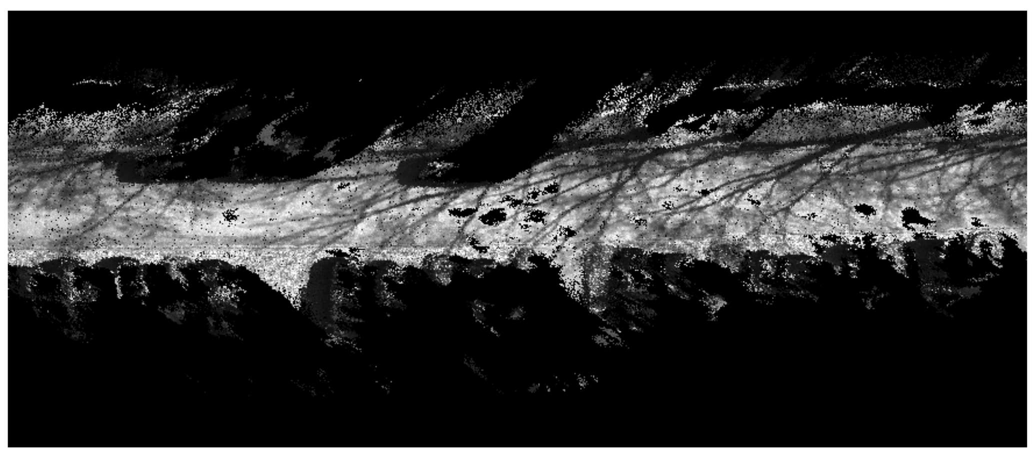
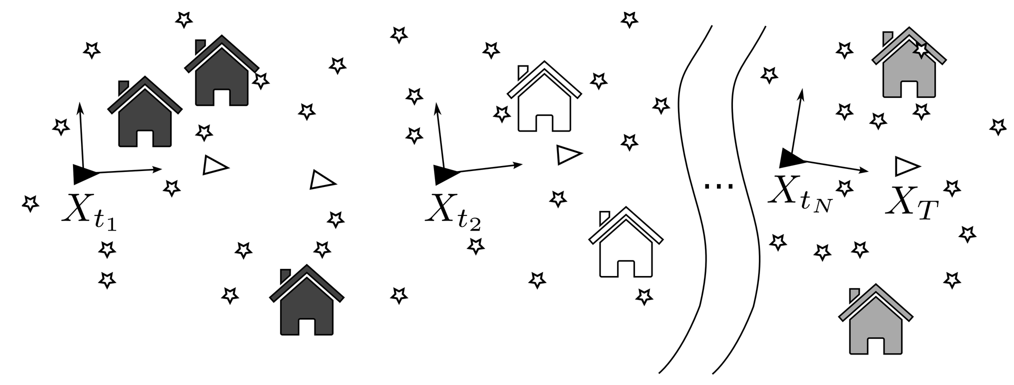
Visual SLAM for Autonomous Ground Vehicles

Motivation



In V-SLAM the main focus is most often laid on the localization part of the problem. To this end, a sparse set of landmarks is tracked and their position is estimated. However, this set of landmarks (rendering the map) is often too sparse for tasks in autonomous driving hence a dense map is sought.

