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Self-calibration of digital aerial camera using combined orthogonal models

Hadi Babapour, Mehdi Mokhtarzade *, Mohamad Javad Valadan Zoej

K. N. Toosi University of Technology, 19697-64499 Tehran, Iran

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ABSTRACT

The emergence of new digital aerial cameras and the diverse design and technology used in this type of cameras require in-situ calibration. Self-calibration methods, e.g. the Fourier model, are primarily used; however, additional parameters employed in such methods have not yet met the expectations to desirably model the complex multiple distortions existing in the digital aerial cameras. The present study proposes the Chebyshev–Fourier (CHF) and Jacobi–Fourier (JF) combined orthogonal models. The models are evaluated for the multiple distortions using both simulated and real data, the latter being derived from an UltraCam digital camera. The results indicate that the JF model is superior to the other methods where, e.g., in the UltraCam scenario, it improves the planimetric and vertical accuracy over the Fourier model by 18% and 22%, respectively. Furthermore, a 30% and 16% of reduction in external and internal correlation is obtained via this approach which is very promising.

1. Introduction

The cameras deployed on aerial platforms are the primary input data sources and the first operational ring in the chain of the photogrammetry process. During recent years, technological advances have led to production of high-quality digital cameras which promise to provide necessary spatial information with high accuracy, speed and efficiency. This can only be achieved if the physical process of the image formation, including all sources of image distortion, are precisely modeled and taken into consideration in the photogrammetric models. Any imperfection in the modeling of aerial digital camera distortions will lead to inaccurate and unreliable spatial information that could be the basis of wrong decisions on behalf of the beneficiaries of this information.

The traditional camera calibration (laboratory or field based) is performed periodically to minimize and model distortions in the image space. New digital aerial cameras are diverse in design and construction and, hence, traditional calibration organizations cannot support all of them. Therefore, the users prefer to calibrate their digital cameras individually as a part of their routine photogrammetric procedures (Clarke and Fryer, 1998).

Brown (1976) developed and applied the theoretical and operational groundworks for parallel determination of lens calibration parameters and exterior orientation parameters of an image and the 3D coordinates of targeted points using bundle adjustments (Clarke and Fryer, 1998; Clarke et al., 1998). This procedure, called the self-calibration method, efficiently applies targeted points in all of the images to estimate the unknown adjustment parameters.

Three major classes of self-calibration have been developed based on the additional parameters for aerial cameras (Faig and Owolabi, 1988). The two more conventional classes include physical models (Brown, 1971, 1976; Moniwa, 1977), and algebraic polynomials; where the latter includes a variation of subclasses such as spherical harmonics (El-Hakim and Faig, 1977), the Ebner and Grün quadratic and forth degree algebraic polynomials (Ebner, 1976; Grün, 1978), and, the Legendre model (Tang et al., 2012a). The third and newest class of self-calibration is based on the Fourier series (Tang et al., 2012b).

Physical models, proposed initially by Brown (1971), suffer from high correlation between parameters and cannot properly model distortions in multi-lens digital cameras (Honkavaara, 2004; Honkavaara et al., 2006). This has also been reported by Cramer (2009), who proposed the use of extended or modified models instead of the Brown standard self-calibration method. Jacobsen (2007) also pointed to the correlation between physical-model parameters and other interior and exterior orientation parameters.

Additional parameters based on algebraic polynomials offer higher impact and flexibility than their physical counterparts (Lichti and Chapman, 1997). The Legendre model can be considered

* Corresponding author.
E-mail addresses: hbabapour@mail.kntu.ac.ir (H. Babapour), m_mokhtarzade@kntu.ac.ir (M. Mokhtarzade), valadanzouj@kntu.ac.ir (M.J. Valadan Zoej).

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generally superior to the Ebner and Grün models (Tang et al., 2012a; Tang, 2013). However, the need to omit some polynomial parameters, which is due to the high correlation between the parameters, is an inherent problem of all of the algebraic polynomials, including the Ebner, Grün and Legendre models. This is a drawback because these polynomials need large number of parameters in order to properly model the image distortions. Hence, a trade-off should be made by the user regarding the number of the parameters. This compromise is the main shortcoming of these models (Tang, 2013).

In recent studies, additional parameters have been used in different areas such as close range (Lichti et al., 2015), aerial (Tang et al., 2012a) and satellite (Jiang et al., 2015) sensors, as well as some more modern sensors, e.g., Light Detection and Ranging (LIDAR) (Gneeniss et al., 2015) and Microsoft Kinect (Chow and Lichti, 2013). There is a great deal of literature dealing with this issue via different calibration methods. However, most of the previous attempts are either based on interior calibration schemes (see, for instance, Jiang et al., 2015) or traditional self-calibration methods via physical or algebraic polynomials models (see, for instance, Tao et al., 2014). In this context, other flexible models have not been extensively employed. Recently, Tang et al. (2012b) applied algebraic polynomials for self-calibration of aerial cameras and, eventually, proposed and evaluated the Fourier series to model the complex nature of distortions in modern aerial digital cameras. They reported promising results over traditional physical and mathematical self-calibration models.

