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Research paper

Bundle block adjustment of large-scale remote sensing data with Block-based Sparse Matrix Compression combined with Preconditioned Conjugate Gradient

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ABSTRACT

In recent years, new platforms and sensors in photogrammetry, remote sensing and computer vision areas have become available, such as Unmanned Aircraft Vehicles (UAV), oblique camera systems, common digital cameras and even mobile phone cameras. Images collected by all these kinds of sensors could be used as remote sensing data sources. These sensors can obtain large-scale remote sensing data which consist of a great number of images. Bundle block adjustment of large-scale data with conventional algorithm is very time and space (memory) consuming due to the super large normal matrix arising from large-scale data. In this paper, an efficient Block-based Sparse Matrix Compression (BSMC) method combined with the Preconditioned Conjugate Gradient (PCG) algorithm is chosen to develop a stable and efficient bundle block adjustment system in order to deal with the large-scale remote sensing data. The main contribution of this work is the BSMC-based PCG algorithm which is more efficient in time and memory than the traditional algorithm without compromising the accuracy. Totally 8 datasets of real data are used to test our proposed method. Preliminary results have shown that the BSMC method can efficiently decrease the time and memory requirement of large-scale data.

1. Introduction

Bundle block adjustment is an inevitable and crucial procedure in the photogrammetry, remote sensing and computer vision area. Especially in the 3D model reconstruction with multiple sensors such as UAV camera, oblique camera system and even cell phone cameras. A lot of research works have been done for UAV camera systems (Mathews and Jensen, 2013; Ai et al., 2015; Tong et al., 2015; Frueh et al., 2004; Dahlke and Wieden, 2013). Oblique images (Besnerais et al., 2008), ordinary digital cameras (Dandois and Ellis, 2010), and even internet images (Snavely et al., 2008; Agarwal et al., 2010, 2011). Those images are always large-scale data. They bring us more redundant observations, but in the mean time, they need more computation and memory resources. The main challenge of bundle block adjustment of these large-scale data is storing and computing the super large normal equation produced by a large number of images and tie points. Thus how to solve the big normal equation is a key issue. There are usually two categories of solutions, direct method and iterative method. Direct method is always referred to the conventional Levenberg–Marquardt (LM) algorithm. It was a most popular algorithm in the last few decades for solving non-linear least square problems. Conventional aerial photogrammetry procedure acquired images on an airborne platform and the images are regularly arranged. Thus the normal matrix has a sparse band structure which can be easily solved with memory space equal to the bandwidth of the sparse band structure. But the UAV images, oblique images, cell phone image and especially the internet images are mostly arranged irregularly. So the normal matrix of these data has no band characteristics. The LM method has to invert the full sparse matrix. It is no longer suitable for processing the large-scale remote sensing data. The iterative method includes a lot of algorithms. The most widely used iterative method is Conjugate Gradient (CG) algorithm which was firstly proposed in 1952 (Hestenes and Stiefel, 1952), but it's not widely used due to its drawbacks in precision and stability until recently. This method multiplies the normal matrix and the residuals vector of normal equation, forming a Krylov subspace (Saad, 1981), and then iteratively computes the answer of normal equation, and eventually end up to a convergence value which is close enough to the true answer (Hestenes and Stiefel, 1952). CG was further extended to an advanced method called Preconditioned Conjugate Gradient (PCG) which uses a preconditioner to reduce the condition

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of the normal matrix so as to improve the converging speed (Bru et al., 2008; Byröd and Åström, 2009, 2010; Jian et al., 2011; Li and Saad, 2013).

The main advantage of the iterative method is that the normal equation can be solved without explicitly forming the full normal matrix which is a relatively high cost in both computation and storage phase. It gives us a chance to solve the super large normal equation produced by large-scale data consisting of more than hundreds of thousands even millions of images on a common personal computer. The normal matrix is always sparse and includes a lot of zero elements. So only non-zero elements and their position indexes in the sparse matrix need to be stored, this strategy can largely compress the normal matrix. A widely used matrix compress method called Compressed Sparse Row (CSR) uses three one dimension data arrays to store non-zero elements and the corresponding necessary information. But we found in practice that this storage method is not suitable for the normal matrix update since that the normal matrix are formed and updated point by point in bundle block adjustment. After the sub-normal-matrix of each point is calculated, the whole normal matrix needs to be updated. When a CSR storage method is adopted, finding the position of the sub-normal-matrix of current point in the full normal matrix is very time consuming and complicated. Because the CSR stores matrix elements one by one while the sub-normal-matrix is an n^*n block (n is the number of unknown parameters related to the current point), all the elements of the sub-normal-matrix have to be updated one by one. So we propose a Block-based Sparse Matrix Compression (BSMC) format to compress the whole normal matrix in order to decrease its memory requirement while making the normal matrix easy to be updated.