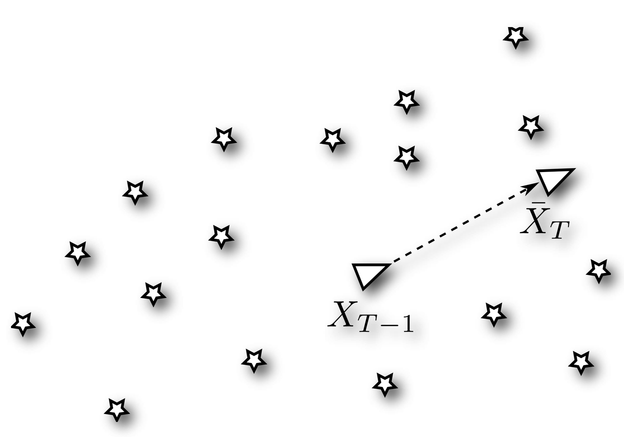
Overview



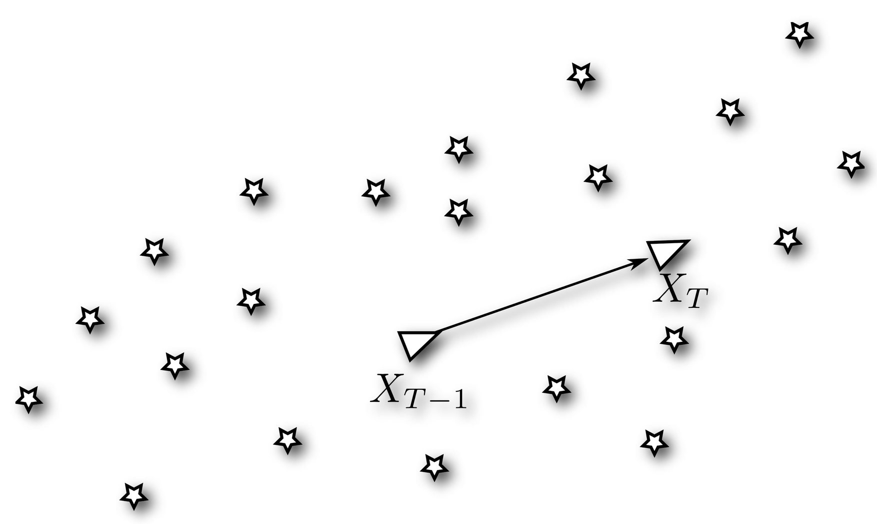
The main contribution is to couple a sparse EKF SLAM system with a dense mapping algorithm. The sparse SLAM estimate contains a subset of previous poses. Each such pose spans a coordinate system in which fragments of the dense map are expressed in.

Approach

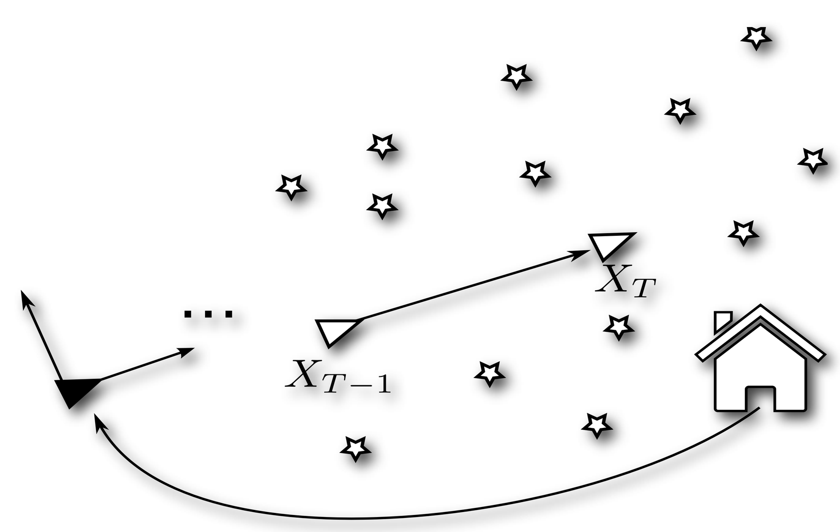
Visual Odometry Priors



EKF Update (CI-Submap)



Dense Mapping and Embedding



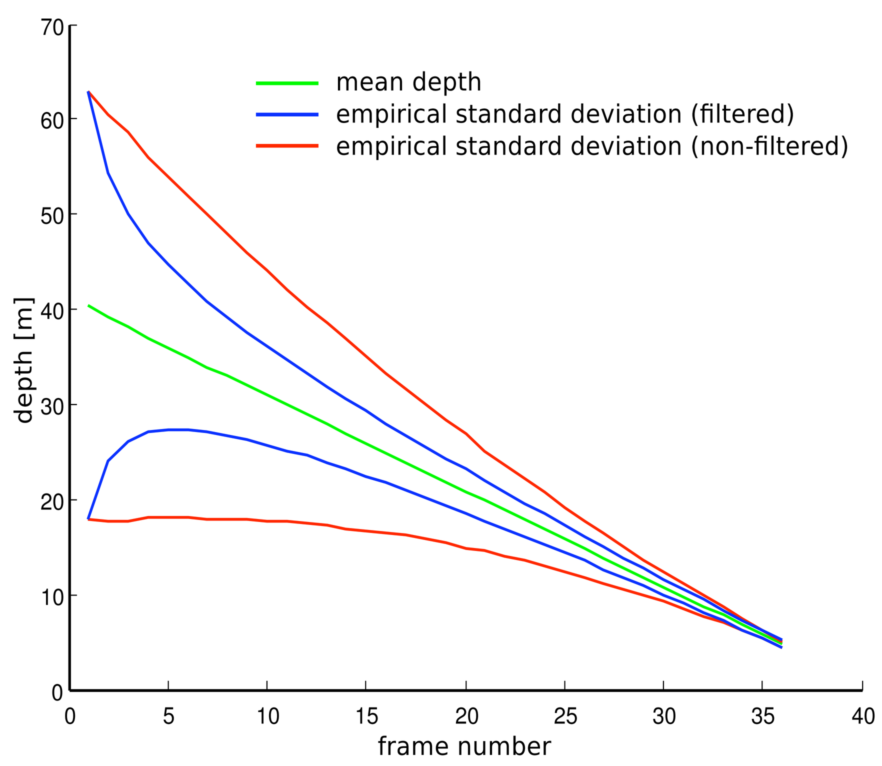
The system uses visual odometry prirors to predict the state vector of the sparse SLAM estimate. This includes the current robot pose. As VO the method of Kaess et al. 2009 is used.

