SELF-OPTIMIZING LOOP SIFTING AND MAJORIZATION FOR 3D RECONSTRUCTION

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ABSTRACT

Visual simultaneous localization and mapping (vSLAM) and 3D reconstruction methods have gone through impressive progress. These methods are very promising for autonomous vehicle and consumer robot applications because they can map large-scale environments such as cities and indoor environments without the need for much human effort. However, when it comes to loop detection and optimization, there is still room for improvement. vSLAM systems tend to add the loops very conservatively to reduce the severe influence of the false loops. These conservative checks usually lead to correct loops rejected, thus decrease performance. In this paper, an algorithm that can sift and majorize loop detections is proposed. Our proposed algorithm can compare the usefulness and effectiveness of different loops with the dense map posterior (DMP) metric. The algorithm tests and decides the acceptance of each loop without a single user-defined threshold. Thus it is adaptive to different data conditions. The proposed method is general and agnostic to sensor type (as long as depth or LiDAR reading presents), loop detection, and optimization methods. Neither does it require a specific type of SLAM system. Thus it has great potential to be applied to various application scenarios. Experiments are conducted on public datasets. Results show that the proposed method outperforms state-of-the-art methods.

INTRODUCTION

Due to rapid development in autonomous vehicles and consumer robots, there is an increasing need for precise 3D maps for route and action planning and navigation. Among 3D mapping methods, visual simultaneous localization and mapping (vSLAM) and 3D reconstruction methods are very promising because they can map large-scale environments such as cities and indoor environments without the need for much human effort involved.

vSLAM and 3D reconstruction methods have gone through impressive progress. In camera tracking, there are different methods, such as sparse keypoint point-based methods [1, 2, 3, 4, 5], direct methods [6, 7], and dense surface-based methods [8, 9]. Additionally, IMU are added to methods [10, 11, 12, 13, 14, 15, 16] to make tracking more accurate. Even though camera tracking algorithms have good performance and low drift, the build-up error can still not be ignored [16]. To solve this problem, loop closure detection [17, 18] and optimization [19] are often leveraged to counter the problem, and it has provided plenty of improvements. However, the problem is not fully solved yet. Intuitively, the more loops in data, the more information to recover more precise camera trajectories and 3D models. But, in practice, when running existing vSLAM systems on datasets with loopy motions, mismatches can always be found in the final results. This means that loops are not successfully detected and utilized.

vSLAM systems tend to add the loops very conservatively to reduce the severe influence of the false loops [16]. These conservative checks are the result of the non-perfect precision performance of loop detection methods. There are high chances that detected loops are incorrect ones.

To solve this challenging problem, we propose an algorithm that can sift and majorize loop detections so that only correct and essential loops are fed into the following optimization steps. The proposed method highly couples with the dense map posterior (DMP) metric [20] that can evaluate 3D reconstruction performance without ground truth measurement. Our proposed algorithm can compare the usefulness and effectiveness of different loops and ultimately sifts out false and unimportant loops. To the best of our knowledge, the contributions of the proposed algorithm are:

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1. The proposed algorithm can sift loop detections based on their impact on loop optimization results.
2. It is the first algorithm that can marjorize loop detection only to keep the important ones while ignoring the less relevant ones.
3. Experiments on public datasets show it outperforms state-of-the-art methods.

RELATED WORK
To avoid the severe consequence of optimizing with false loops, vSLAM and 3D mapping systems tend to add the loops very conservatively. ORB-SLAM2 \cite{1} requires the presence of several consistent loops in consecutive keyframes to accept them, where at least one keyframe must be shared in order to be classified as consistent. With this consistency check, ORB-SLAM2 merely takes false loops into optimization but at the price that plenty of correct loops are rejected. ElasticFusion \cite{9} evaluates several characteristics before taking a loop detection into optimization pipelines, including deformation cost and final state of the Gauss-Newton system. Even after all the evaluations, a good loop is often rejected, and not rare to see that an incorrect loop is accepted. BundleFusion \cite{4} filters loop correspondences with cascade checks including local geometric and photometric consistency checks and check on correspondence residual after optimization. The local depth discrepancy check shares a small similarity with our work. However, the check is limited to a very local region with a downsampled depth resolution together with a user-specified threshold. Thus it is not informed about the effect of loop data correspondences impacting a full 3D model. A requirement on a user parameter also makes it ineffective and less adaptive. \cite{2} do this by pruning edges after optimization based on the discrepancy between the individual transformation estimates before and after optimization. We share the idea of observing optimization consequences brought in with a loop, but their impact is measured on a sparse graph while ours is observed on a full 3D dense model.

