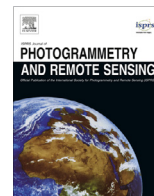




Contents lists available at ScienceDirect

ISPRS Journal of Photogrammetry and Remote Sensing

journal homepage: www.elsevier.com/locate/isprsjprs

Global robust image rotation from combined weighted averaging

Martin Reich^{a,*}, Michael Ying Yang^c, Christian Heipke^b

^aLeica Geosystems Technology A/S, Telehøjten 8, DK-5220 Odense, Denmark

^bInstitute of Photogrammetry and Geoinformation, Leibniz Universität Hannover, Nienburger Str. 1, D-30167 Hannover, Germany

^cUniversity of Twente, Hengelosestraat 99, Enschede, The Netherlands

ARTICLE INFO

Article history:

Received 29 January 2016

Received in revised form 6 January 2017

Accepted 12 January 2017

Available online xxx

Keywords:

Image orientation

Pose estimation

Rotation averaging

Lie algebra

Convex optimization

ABSTRACT

In this paper we present a novel rotation averaging scheme as part of our global image orientation model. This model is based on homologous points in overlapping images and is robust against outliers. It is applicable to various kinds of image data and provides accurate initializations for a subsequent bundle adjustment. The computation of global rotations is a combined optimization scheme: First, rotations are estimated in a convex relaxed semidefinite program. Rotations are required to be in the convex hull of the rotation group $SO(3)$, which in most cases leads to correct rotations. Second, the estimation is improved in an iterative least squares optimization in the Lie algebra of $SO(3)$. In order to deal with outliers in the relative rotations, we developed a sequential graph optimization algorithm that is able to detect and eliminate incorrect rotations. From the beginning, we propagate covariance information which allows for a weighting in the least squares estimation. We evaluate our approach using both synthetic and real image datasets. Compared to recent state-of-the-art rotation averaging and global image orientation algorithms, our proposed scheme reaches a high degree of robustness and accuracy. Moreover, it is also applicable to large Internet datasets, which shows its efficiency.

© 2017 Published by Elsevier B.V. on behalf of International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS).

1. Introduction

In photogrammetry, the goal of image orientation (or structure-from-motion, pose estimation) is to derive the 6 DoF orientation information for every item in a set of overlapping images. These six parameters per image comprise three translation and three rotation parameters. We refer to these parameters as “global orientation”,² i.e. orientation in a pre-defined, common coordinate system, whereas “relative orientation” expresses the orientation between a pair of images in an arbitrary coordinate system.

In this work we concentrate on offline orientation, meaning all the estimation is done in postprocessing. In general, the whole set of image is available, which in principle allows for a simultaneous estimation of all orientation parameters. The most accurate way to accomplish this is a nonlinear bundle adjustment. The nonlinear

nature of bundle adjustment, however, requires proper initialization for convergence to a correct solution. For the computation of initial values one can distinguish between three different strategies: (1) Sequential approaches start with an initial subset of images (often only two or three) and sequentially add further images to the block (e.g. Agarwal et al., 2009; Wu et al., 2011). At various stages, intermediate bundle adjustment is performed to reduce the resulting drift. (2) Hierarchical approaches (e.g. Fitzgibbon and Zisserman, 1998; Havlena et al., 2009) compute local orientations of small image blocks and subsequently merge these blocks in order to register all images in a common coordinate system. (3) Global approaches use all available information simultaneously, mostly in the form of pairwise or tripletwise relative orientations, to estimate image orientations (Martinec and Pajdla, 2007; Arie-Nachimson et al., 2012; Sinha et al., 2012; Jiang et al., 2013; Moulon et al., 2013; Özyesil et al., 2015). In general, rotations and translations are estimated separately, one after another. The global approaches do not suffer from heuristic decisions such as the selection of an initial image set and the order in which images are added or merged and have the ability to equally distribute the uncertainty to all relative orientations.

In this work we present a novel model for an accurate and robust estimation of global rotations from pairwise relative rotations that is part of our global image orientation approach, as

* Corresponding author.

E-mail addresses: martin.reich@leica-geosystems.com (M. Reich), michael.yang@utwente.nl (M.Y. Yang), heipke@ipi.uni-hannover.de (C. Heipke).

¹ This paper was written when the first author held a position at the Institute of Photogrammetry and Geoinformation at Leibniz Universität Hannover.

² Global orientation consists of global translation and global rotation. In some occasions the term “global” is also used in the context of optimization, e.g. as the globally optimal solution. In the context of image orientation, global approaches comprise approaches that take into account all relative information simultaneously.