During the update new observations are exploited to refine the pose estimate (and land-mark positions).

The map of landmarks is partioned into conditionally independent submaps (Pinies et al. 2008) to assure constant run time most of the time.

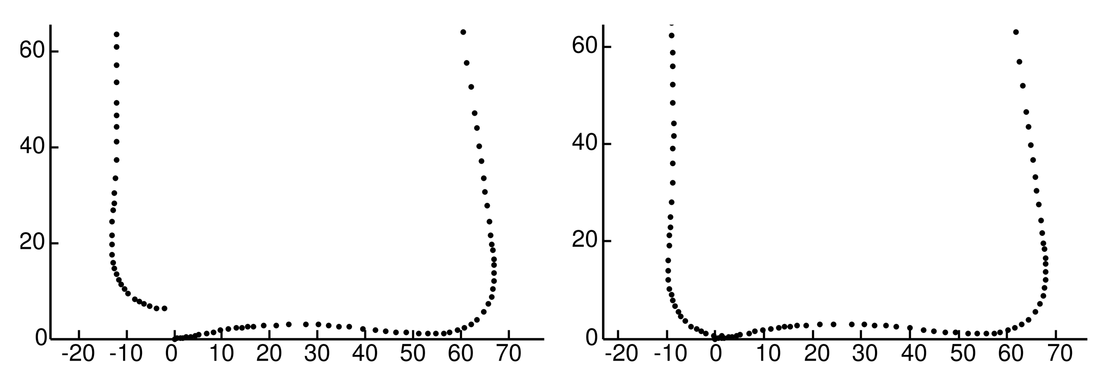
The transition from pose X_{T-1} to X_T is assumed to be of sufficient accuracy. The ego motion is used to compute a dense map of the environment. To this end, each pixel of the image is filtered by an iconic EKF. The state of each filter is the 3D position expressed in the coordinate system spanned by one specific previous pose.

Simulation Results

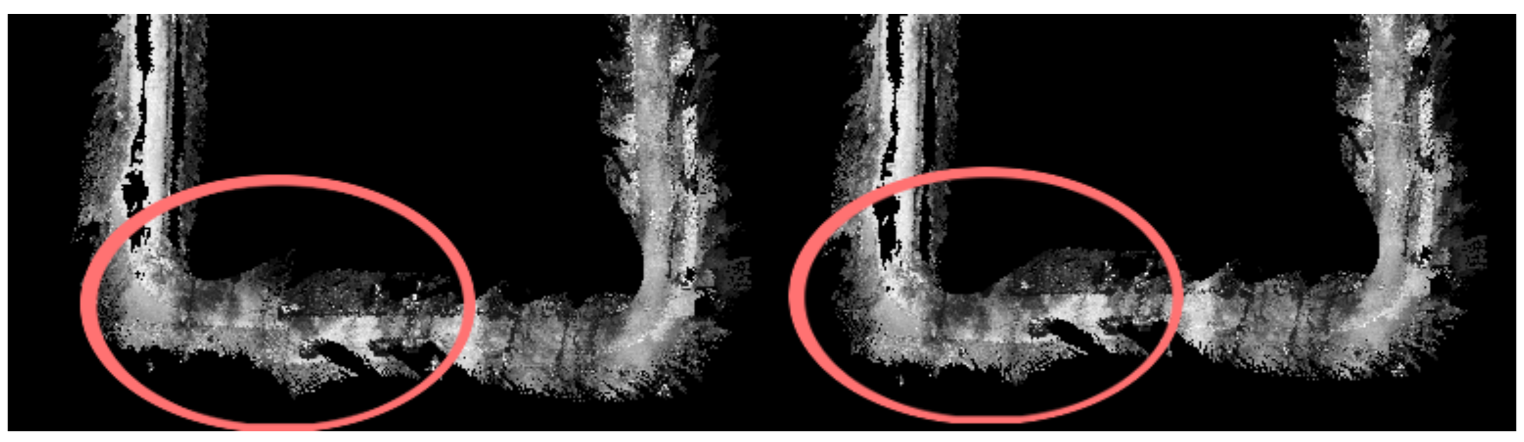


A Monte Carlo simulation was run. During simulation the robot moves with constant velocity. One point of the dense map is replicated 1000-fold and each instance is filtered by an iconic EKF. The empirical standard deviations for the filtered and non-filtered cases are shown for the reconstructed distance.

Real World Data



The algorithm was tested on a test sequence of a loopy trajectory. The car like robot moved with speeds of up to 30 km/h. The drift before closing the loop (shown above) is approximately 5m. After closing the loop drift is resolved. The bottom shows the dense map associated with that trajectory. It can be seen how the dense maps align well after loop closure. Loop closure was triggered manually.



Future Work

- Integrating a place recognition system (e.g. Cummnis et al.)
- Fusing dense optical flow during estimating the dense map
- Developing more advanced dense 3D mapping algorithms
- Handling moving objects more explicitly

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