In order to model the large error vectors mainly caused by radial lens distortion effects, a higher order Fourier model should be used. This enforces the presence of more additional parameters which have high correlation with the exterior orientation parameters of the block images (Tang et al., 2012b; Tang, 2013). Tang et al. (2012b) proposed an optimized Fourier model consisting of 16 parameters. They found higher orders of the Fourier model (e.g., 48 parameters) decreased the performance due to the correlation problems between the additional and exterior-orientation parameters (Tang, 2013).

Recently, combined orthogonal models have been highlighted as powerful image descriptors, because these mathematical models show good potential for modeling complex image behaviors. These models are a combination of radial orthogonal equations and Fourier series that benefit from the ability to describe complex functions using a small number of independent terms (Ping et al., 2002, 2007). Nonetheless, these combined models have not been specifically employed for the self-calibration purposes.

The present study proposes two of the most well-known combined orthogonal models, the Chebyshev–Fourier and Jacobi–Fourier, to produce a self-calibration model for digital aerial cameras. These models were implemented and evaluated on simulated and real images from an UltraCam XP digital camera.

First, a brief review of the Fourier model is presented, followed by the introduction of two new models, namely, the Chebyshev and the Jacobi. Next, these individual models are employed to propose two new combined orthogonal models, Chebyshev–Fourier and Jacobi–Fourier. Afterwards, simulated input data and real data image blocks from the UltraCam sensor are introduced. Subsequently, the implementation results via different self-calibration models are presented and evaluated from different perspectives. The conclusions and recommendations are then presented.

2. Individual models

In the following, the individual Fourier, Chebyshev and Jacobi models are reviewed as self-calibration models consisting of additional parameters. While the former is a well-known self-calibration model, the two latter have not previously been utilized for this purpose.

2.1. Fourier model

The Fourier theorem in a 2D form states that any function of two variables $f(x,y)$ where $\{x,y\} \in [-\pi,\pi]$ can be estimated by the combination of variable *sine* and *cosine* terms at different frequencies:

$$\cos(mx \pm ny), \sin(mx \pm ny); \quad m,n = 0,1,2,\ldots \tag{1}$$

These series are used to estimate the behavior of geometric distortions in images (Δx and Δy) as follows (Tang et al., 2012b):

$$\begin{aligned}\Delta x &= \sum_{m=1}^{M}\sum_{n=-N}^{N}(a_{m,n}C_{m,n} + b_{m,n}S_{m,n}) + \sum_{n=1}^{N}(a_{0,n}C_{0,n} + b_{0,n}S_{0,n})\\ \Delta y &= \sum_{m=1}^{M}\sum_{n=-N}^{N}\left(a'_{m,n}C_{m,n} + b'_{m,n}S_{m,n}\right) + \sum_{n=1}^{N}\left(a'_{0,n}C_{0,n} + b'_{0,n}S_{0,n}\right)\end{aligned} \tag{2}$$

where

$$\begin{aligned}C_{m,n} &= 10^{-6}\cos(mu + nv)\\ S_{m,n} &= 10^{-6}\sin(mu + nv)\end{aligned} \tag{3}$$

$$\begin{aligned}&-b_x \leqslant x \leqslant b_x, -b_y \leqslant y \leqslant b_y\\ &u = x\pi/b_x, \quad v = y\pi/b_y; \quad \{u,v\} \in [-\pi,\pi]\end{aligned}$$

considering $2b_x$ and $2b_y$ as the width and length of the image, respectively, where x and y are the image coordinates of the points. Furthermore, $C_{m,n}$ and $S_{m,n}$ create orthogonal equations. In Eq. (3), the factors 10^{-6} are used to improve the numerical stability. In Eq. (2), $a_{m,n}$, $a'_{m,n}$, $b_{m,n}$ and $b'_{m,n}$ are unknown coefficients (additional parameters) that are estimated in the self-calibration procedure. M and N are the degrees of the series selected by the user, and determine the number of applied terms.

2.2. Chebyshev model

Chebyshev polynomials are commonly used to estimate functions that include prominent errors (Mason and Handscomb, 2002). The Chebyshev polynomials are defined as T_n and U_n in the following equations (Ping et al., 2002; Jiang et al., 2010):

$$\begin{aligned}T_n(\tau) &= \left(\frac{1-\tau}{\tau}\right)^{\frac{1}{4}}U_n(\tau)\\ U_n(\tau) &= \sum_{k=0}^{\lfloor\frac{n}{2}\rfloor}(-1)^k\frac{(n-k)!}{k!(n-2k)!}(4\tau-2)^{n-2k}\end{aligned} \tag{4}$$

in which, τ is the independent variable and n is the user selected degree of the polynomial. In this study, image distortion components (Δx and Δy) are modeled using orthogonal Chebyshev functions as:

$$\begin{aligned}\Delta x &= \sum_{i=0}^{N}a_iT_i(x_n) + \sum_{i=0}^{N}b_iT_i(y_n)\\ \Delta y &= \sum_{i=0}^{N}a'_iT_i(x_n) + \sum_{i=0}^{N}b'_iT_i(y_n)\end{aligned} \tag{5}$$

where a_i, a'_i, b_i and b'_i are unknown coefficients that are estimated in the self-calibration procedure. N is the maximum degree for the Chebyshev model selected by the user and determines the number of applied terms. Finally, $0 \leqslant \{x_n, y_n\} \leqslant 1$ are the normalized image coordinates in image space.