Information-based Reduced Landmark SLAM: Supplementary Material

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I. Comparison of various landmark removal techniques

We compare various landmark removal techniques as described below.

A. Least Degree based Removal

In this technique, the landmarks which have the least degree are removed first. This results in removing the least visible landmarks which however can be an important unique landmark.

B. Maximum Uncertainty based Removal

In this technique, the landmarks which are least certain or have the maximum uncertainty are removed first.

C. K-Cover based Removal

For K-Cover based removal, we first run K-Cover algorithm which greedily adds landmarks that cover the most number of uncovered poses. After running the K-Cover, we remove landmarks in the reverse order by removing the last added K-Cover landmark first. This ensures that the remaining landmarks cover all the poses.

D. Least Informative Landmark based Removal

In this technique, we compute the mutual information of each landmark with respect to rest of the landmarks and poses followed by removing the landmark which has the least information gain. After every removal, we recompute the mutual information of each landmark with rest of the landmarks and poses.

E. Least Reprojection Error based Removal

In this technique, we remove landmarks in the order of their reprojection error (from low to high). This method removes landmarks that comply with the current estimate.

II. Evaluation Metrics

The algorithms are compared using the following evaluation metrics.

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A. Average trajectory error (ATE (m))

Average trajectory error compares the absolute distance between the trajectories estimated using standard graph SLAM and reduced landmark based SLAM. ATE evaluates the RMSE (root mean squared error) over the difference of pose translation (for the reduced set of poses) estimated using all landmarks and poses and reduced set of landmarks and poses. Formally ATE is defined as follows,

$$ATE = \left(\frac{1}{n} \sum_{i=1}^{n} \| trans\left(X^i - X^i_s\right) \|^2 \right)^{\frac{1}{2}} \tag{1}$$

B. Average rotation error (ARE (deg))

Average rotation error is evaluated by averaging the angular difference in the pose heading directions over the reduced set of poses.

$$ARE = \frac{1}{n} \sum_{i=1}^{n} \| rot\left(X^i - X^i_s\right) \| \tag{2}$$

C. Difference in determinant of uncertainty of the latest pose (UD)

Uncertainty of the latest pose is computed by marginalizing out the latest pose and evaluating its covariance determinant. We increase in uncertainty of the latest pose when using all landmarks and poses as compared to using reduced number of landmarks and poses.

III. Dataset

The experiments are run on a synthetic dataset which consists of 24 landmarks. A simulated robot takes 422 range and bearing measurements along a trajectory of 95 poses. Figure 1 shows the dataset. The area covered by this trajectory is around 50×50 squared m.

IV. Results and Conclusion

Figure 2 shows the average trajectory error as landmarks are removed using different removal techniques. Figure 3 shows the average rotation error and 4 shows the difference in determinant of uncertainty of the latest pose as landmarks are removed using different removal techniques. As we can see from Figure 4, removing the least informative landmark show the least change in the uncertainty of the last pose with every deletion as compared to other landmark removal techniques. The average trajectory and rotation errors increase slowly with every deletion as compared to other algorithms. The overall performance of removing landmarks based on information gain is similar to K-Cover based removal and it is better than other removal technqiues. We prefer information gain based landmark removal technique over K-Cover since it is straightforward to include other metrics of interest (like memory and semantics) in a common objective function that is minimized.

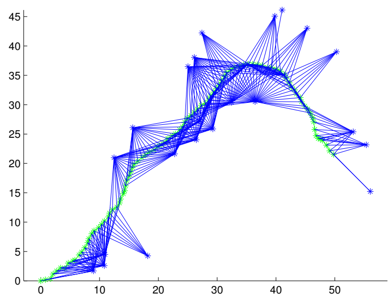

Fig. 1. Dataset used in the experiment

V. Monte-Carlo Experiments with Varying Number of Landmarks

In another experiment, we evaluated the absolute trajectory error (ATE) and Covariance determinant of the poses as compared to the number of landmarks in the map. Landmarks are randomly sprinkled in a map with known groundtruth poses. Trajectory is re-estimated after every landmark is added and the trajectory error is evaluated w.r.t the known groundtruth. This experiment is re-run 100 times with the same groundtruth trajectory. Figure 5 shows the trajectory error and Figure 6 shows the covariance determinant of the trajectory with the increasing number of landmarks. As we can see from the results, the error and uncertainty becomes constant after adding a few landmarks.

