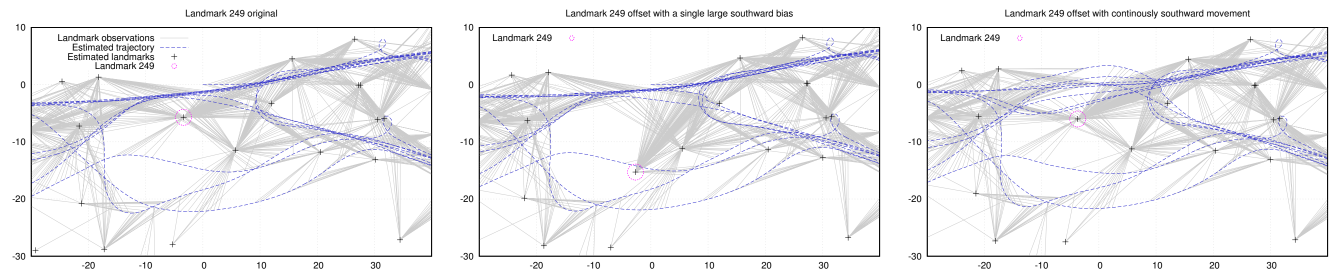

Fig. 3: The optimal estimates of the trajectory and landmark positions obtained by Max-Mixture graph SLAM on the Victoria Park dataset. Left: low convergence uncertainty (measured by objective value). Middle: high convergence uncertainty because of rejection of outlier observations of landmark 249. Right: low convergence uncertainty, no outlier detected by Max-Mixture.

reject any unlikely landmark observations and largely distorts the resulting trajectory when given moving landmark measurements. An explanation for this is that each clique of landmarks with coherent motion forms a plausible reference frame for related observations. Inference based on each independent reference frame will reach plausible estimate of robot trajectory and the map, however robust SLAM methods which assume stationary landmarks will average over a sum of different reference frames and lead to wrong conclusions.

C. Comparison with Prior Methods

To benchmark the robustness of the proposed approach and to show its correctness and feasibility, we use the Victoria Park dataset that has been used in a number of publications before. The dataset consists of pose graphs in 2D and contain several thousand poses and landmark constraints. We corrupted the data by setting landmark "249" (circled in red) in a constant northward movement, where its eventual position is roughly 7 meters north of its original location. We chose landmark "249" due to the relatively large amount of observations associated with this particular landmark in the dataset. We expect the more observations there are on a landmark, the greater its movement would corrupt the final optimization results and the more possible that existing robust SLAM methods would fail.

We compare the results of Dynamic Covariance Scaling robust kernel as discussed in our formulation, and also the SLAM with EM approach proposed in [11]. Figure 4 shows the results for DCS, standard EM, and our approach. As shown in the figure, robust observations alone are unable to handle moving landmarks. Because observation-based robust methods do not characterize the mobility of the landmark, its effect on associated observations and assume independence between observations, which is not the case for moving landmarks. A moving landmark will cause associated observations to be inconsistent in a plausible way such that a subgroup of the observations might be able to converge to a local minimum but the rest of the observations would distort the result elsewhere.

Normal SLAM with EM was proposed in [11] for datasets with very large movement. Their formulation is similar with ours except it is without the robust factor v_k. As shown in Figure 4, the resulting trajectory is distorted. One explanation

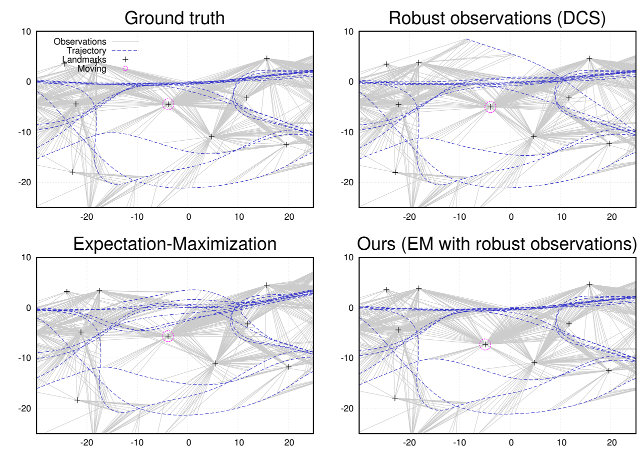

Fig. 4: Dataset corrupted by the landmark with small movement on the Victoria Park dataset

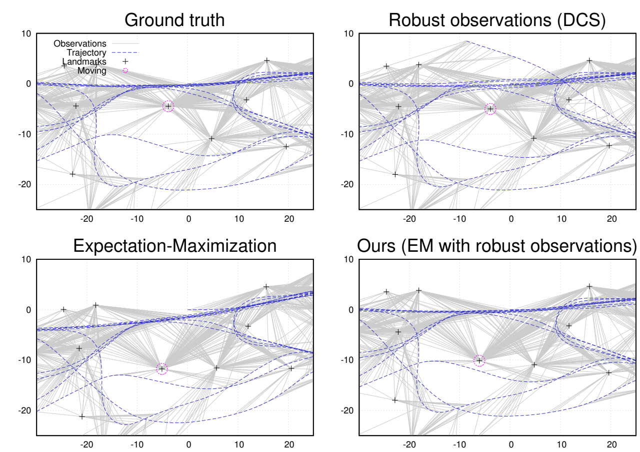

Fig. 5: Dataset corrupted by the landmark with large movement on the Victoria Park dataset

for this is from the characteristics of the datasets. In their paper, they investigated datasets containing landmarks moved from one room to another room over a long period of time. Such long-duration mobility is not the case in the Victoria Part dataset, where the motion of the landmark is relatively small and continuous. In fact, the motion of the corrupted landmark is doubled and normal EM is able to learn the mobility correctly.

Our robust back-end however, is able to converge to a