During the update new observations are exploited to refine the pose estimate (and landmark positions). The map of landmarks is partitioned into conditionally independent submaps (Pinies et al. 2008) to assure constant run time most of the time.

The system uses visual odometry priors 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 landmark positions). The map of landmarks is partitioned 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.

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.

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.

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