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Peer Review

Review of: "A Minimal Subset Approach for Efficient and Scalable Loop Closure"

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1. Independent researcher

The authors propose to employ an optimization strategy based on redundancy minimization and information preservation using a sliding window technique to efficiently sample keyframes for loop closure detection. The authors highlight that the proposed method reduces redundant keyframes while improving scalability and computational performance.

In general, the paper is well-written with clear details and explanations.

The paper has open-source code and has been evaluated against a widely used loop closure detection algorithm; hence, this paper adds value to the research community.

1. This paper assumes that keyframes are extracted for every 1m, 2m, or 3m and that a keyframe is a lidar scan. If another approach for keyframe extraction is used, for example, time-based, or if a single keyframe represents a submap (a set of consecutive frames), then the effectiveness of the proposed approach is unclear.
2. While the authors' proposed method reduces the keyframe set, there are still false positives, and hence a robust pose graph optimizer should still be used. In that case, compared to the 1m keyframe set and the author's proposed set, how much of a difference does it bring in optimized poses, after PGO on the original set and the reduced set of keyframes?
3. In the proposed method, as detailed in Sec III A, the authors propose to use a similarity metric to reduce the keyframe set from an initial larger set to a reduced number of keyframes while maintaining map coverage. Does this mean that users have to first gather an initial set of many loop closure candidates, apply the authors’ proposed algorithm to get the resultant smaller set?

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In this case, the authors must present the computational effort that is needed for calculating the similarity metric to reduce the keyframe size in the presented experiments. The authors should also consider the computational costs of sliding window optimization while presenting the results.

4. It is recommended that the authors highlight the key differences between their other paper [30], which is on arXiv.
5. For the completeness of this paper, it is highly recommended that the authors present results with at least one machine learning-based descriptor and one hand-crafted descriptor to show the reproducibility of the proposed method's effectiveness in reducing memory and computational needs. Just presenting on one descriptor, OverlapTransformer, shows only the effectiveness with a machine learning descriptor and not hand-crafted ones.
6. From Fig. 4, the proposed method does not seem to offer any significant advantages in terms of ATE discrepancy, memory, and execution time compared to results from keyframes extracted at 1m. Can you provide examples or scenarios where the proposed method might outperform the baseline approaches (keyframes extracted at 1m)? What specific improvements or comparisons would you suggest to demonstrate the advantages of MSA over keyframes at 1m?

Declarations

Potential competing interests: No potential competing interests to declare.