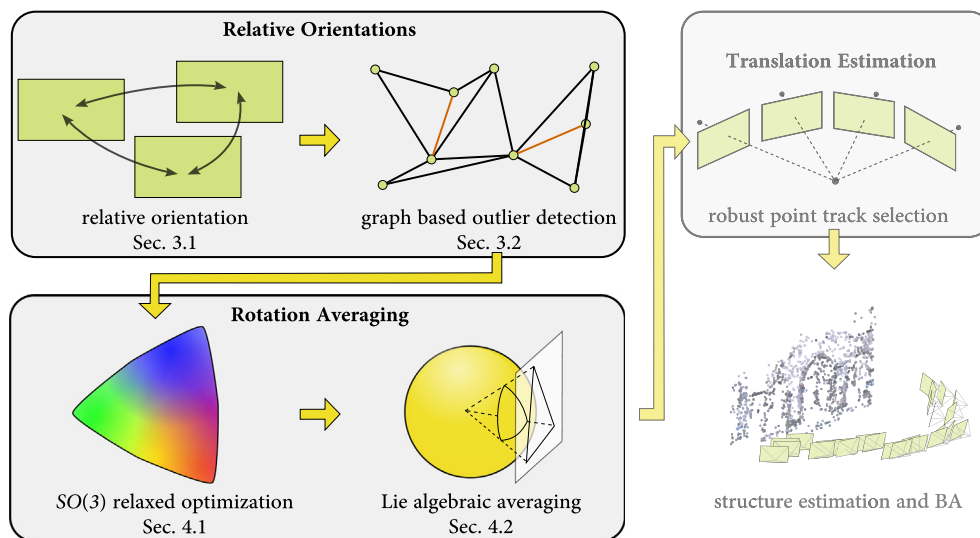


Fig. 1. Workflow of our image orientation model. The highlighted part on the left side is investigated in this paper.

illustrated in Fig. 1. First, pairwise relative orientations estimated from homologous points with a RANSAC estimation are refined in a Gauss-Helmert model (Section 3.1). Then, gross errors in the relative orientations are detected and eliminated using a novel heuristic graph propagation algorithm (Section 3.2). Second, rotations are averaged from relative estimates in a global semidefinite program (SDP).³ This formulation requires a relaxation of the original optimization problem (Section 4.1). We follow recent developments in optimization on algebraic groups (Saunderson et al., 2014) and constrain the solution to be inside the convex hull of the group of 3D rotations $SO(3)$. These authors show that this constraint often leads to exact solutions which are inside $SO(3)$. The third step is a least-squares refinement of these rotations in the Lie algebra of $SO(3)$ (Section 4.2). In order to improve the results, we propagate the covariance information during the estimation of relative rotations which is an extension of our previous investigations (Reich and Heipke, 2015). This allows for an individual weighting of relative rotations based on their quality.

The remainder of this paper is organized as follows. In Section 2 we give an overview over existing work in the field of image orientation and rotation averaging. The following two sections are dedicated to our methodology. Section 3 gives an insight into how we compute relative orientations and how our novel graph optimization algorithm works. The two-step estimation of global rotations is developed in Section 4. An extensive evaluation of our approach is given in Section 5. Finally, Section 6 concludes this work.

2. Related work

In recent years research in image orientation was highly supported by the growing number of publicly available image data. Many of the developed approaches are able to estimate the orientation of very large sets of images (e.g. Agarwal et al., 2009; Wu et al., 2011; Wilson and Snavely, 2014; Özyesil and Singer, 2015). To accelerate the process Agarwal et al. (2009) and Wu et al. (2011), for instance, compute orientations in a sequential manner which avoids an exhaustive matching between all possible pairwise combinations of images. Consequently, the results depend on the initial subset of images and the order in which the rest of

the images is added. Besides, intermediate bundle adjustments need to be carried out in order to reduce a drift of the solution, leading to additional computational effort. To overcome these effects, global orientation models evolved recently (Martinec and Pajdla, 2007; Arie-Nachimson et al., 2012; Sinha et al., 2012; Jiang et al., 2013; Moulon et al., 2013; Arrigoni et al., 2015b). In general, these works address the image orientation problem by subsequently solving for rotations and translations. Because in this publication we focus on the estimation of rotations, in the following our review of related work concentrates on this part only.

2.1. Global rotation averaging

Research on the estimation of global rotations from relative rotations can be traced back to the fundamental work of Govindu (2001). Rotations, represented as quaternions, are estimated in an unconstrained least squares optimization. Constraints, which take the norm (only unit-quaternions represent valid rotations) or the sign ambiguity (two quaternions, which differ only in sign, represent the same rotation) into account are not introduced. A few years later Govindu proposed a new approach using Lie group theory (Govindu, 2004). Initialized by results from Govindu (2001) rotations are refined iteratively in the Lie algebra of $SO(3)$. Another fundamental work about rotation averaging is given by (Hartley et al., 2013). In this work numerous aspects like different norms and convexity properties on the rotation manifold are investigated. Martinec and Pajdla (2007) propose a least squares model to estimate rotations but do not include an orthonormality constraint during averaging. Orthonormality is enforced subsequently by a mapping to the closest valid rotation using the Frobenius norm. Arie-Nachimson et al. (2012) extend this linear model and propose a more robust spectral method with the ability to solve an SDP that comprises an orthogonality constraint. Recently, a more tight relaxation for rotation averaging was developed (Horowitz et al., 2014; Saunderson et al., 2014). They formulate an SDP with a constraint that requires the rotations to be part of the convex hull of $SO(3)$. In our model we follow these approaches in order to derive precise initializations for a subsequent least-squares estimation.

Least-squares rotation averaging algorithms are sensitive to outliers in the relative rotations. In order to achieve robustness either outliers have to be eliminated in advance or a robust cost function has to be used for optimization. Govindu (2006) follows an inlier set maximization using a RANSAC algorithm (Fischler

³ An SDP optimizes a linear objective function over symmetric matrices. These matrices are constrained to be positive (or negative) semidefinite (see Boyd and Vandenberghe, 2004).

Download English Version:

<https://daneshyari.com/en/article/4972965>

Download Persian Version:

<https://daneshyari.com/article/4972965>

[Daneshyari.com](https://daneshyari.com)