Xiao-long SHEN, Yong DOU, Steven MILLS, David M EYERS, Huan FENG, Zhiyi HUANG, 2018. Distributed sparse bundle adjustment algorithm based on three-dimensional point partition and asynchronous communication. *Frontiers of Information Technology & Electronic Engineering*,19(7):889-904.
https://doi.org/10.1631/FITEE.1800173

Distributed sparse bundle adjustment algorithm based on three-dimensional point partition and asynchronous communication

Key words: Sparse bundle adjustment; Parallel; Distributed sparse bundle adjustment; Three-dimensional reconstruction; Asynchronous

Corresponding author: Xiao-long SHEN
E-mail: shenxiaolong11@nudt.eud.cn
ORCID: Xiao-long SHEN, https://orcid.org/0000-0002-6481-4287

Motivations

1. Recently, using the structure from motion (SfM) method to solve large-scale three-dimensional (3D) reconstruction problems has received considerable attention in the computer vision community.
2. Over the last decade, large-scale 3D reconstruction problems have been extensively studied to improve the computational efficiency and storage scalability.
3. The scalability and speed in bundle adjustment (BA) are limited by the number of 3D points.
4. Sparse bundle adjustment (SBA) is the most time-consuming section in 3D reconstruction.

Main ideas

1. A 3D point set partition algorithm, DSBA, is proposed to improve the scalability by eliminating the data correlation within the BA problem.
2. A circulant matrix based asynchronous distributed algorithm, A-DSBA, is proposed to solve the equation set.
3. A-DSBA develops an asynchronous communication protocol to reduce the Schur complement ***S*** when solving the equation.

Methods

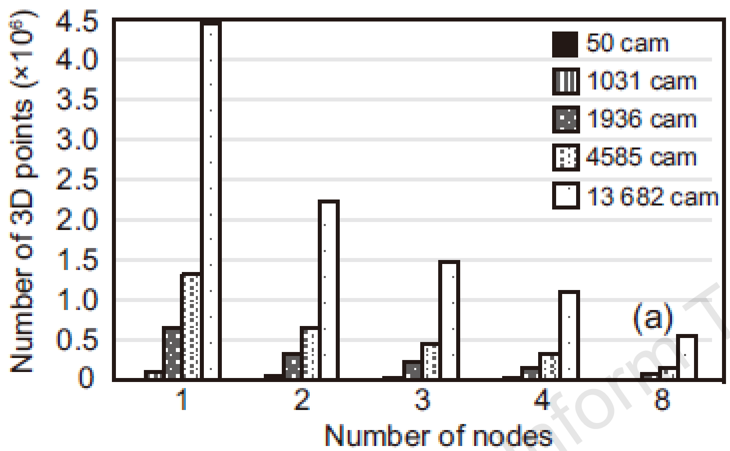
1. The 3D-points based algorithm is used to divide the dataset into different nodes.

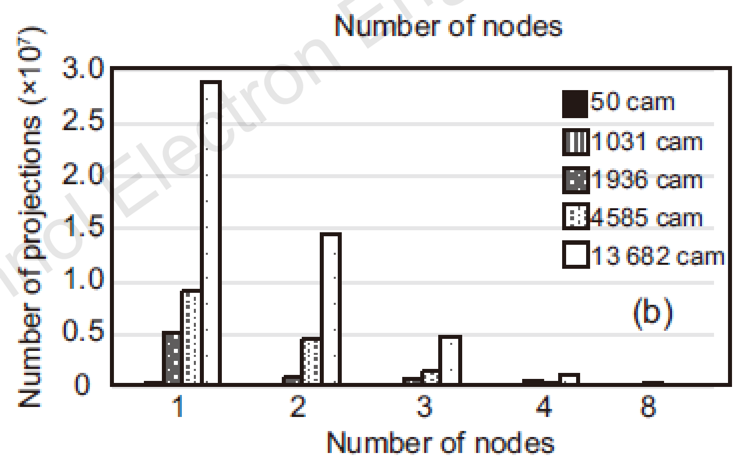
2. The matrices are separated into blocks for easy computation.

3. An asynchronous communication algorithm is used to decrease the time of data transfer.

Major results

1. The DSBA algorithm considerably reduces the memory consumption and improves the scalability by distributing the 3D reconstruction model's parameters into different nodes.