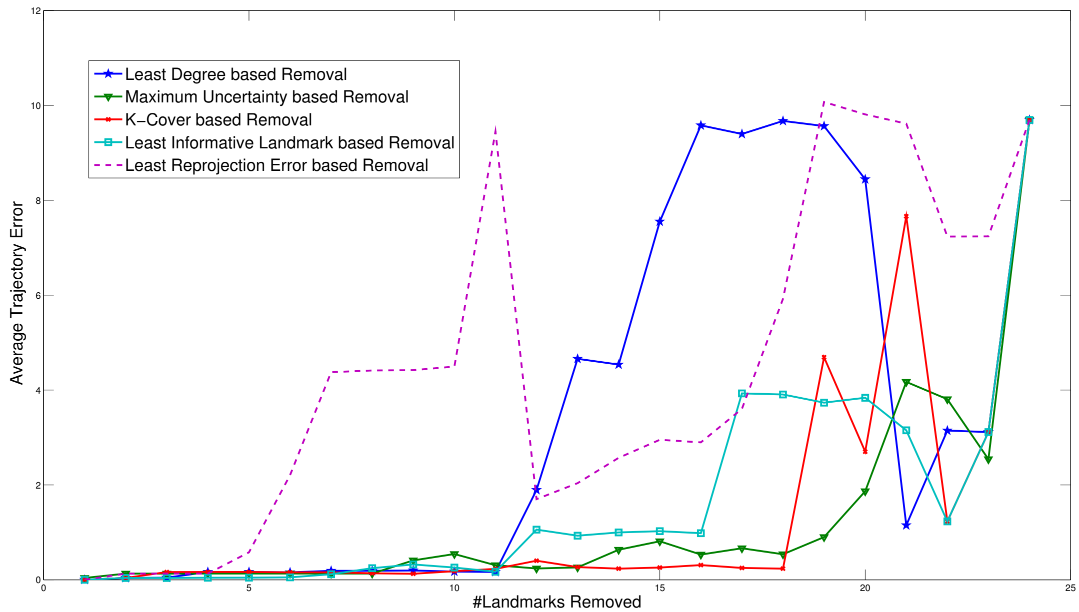

Fig. 2. Comparison of average trajectory error (ATE, m) as a function of the number of landmarks removed using different landmark removal techniques

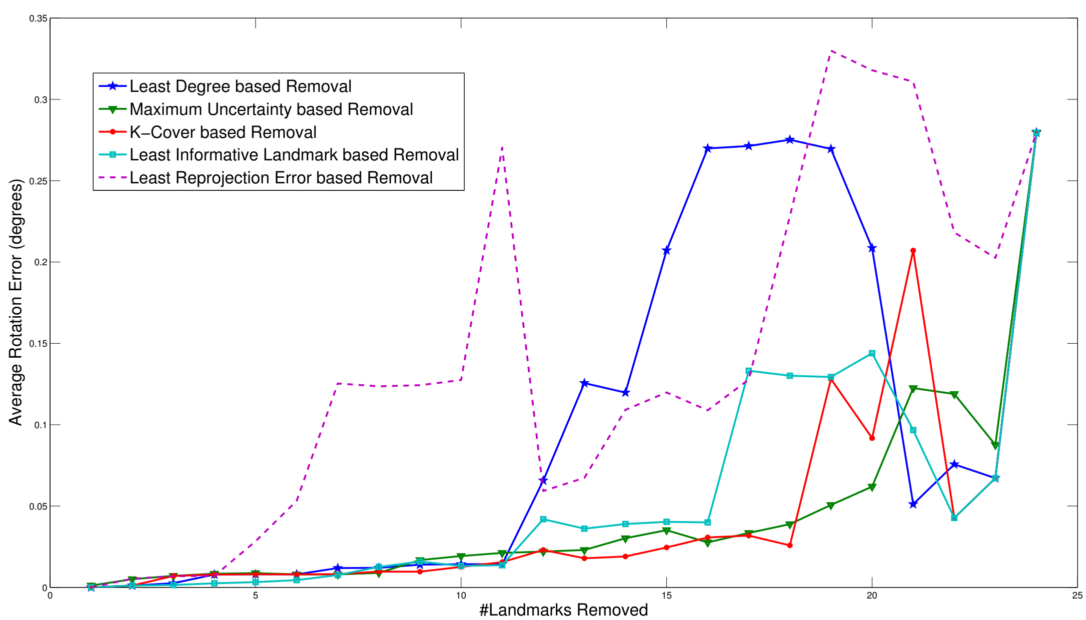

Fig. 3. Comparison of average rotation error (ARE, degrees) as a function of the number of landmarks removed using different landmark removal techniques