In this paper, PCG algorithm is applied to solve the large normal equation. The Jacobi preconditioner is chosen to decrease the iteration times of PCG process. The BSMC method is introduced to combine with PCG aiming to decrease the memory requirement. The main purpose of this work is to build a stable and efficient bundle block adjustment system to deal with large-scale remote sensing data. Part of the test data are downloaded from a public data source website which was built and shared by Sameer Agarwal in University of Washington (Agarwal et al., 2010). UAV images, oblique images and cell phone images are also used as test data. We have analyzed and compared the memory and time requirement of different methods including the conventional LM algorithm and proposed BSMC method with PCG. A final summary of this work is given in the last section.

2. Related works

LM algorithm has been well studied for a long time. The mathematic theory and equation derivation are well-defined. Recently, the structure from motion is widely discussed in computer vision community. Most of the researchers working on structure from motion applied iterative methods to deal with bundle block adjustment problems of large-scale data (Snavely et al., 2008; Jian et al., 2011). The most famous and widely used method is PCG which is an extension version of the CG algorithm. CG belongs to the algorithms family called Krylov method (Saad, 1981). It multiplies the normal matrix and the residuals vector, forming a Krylov subspace which is used to iteratively solve the normal equations. It's been reported that the iteration times of convergence is related to the condition number of the normal matrix. Thus a PCG algorithm uses a preconditioner to decrease the condition of the normal matrix, so as to improve the converging speed (Byröd and Åström, 2010; Jian et al., 2011). A lot of works have focused on how to choose a proper preconditioner. Some efficient and stable preconditioners have been introduced, such as Jacobi preconditioner (Agarwal et al., 2010, 2011) (Byröd and Åström, 2010; Jian et al., 2011), Symmetric Successive Over-relaxation (SSOR) preconditioner (Byröd and Åström, 2010; Jian et al., 2011), QR factorization preconditioner (Byröd and Åström, 2010), Balanced Incomplete Factorization based preconditioner (Bru et al., 2008), multiscale preconditioner (Byröd and Åström, 2009), subgraph preconditioner (Jian et al., 2011) and so on. Among the above preconditioners, Jacobi is simplest and most widely used in the real case. Iterative methods can be also explored in remote sensing community since more and more large-scale remote sensing data have emerged, such as UAV images, Oblique images, and mobile phone images even internet images. When the images increased to a certain large number, the conventional LM method is no longer suitable for solving such big normal equations. Then, the iterative method is considered to be a necessary alternative.

Matrix-vector product is the most frequently computed procedure in the PCG iteration. The multiplications of normal matrix and residuals vector need to be calculated during each iteration of PCG. It means that the normal matrix will be frequently read and used during each iteration of PCG. Thus it has to be stored whatever in RAM or external memory. Some methods use mathematic trick to avoid storing the normal matrix (Agarwal et al., 2010; Byröd and Åström, 2010). However, this will take even more computational cost which will largely slow down the iteration speed. But to store the whole normal equation will need a very large memory space especially for the large-scale data. So the normal matrix should be compressed. As mentioned before, the normal matrix is often sparse and includes a lot of zero elements. Only non-zero elements and their position indexes in the sparse matrix need be stored. A famous and widely used normal matrix compression method is called CSR. This method only needs three one dimensional data arrays to store the non-zero elements and their position indexes while abandoning all the zero elements (Bell and Garland, 2009). But we found in practice that this storage method is not suitable for the normal matrix update. So the BSMC method is introduced to decrease its memory requirement while making the normal matrix easy to be updated.

3. Methodology

3.1. Imaging geometry

A ground point $P(X, Y, Z)$ is imaged by a camera with parameters (Xs, Ys, Zs, phi, omega, kappa) known as Exterior Orientation Parameters (EOPs) and (f, $x0$, $y0$, $k1$, $k2$) known as Interior Orientation Parameters (IOPs). Then an image point $p(x, y)$ corresponding to the ground point P can be obtained in the image as shown in Fig. 1. The camera lens center is defined as the perspective center S. The ground point P, it's corresponding image point p and the perspective center S is on a line, the relationship can be described by formulae as Eqs. (1), (2), (3) and (4).

$$\begin{bmatrix} x-\Delta x \\ y-\Delta y \\ -f \end{bmatrix} = \mathbf{R}^{\mathrm{T}} \begin{bmatrix} X-Xs \\ Y-Ys \\ Z-Zs \end{bmatrix} \tag{1}$$

$$\mathbf{R} = \begin{bmatrix} a_1 & a_2 & a_3 \\ b_1 & b_2 & b_3 \\ c_1 & c_2 & c_3 \end{bmatrix} \tag{2}$$

where $\mathbf{R}$ is a rotation matrix consisting of three rotation angles: phi, omega, and kappa. Δx, Δy is the correction terms for image point coordinates.