Another approach to solving the problem is to treat false loops as outlier data and decrease their impact on the optimization \cite{21,22,23,24}. They work well in some cases, but the dependence on initial conditions and the ratio of outliers makes them prone to failures. Choi et al. further develop this idea into an algorithm that is highly coupled with the dense 3D reconstruction problem by specifying both pose graph construction and least square information calculation \cite{25}. This method is very effective when a desired camera scan pattern is followed but it requires keeping surface within camera range all the time thus limiting its flexibility. It also suffers dependence on initial condition and outlier ratio.

Due to the difficulty of balancing precision and recall of loop detections, SUN3D \cite{26} turns to a human-in-the-loop approach by labeling objects in scenes and connect the same objects across frames. This method performs very well in terms of loop precision and recall, but it requires too much effort in labeling; thus is not practical to process data on a large scale.

METHOD
To solve the loop sifting problem, we propose an algorithm specified in Algorithm 1. In the algorithm, a given set of loop detections is denoted as $O$ among which each individual one is denoted as $O_i$. The supporting optimization pose graph is denoted as $G$. The sensor (e.g. camera and LiDAR) data are denoted as $Z$.

There are two parts in the algorithm. In the first part, all the loops are tested and evaluated individually on the given initial pose graph. This step first runs optimization with a single loop and then fuses a model with the optimized results $T'$. Then a DMP value $r$ is evaluated for the fused 3D model $M$. This means that it tests each loop and sees how much improvement it provides by itself. Finally, all these loops are ranked by the calculated DMP value $r$ in ascending order (more effective $ightarrow$ less effective $ightarrow$ negative impacts).

In the second part, all the loops are tested and evaluated one more time, but in a way that is different from the first time. In this part, the loops are tested in sorted order: the ones that provide more improvements are tested first. When a loop can provide performance improvement on the previous result, it will be added to an accepted set, thus will also impact consequent loop tests. In this way, loops are accepted when they can provide performance improvement on the current status. The first accepted one should make an improvement to the original results from tracking.

IMPLEMENTATION
The proposed method is general and agnostic to loop detection and optimization methods. Neither does it require a specific type of vSLAM system. For our experiments, we choose several well know implementations.

Tracking and optimization pose graph
The proposed method requires an optimization pose graph as input data. The only requirement of the pose graph optimization is that it can handle loop closure optimization. In our implementation, we use sparse image feature-based tracking and mapping method implemented by ORB-SLAM2 \cite{1} with loop detection disabled. The pose graph from ORB-SLAM2 is utilized as the optimization graph for the proposed method. For the purpose of loop sifting and majorization, we find pose graph optimization is more improvements are tested first. When a loop can provide performance improvement on the previous result, it will be added to an accepted set, thus will also impact consequent loop tests. In this way, loops are accepted when they can provide performance improvement on the current status. The first accepted one should make an improvement to the original results from tracking.

The ORB-SLAM2 is a very well implemented sparse feature-based SLAM system. Inside this tracking module, the
Initialization timestamp \( t \)

Fels can easily be moved rigidly in space. We fuse to speed up the efficiency, we leverage the advantage that sur-

p \( \begin{array}{l}
\text{plementation of 3D model. Each surfel has seven attributes: a position}
\end{array} \)

3D models. For this step, surfels \( [27] \) are used as a data represen-

Graph across keyframes.

Correct the re-projection error of feature correspondences among

the local bundle adjustment thread is free. Local BA is used to

correct the re-projection error of feature correspondences among

co-visible keyframes in a background thread. This tracking mod-

ule provides camera poses for each frame and a co-visibility

graph across keyframes.

Algorithm 1: Loop sifting and majorization algorithm

Input : \( O, G, Z \)

Output: filtered loops \( O^* \)

1. \( O^* \leftarrow \emptyset, r^* \leftarrow r(\emptyset, Z), r \leftarrow \emptyset \)

2. for \( i \leftarrow 0 \) to \( \text{len}(O) \) do

3. \( T' \leftarrow \text{optimize}(G, O[i]) \)

4. \( M' \leftarrow \text{fuseModel}(T', Z) \)

5. \( r[i] \leftarrow r(M', Z) \)

6. end

// Ranking \( O \) by our metric

7. \( O' \leftarrow \text{rank}(O, by = r, order = \text{descending}) \)

// Try \( O' \) one by one and add the ones making improvements

8. for \( i \leftarrow 0 \) to \( \text{len}(O') \) do

9. \( O_{imp}^* \leftarrow \text{union}(O^*, O[i]) \)

