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DEM matching for bias compensation of rigorous pushbroom sensor models

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ABSTRACT

DEM matching is a technique to match two surfaces or two DEMs, at different reference frames. It was originally proposed to replace the need of ground control points for absolute orientation of perspective images. This paper examines DEM matching for precise mapping of pushbroom images without ground control points. We proved that DEM matching based on 3D similarity transformation can be used when model errors are only on the platform's position and attitude biases. We also proposed how to estimate bias errors and how to update rigorous pushbroom sensor models from DEM matching results. We used a SPOT-5 stereo pair at ground sampling distance of 2.5 m and a reference DEM dataset at grid spacing of 30 m and showed that rigorous pushbroom models with accuracy better than twice of the ground sampling distance both in image and object space have been achieved through DEM matching. We showed further that DEM matching based on 3D similarity transformation may not work for pushbroom images with drift or drift rate errors. We discussed the effects of DEM outliers on DEM matching and automated removal of outliers. The major contribution of this paper is that we validate DEM matching, theoretically and experimentally, for estimating position and attitude biases and for establishing rigorous sensor models for pushbroom images.

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1. Introduction

Since the public release of high resolution satellite images, they have become one of the most popular and powerful data sources to study the earth surface. They are now offering the resolving power comparable to aerial images. GeoEye-1, for example, delivers images at the ground sampling distance (GSD) of 0.5 m (Fraser and Ravanbakhsh, 2009). To retrieve precise positional information from images at such a fine GSD, one needs to establish very accurate geometric relationship between the image and the object space. In general, the geometric relationship for satellite images is explained by two types of sensor models: rigorous sensor model and generalized sensor model. For both types, the metadata provides the necessary information for sensor modelling. For the first type, the metadata contains the platform's ephemeris and attitude information so that the model based on physical parameters can be established (Salamonowicz, 1986; Westin, 1990; Radhadevi et al., 1998; Kim and Dowman, 2006). For example, the metadata of SPOT-5 images include look angles of detector cells, position and velocity vectors of the satellite, and attitude rates in pitch, roll and yaw axes (SPOT Image, 2002). For the second type, the metadata provides coefficients of pre-defined equations so that the sensor model can be established directly. For example, IKONOS and GeoEye-1 are providing rational polynomial coefficients (RPCs) to construct rational function models (Grodecki and Dial, 2003; Fraser et al., 2006; Fraser and Ravanbakhsh, 2009).

For both types, the sensor models constructed from the metadata alone do not meet accuracy requirements of large scale mapping. This is due to the limited accuracy of various on-board sensors such as GPS receivers, star sensors and gyroscopes. To improve the accuracy, one usually hires ground control points (GCPs), the points with known ground coordinates, and their corresponding image points. For rigorous sensor models, the platform's ephemeris and attitude errors were modelled by polynomial equations and coefficients of the error equations were estimated by GCPs (Gugan and Dowman, 1988; Chen and Lee, 1993; Orun and Natarajan, 1994; Radhadevi et al., 1998). There are studies reported on the effect of different polynomial equations and on how to determine the type of polynomial equations (Orun and Natarajan, 1994; Kim et al., 2007). For rational function models, error compensation equations were defined at the image space and coefficients of the compensation equations were estimated by GCPs (Grodecki and Dial, 2003; Fraser et al., 2006; Fraser and Ravanbakhsh, 2009). For example, 2D affine transformation was suggested to compensate bias errors caused within IKONOS satellites (Grodecki and Dial, 2003). Others reported that 2D affine transformation had been sufficient for bias compensation of most high resolution satellite images (Fraser et al., 2006).

However, the use of GCPs makes the overall application costly and time consuming. Moreover, there are areas or situations where GCPs of sufficient accuracy cannot be retrieved (Heipke et al., 2004).

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Due to these reasons, various ways to alleviate the necessity of GCPs have been explored (Heipke, 1997). Previously acquired GCPs were maintained and reused to solve the geometric relationship of new images (Kim and Im, 2003). More advanced position and angular sensors were installed on aerial or satellite platforms to provide accurate orientation information (Heipke, 1997). Existing orthoimage and elevation dataset were used to extract ground control points in an automated manner (Gianinetto and Scaioni, 2008). In this paper, we aim to use existing digital elevation models (DEMs) for precise sensor modelling of high resolution satellite images.

DEM matching is a technique to match two surfaces, or two DEMs, at different reference frames. DEM matching was originally proposed to replace the need of GCPs for absolute orientation of perspective images (Rosenholm and Torlegard, 1988; Ebner and Strunz, 1988) and had been demonstrated so (Rosenholm and Torlegard, 1988; Ebner and Ohlhof, 1994). The relationship between relative and absolute frames was modelled by 3D similarity transformation and DEM matching was applied to find parameters of the 3D similarity transformation (Rosenholm and Torlegard, 1988; Ebner and Ohlhof, 1994). DEM matching was further extended to 3D surface matching to solve the problem of 3D object registration (Gruen and Akca, 2005). DEM matching for pushbroom images was also suggested (Ebner et al., 1991). It was applied to pushbroom images taken by Mars Express (Heipke et al., 2004) and to Cartosat-1 images (d'Angelo et al., 2009). However, the validity of DEM matching for pushbroom images has not been investigated thoroughly. For example, the transformation between the relative and absolute frames for pushbroom images was modelled as that of perspective images (Heipke et al., 2004) or as 3D affine transformation (d'Angelo et al., 2009). Theoretical justification for the use of such transformations, however, was not provided.

