correct solution in a few iterations. Our result is also verified by examining the learned parameters w_{j_k} and v_k of all landmarks, which is close to zero for the actual outlier landmarks, thus correctly deactivating associated corrupted observations. The improvement is explained by our utilization of the robust kernel to make the EM algorithms reliably learn the mobility indicators of the landmarks correctly identify the actual moving landmarks. Thus our approach is able to obtain the best results in both situations.

In Figures 6 and 7, the result also shows additionally comparison of different methods on the Alcazar of Seville dataset. As can be seen, the trajectory estimation obtained with only robust observations using DCS kernel is significantly distorted. Our method is able to recover the trajectory approximately. The estimated trajectory does not completely converge on the ground truth trajectory due to less than full coverage of extracted landmarks and limited accuracy in depth estimation.

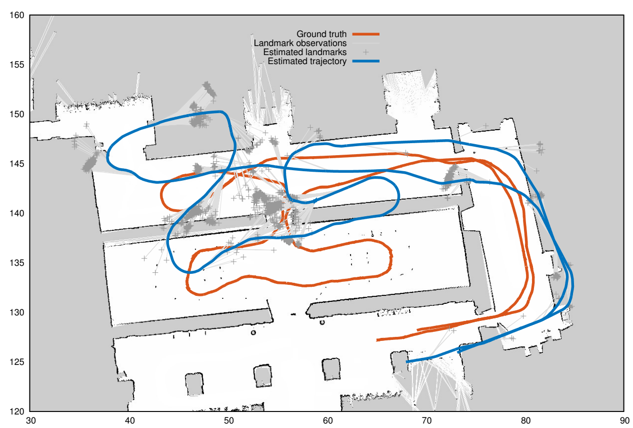

Fig. 6: Estimation with only robust observations (DCS) on the Alcazar of Seville dataset. Background is the ground truth map.

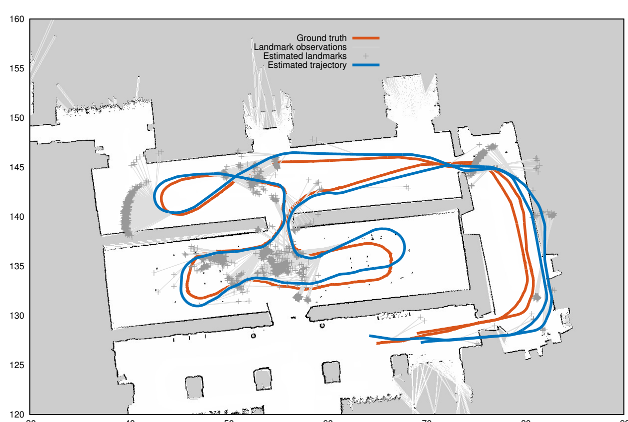

Fig. 7: Estimation with our method on the Alcazar of Seville dataset.

VI. Discussion and Future Work

We have shown the basic efficacy of our approach, but the evaluation is far from being comprehensive. The performance under different percentage of randomly generated outliers, and different sources and types of datasets including 3-D datasets are needed for a complete understanding of the performance in our approach. Due to the different nature of source of errors of moving landmarks than spurious loop closure, the effect of different numbers of observations associated with landmarks also needs to be taken into account for systematic evaluation.

We have examined the theoretical basis for the incremental variant of the EM algorithms. Considering the fast convergence of our batch EM algorithm it might be possible to integrate the incremental algorithm into the graph optimization process without loss of the correctness of the EM algorithms, and making our approach suitable for real-time update.

In our formulation, there are pre-defined parameters λ for penalizing against removing too many landmarks, which is essentially a decision boundary, and Φ for the robust kernel. The appropriate method to choose the parameters and their sensitivity to environmental factors and dataset characteristics need to be examined. There are multiple robust SLAM methods proposing different penalty terms which derive into these parameters. A comparison of the alternative choices of penalty terms is also necessary.

VII. Conclusion

This paper proposed a new method to characterize and identify the mobility of potentially moving landmarks by using the EM algorithms with robust kernel. The feasibility of the proposed approach was shown and evaluated on synthesized datasets from a standard dataset. We compared with existing state-of-the-art methods and showed that observation based robust methods are unable to handle moving landmarks while EM alone without robust kernel does not deal with small continuous movement robustly. We also propose an incremental variant of our approach which will be suitable for real-time incremental update in future implementation.

Appendix

A. *SLAM as a Least Squares Problem*

For completeness of the paper, we review how to form the SLAM optimization problem as a least squares problem, following the derivation in [4]. Recall that in equation 7, we need to solve a quadratic program, however we may approximate the terms with first order polynomials. For the process term,

$$\begin{aligned} & f_i(\boldsymbol{x}_{i-1}, \boldsymbol{u}_i) - \boldsymbol{x}_i \\ & \qquad \approx f_i(\boldsymbol{x}^0_{i-1}, \boldsymbol{u}_i) + \boldsymbol{F}^{i-1}_i \delta\boldsymbol{x}_{i-1} - (\boldsymbol{x}^0_i + \delta\boldsymbol{x}_i) \\ & \qquad = \boldsymbol{F}^{i-1}_i \delta\boldsymbol{x}_{i-1} + \boldsymbol{G}^i_i \delta\boldsymbol{x}_i - \boldsymbol{a}_i \end{aligned} \tag{11}$$

where $\boldsymbol{I}$ is the identity and

$$\begin{aligned} \boldsymbol{F}^{i-1}_i &= \frac{\partial f_i(\boldsymbol{x}_{i-1}, \boldsymbol{u}_i)}{\partial \boldsymbol{x}_{i-1}}\Big|_{\boldsymbol{x}^0_{i-1}}, \\ \boldsymbol{G}^i_i &= -\boldsymbol{I}, \text{(Identity matrix)} \\ \boldsymbol{a}_i &= \boldsymbol{x}^0_i - f_i(\boldsymbol{x}^0_{i-1}, \boldsymbol{u}_i). \end{aligned}$$