10. \( T' \leftarrow \text{optimize}(G, O_{imp}^*) \)

11. \( M' \leftarrow \text{fuseModel}(T', Z) \)

12. \( r' \leftarrow r(M', Z) \)

13. if \( r' > r^* \) then

14. \( O^* \leftarrow O_{imp}^* \)

15. \( r^* \leftarrow r' \)

16. end

17. end

Oriented FAST and Rotated BRIEF (ORB) features are ex-

tracted for keypoint matching. Then frames are tracked against

keyframes with motion estimate and then refined with a local sparse

map. Keyframes are generated when tracking is weak, or

the local bundle adjustment thread is free. Local BA is used to

correct the re-projection error of feature correspondences among

co-visible keyframes in a background thread. This tracking mod-

ule provides camera poses for each frame and a co-visibility

graph across keyframes.

Model fusion

It is a important step to fuse camera reading data into dense

3D models. For this step, surfels [27] are used as a data representa-
tion of 3D model. Each surfel has seven attributes: a position

\( p \in \mathbb{R}^3 \), normal \( n \in \mathbb{R}^3 \), color \( c \in \mathbb{N}^3 \), weight \( w \in \mathbb{R} \), radius \( r \in \mathbb{R} \),

initialization timestamp \( t_0 \) and last updated timestamp \( t \). With a

radius property, a surfel can represent a local flat surface around

given a position \( p \).

Even though surfel fusion is fast with efficient implemen-
tation running on GPU, it takes a considerable amount of time.

To speed up the efficiency, we leverage the advantage that sur-

fels can easily be moved rigidly in space. We fuse \( k \) consecutive

frames scene fragments as basic blocks and transform them

based on optimized camera trajectories. In this way, the fusion of

updated camera pose estimates is approximated with transform-
ing scene fragments to updated location. Thus final results are

calculated more efficiently.

Fragment loop to frame loop conversion

Since there are fewer scene fragments than frames, there is a need
to convert scene fragment matches to camera frame loops. We do this by connecting a reference frame in one scene frag-

ment and connecting it to all the frames of the other scene frag-

ments and repeat for the other direction.

EXPERIMENTS

Extensive experiments are performed to evaluate our pro-

posed method on two datasets: augmented ICL-NUIM [25] and

SUN3D dataset [26]. SMD is short for surface mean distance.

Augmented ICL-NUIM dataset

We run experiments on the Augmented ICL-NUIM dataset [25]. This dataset is a synthetic dataset with ground-truth

surface models and camera trajectories. The dataset has four data

sequences of RGB-D data. For each sequence, there are merged

scene fragments available with ground truth registration results.

For this dataset, our baseline method is CZK [25] which is pub-

lished in the same work as the Augmented ICL-NUIM dataset.

Experiments are conducted to evaluate the loop sifting and

majorization performance of the proposed method. Performance

is evaluated based on precision and recall of loops detected and

remaining. Results are reported in table 2. We can see that our

method gets 100% percent precision, which is desired. You may

notice that the recall reduced dramatically after sifting. The de-

crease is not because of the strict requirement but because many

loops are not very useful. We note that the remaining loops are

the core ones that matter most for a better reconstruction quality,

which we call it loop majorization.

Many of the original loops are close to each other and con-
nected accurately by ORB-SLAM tracking already. We prove this

in another experiment that evaluates the trajectories and recon-

structed 3D models of optimization with the key loops identified

by our method and all the loops that agree with ground truth. Re-

sults are shown in table 1. We can see that more loops do not

improve performance instead decrease the performance. This is

because some of the loops are not very precise. It will decrease

accuracy if two loop regions are well connected originally.

To further understand the proposed method, we draw

precision-recall curves of the loop ranking results in the proposed

algorithm in figure 1. In the results, we can see the curves all

starts from 100% precision. Then the curves keep on high preci-
sion values when recall increases. There are a few drop points,

which means false positive loops. The majority of the false-

positive loops are at the end of the list reflected by the sharp drops

when recall reaches 100%. These mean that the ranking has good
TABLE 1. Performance difference with only key loops vs. all correct loops agreed by ground truth. SMD is short for surface mean distance.

|                | Traj. RMSE |          | SMD |          | DMP |          |
|----------------|------------|----------|-----|----------|-----|----------|
|                | key loops  | all loops| key loops| all loops| key loops| all loops|
| livingroom 1   | 0.082      | 0.175    | 0.027 | 0.059    | 36.9 | 122.8    |
| livingroom 2   | 0.037      | 0.203    | 0.012 | 0.080    | 19.5 | 85.2     |
| office 1       | 0.051      | 0.096    | 0.020 | 0.046    | 143.5| 200.9    |
| office 2       | 0.036      | 0.085    | 0.014 | 0.024    | 110.5| 373.2    |
| Average        | 0.052      | 0.140    | 0.018 | 0.052    | 77.6 | 195.5    |