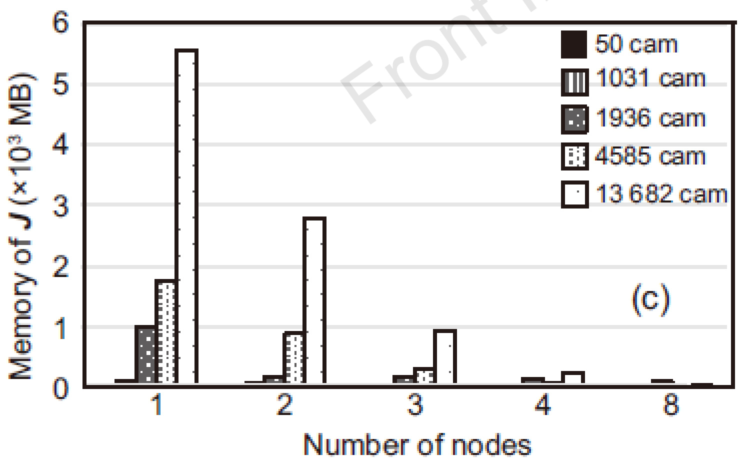


Fig. 10 Memory consumption of the DSBA algorithm: (a) variation in the number of 3D points; (b) variation in the number of projection points; (c) variation in the memory consumption of the Jacobian matrix

Major results

2. Compared with the single-node SBA algorithm, computation of ***J***, ***J***^{T}***J***, ***S***, and ***e****a* achieves speedup ratios of 6.9x, 6.48x, 5.92x, and 5.8x, respectively, in the case of eight nodes.

3. Consider the model with 1936 cameras and 2, 3, 4, and 8 nodes; the speedup ratios of S-DSBA are 1.3x, 1.7x, 2.2x, and 4.4x, while the speedup ratios of A-DSBA are 1.7x, 2.4x, 3.2x, and 6.4x.

4. Compared with the serial single-core SBA algorithm, the speedup ratios of A-DSBA are 10.3x, 14.9x, 19.2x, and 41.3x, given 2, 3, 4, and 8 nodes, respectively, each of which has six cores.

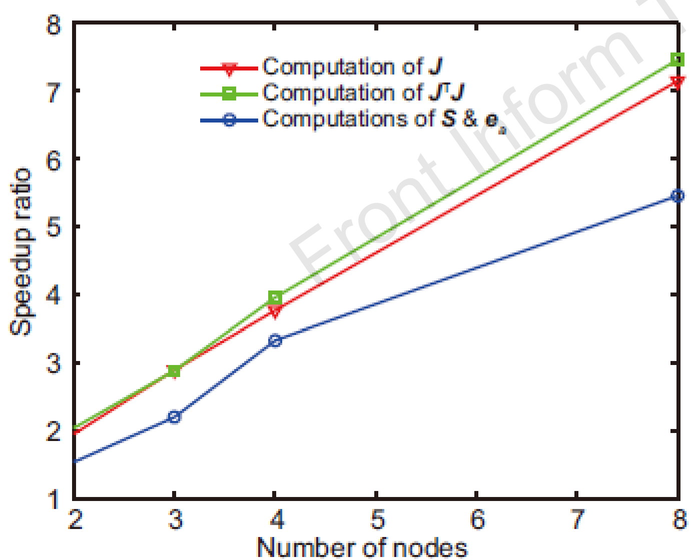


Fig. 13 Speedup ratio of the DSBA key steps

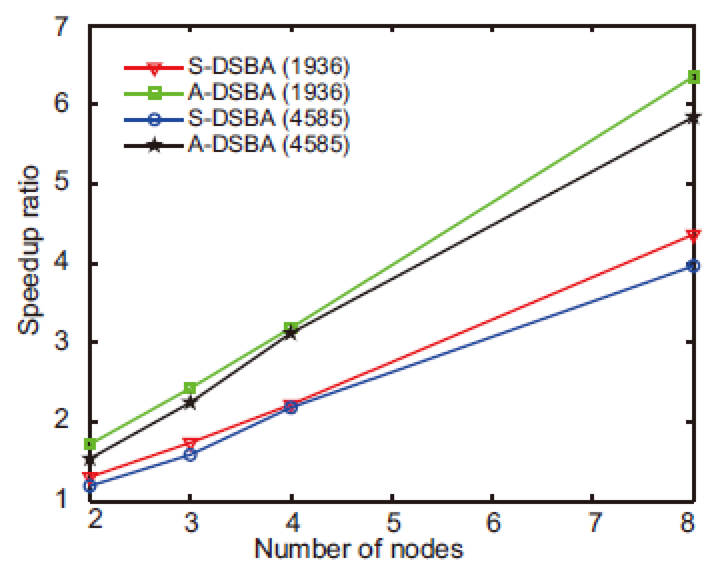


Fig. 14 Speedup ratio of DSBA

Conclusions

1. A distributed SBA algorithm, which is simple, easy to implement, and independent of BA problems, is proposed.
2. Compared with the serial SBA method, the proposed algorithm achieves remarkable speedup ratios without compromise on accuracy.
3. A blocked cyclic based DSBA algorithm is proposed to improve the speed of serial SBA and the scalability of SBA. By adopting the blocked cyclic based asynchronous reduced DSBA algorithm (A-DSBA), the communication time associated with the reduction of ***S*** overlaps with the time taken to solve the equation set.
4. The calculation time of A-DSBA is about 46% shorter than that of S-DSBA.