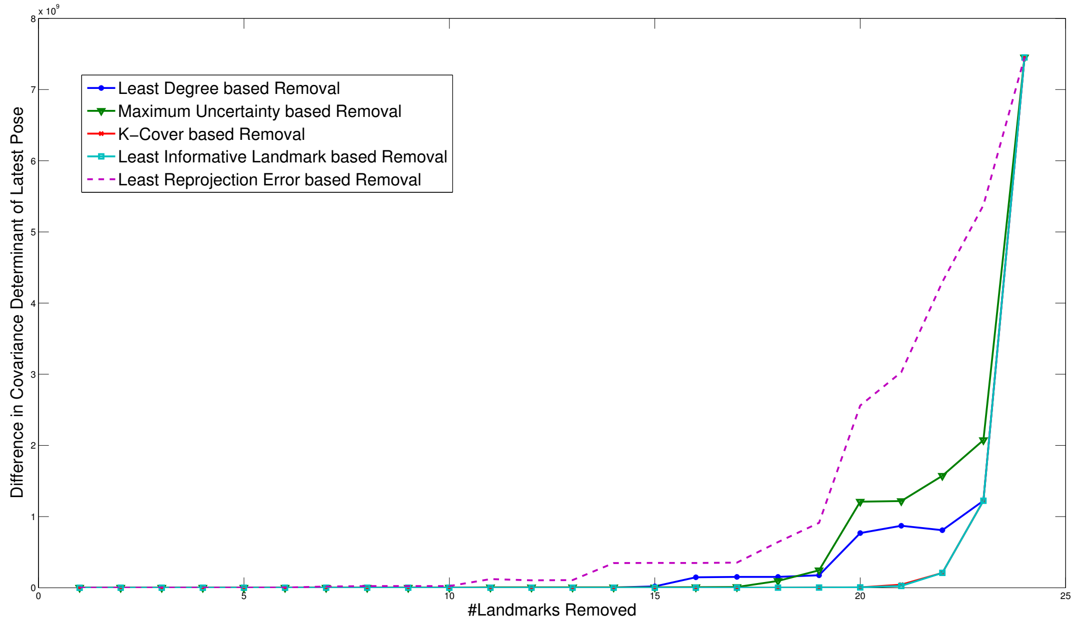

Fig. 4. Comparison of difference in covariance determinant (UD) as a function of the number of landmarks removed using different landmark removal techniques

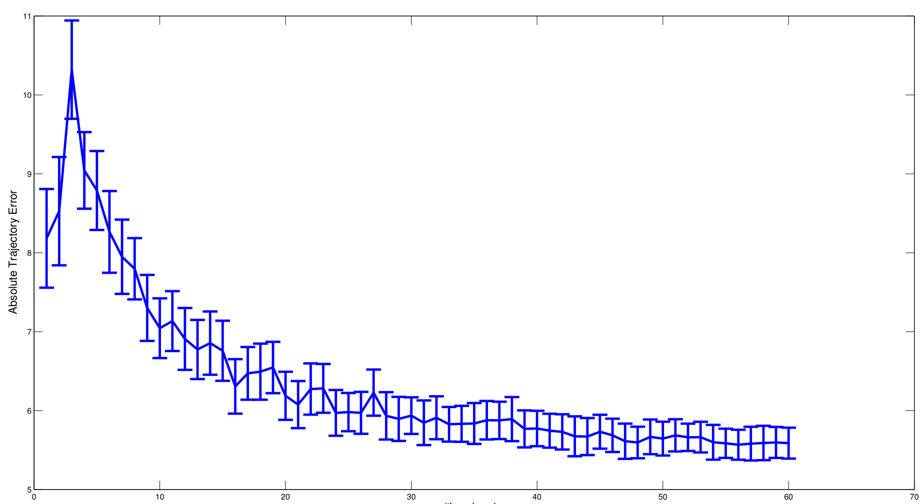

Fig. 5. Absolute trajectory error vs Number of landmarks

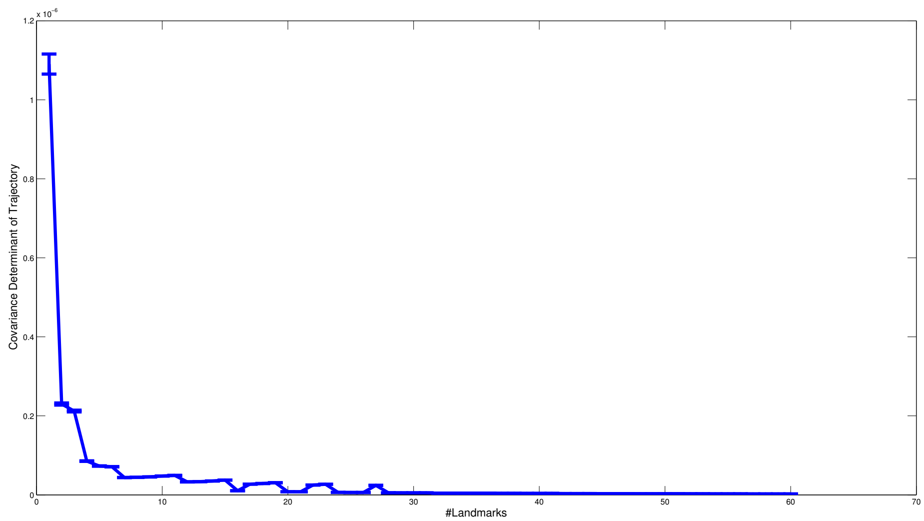

Fig. 6. Covariance determinant of the trajectory vs Number of landmark