TABLE 2. Recall and precision performance on loops before and after loop filtering or sifting.

| Recall/Precision (%) | Registration | ZGK    | Ours |
|----------------------|--------------|--------|------|
| livingroom 1         | 61.2 / 27.2  | 57.6 / 95.1 | 5.5 / 100 |
| livingroom 2         | 49.7 / 17.0  | 49.7 / 97.4 | 3.9 / 100 |
| office 1             | 64.4 / 19.2  | 63.3 / 98.3 | 2.8 / 100 |
| office 2             | 61.5 / 14.9  | 60.7 / 100  | 0.7 / 100 |

performance with exceptions. These false-positive loops that remained in the ranking are well handled by the last part, which tests and decides acceptance of each ranked loop. It shows one more strength of our method: it decides the acceptance of correct loops without a single user parameter, even when the ratio of true/false positive loops are drastically different.

SUN3D dataset

The SUN3D dataset [26] is a large-scale RGB-D database. It contains many data sequences captured at many places. Among them, there are eight sequences (listed here: http://sun3d.cs.princeton.edu/listNow.html) that are labeled with object annotations and widely used for evaluating SLAM and 3D reconstruction systems. We follow this common practice and run experiments on these sequences. For sequences harvard_c5, harvard_c6 and harvard_c8, there is no loops detected on top of tracking. So we do not include results for them.

Quantitatively, we evaluate the DMP metric of different methods and report them in Table 3. We compared with four different methods: 1) CZK, which is an offline method that targets the best surface reconstruction quality; 2) SUN3D, which is an offline method that adds manual object labeling as a source of loop closure; 3) ORB-SLAM2, which is a well known good SLAM that also has a tracking part in our system; 4) Bundle-Fusion which is a well-engineered real-time dense SLAM system. The DMP metric evaluates that the proposed method makes reliable improvements on its initial start point: tracking result. Most importantly, it outperforms most methods. To understand the proposed method, we also include the number of loop detections and the number of loops that pass our algorithm, shown in Table 4.

Qualitative, we show results in the form of screenshots of reconstructed 3D models in Figure 2. In Figure 2, we highlight the mismatches in tracking results so that...
FIGURE 2. Results on sequences of the SUN3D dataset. The left column shows the results of the tracking part. The right column shows the results after our loop optimization. We highlight the mismatches in tracking results so that differences are easier compared.
TABLE 3. DMP Performance difference of different methods on different sequences

|                  | SUN3D  | ORB SLAM2 | CZK    | BundleFusion | Tracking | Ours   |
|------------------|--------|-----------|--------|--------------|----------|--------|
| mit_32_d507      | 573.95 | 750.60    | 334.17 | 441.15       | 904.25   | 296.59 |
| maryland_hotel3  | 145.85 | 107.50    | 108.91 | 128.86       | 111.83   | 96.56  |
| 76_studyroom     | 448.84 | 1191.40   | 282.22 | 256.07       | 358.93   | 193.94 |
| mit_dorm_next    | 46.38  | 51.88     | 734.50 | 944.81       | 87.04    | 30.16  |
| mit_lab_hj       | 180.49 | 162.98    | 244.86 | 207.94       |          | 155.86 |

TABLE 4. Number of loops before and after loop sifting and majorization

| Number of loops | before | after |
|-----------------|--------|-------|
| mit_32_d507     | 2135   | 34    |
| maryland_hotel3 | 224    | 6     |
| 76_studyroom    | 442    | 7     |
| mit_dorm_next   | 621    | 6     |
| mit_lab_hj      | 219    | 7     |

reader can better compare them with our results. SUN3D data sequences are scanned with very loopy motion in some areas but only once for some other scene parts, thus is considered difficult to process. Readers may refer to http://redwood-data.org/indoor/models.html for CZK results and https://graphics.stanford.edu/projects/bundlefusion/recons.html for BundleFusion results for visual comparison.

CONCLUSION

In this work, an algorithm that can sift and majorize loop detections is proposed. The algorithm tests and decides the accept- ance of each loop without a single user-defined threshold. Experiments are conducted on public datasets, including the Aug- mented ICL-NUIM dataset and the SUN3D dataset. Results show that the proposed method outperforms the state-of-the-art method. It can find key loops with 100% precision and eliminate significant mismatches when processing SUN3D sequences.

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