Our purpose is to validate DEM matching, theoretically and experimentally, for solving absolute orientation of satellite images with pushbroom geometry. In particular, we aim to validate DEM matching for estimating the platform's position and attitude bias errors and for establishing accurate rigorous pushbroom sensor models without GCPs. DEM matching in our case is still challenging. DEM matching has not been applied to pushbroom images with rigorous sensor models. We have to find out the relationship between DEM matching and bias compensation of rigorous pushbroom sensor models. We have to analyze the effects of the platform's ephemeris and attitude variation over time on the quality of DEM matching. Besides, the resolution difference between images and the DEMs and the accuracy of the DEMs have to be considered.

We start our discussion by introducing the original DEM matching proposed for perspective images. We re-interpret perspective sensor models and validate the 3D similarity transformation used in the original DEM matching. We will advance our discussion to DEM matching for pushbroom sensors. We will re-interpret rigorous pushbroom sensor models for derivation of the true relationship between relative and absolute frames of pushbroom images. The relationship depends on the nature of errors of rigorous pushbroom sensor models. Unlike perspective images, 3D similarity transformation is not suitable for pushbroom images in general. We will further show that 3D similarity transformation can represent the relationship when the errors are on the platform's position and attitude biases. We will also propose how to update rigorous pushbroom sensor models from DEM matching results.

2. DEM matching for perspective images

Firstly, we explain DEM matching for perspective images proposed by Rosenholm and Torlegard (1988). The relationship between two DEMs was defined by 3D similarity transformation as below,

$$\begin{pmatrix} X \\ Y \\ Z \end{pmatrix} = s\mathbf{R}\begin{pmatrix} x \\ y \\ z \end{pmatrix} + \begin{pmatrix} \Delta X \\ \Delta Y \\ \Delta Z \end{pmatrix}, \tag{1}$$

where (X, Y, Z) is the coordinates of a 3D point in an absolute frame (or in an absolute DEM), (x, y, z) the coordinates of a 3D point in a relative frame (or in a relative DEM), $\mathbf{R}$ a rotation matrix, $(\Delta X, \Delta Y, \Delta Z)$ a shift vector between the two DEMs and s a scale factor. Let (x_k, y_k, z_k) be the kth point in the relative DEM and $(\hat{X}_k, \hat{Y}_k, \hat{Z}_k)$ the estimate of the kth point in the absolute DEM using the above transformation. The height difference v_k between the estimate and the actual point on the absolute DEM is

$$v_k = \hat{H}_k - H(\hat{X}_k, \hat{Y}_k), \tag{2}$$

where $\hat{H}_k$ is the height estimate of the kth point and $H(\hat{X}_k, \hat{Y}_k)$ is the height of a point $(\hat{X}_k, \hat{Y}_k)$ on an absolute DEM. Fig. 1 illustrates the relationship among a 3D point in a relative frame, its estimate and the actual location in an absolute frame, and the height difference.

DEM matching is the problem of adjusting the parameters of the above 3D similarity transformation; s, ΔX, ΔY, ΔZ and rotation angles for $\mathbf{R}$ to minimize the sum of squares of height differences. This is a non-linear adjustment problem. If Z axis in Eq. (1) corresponds to the height axis, the equation is linearized as below,

$$v_k = \hat{H}_k - H(\hat{X}_k, \hat{Y}_k) + dZ_k - \frac{\partial H(\hat{X}_k, \hat{Y}_k)}{\partial X} dX_k - \frac{\partial H(\hat{X}_k, \hat{Y}_k)}{\partial Y} dY_k, \tag{3}$$

where dX, dY, and dZ are calculated from Eq. (1).

The use of 3D similarity transformation, as shown in Eq. (1), is justified by the following considerations. Let Eq. (4) be a sensor model based on the collinear condition between a look vector (d_x, d_y, d_z) in the sensor frame, and the vector connecting a 3D point (x, y, z) and the platform position (x_S, y_S, z_S) in a relative frame. $\mathbf{R}_{sensor}^{rel}$ represents the rotation from the sensor frame to the relative frame and λ a scale factor. The simplest form of Eq. (4) will be when the relative frame coincides with the sensor frame and hence when (x_S, y_S, z_S) is a null vector and $\mathbf{R}_{sensor}^{rel}$ an identity matrix.

$$\begin{pmatrix} x - x_S \\ y - y_S \\ z - z_S \end{pmatrix} = \lambda \mathbf{R}_{sensor}^{rel} \begin{pmatrix} d_x \\ d_y \\ d_z \end{pmatrix}. \tag{4}$$

If Eq. (4) is updated to relate the look vector (d_x, d_y, d_z) with the vector connecting a 3D point (X, Y, Z) and the new platform position (X_S, Y_S, Z_S) in an absolute frame, we can have Eq. (5). $\mathbf{R}_{sensor}^{abs}$ represents the rotation from the sensor frame to the absolute frame and λ' a new scale factor.

$$\begin{pmatrix} X - X_S \\ Y - Y_S \\ Z - Z_S \end{pmatrix} = \lambda' \mathbf{R}_{sensor}^{abs} \begin{pmatrix} d_x \\ d_y \\ d_z \end{pmatrix}. \tag{5}$$

From Eqs. (4) and (5), we can easily derive Eq. (1). We can conclude that for perspective images the relationship between a relative and an absolute frame is represented by 3D similarity transformation as far as the collinear equations in Eqs. (4), (5) hold.

3. DEM matching for pushbroom sensors

We now extend our discussion for pushbroom images. In Eq. (6) one form of rigorous sensor models for pushbroom images using satellite orbit and attitude parameters is presented (Kim and Dowman, 2006). In the model, (d_x, d_y, d_z) is a look vector at the sensor frame, (x, y, z) a 3D point and (x_S, y_S, z_S) the platform position. $\mathbf{R}_{sensor}^{orbit}$ represents the rotation from the sensor frame to the orbit reference frame. For most of satellite images, this matrix can be

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