A Generic Method for RPC Refinement Using Ground Control Information

Zhen Xiong and Yun Zhang

Abstract
Geometric sensor models are used in image processing to model the relationship between object space and image space and to transform image data to conform to a map projection. An Rational Polynomial Coefficient (RCP) is a generic sensor model that can be used to transform images from a variety of different high resolution satellite and airborne remote sensing systems. To date, numerous researchers have published papers about RPC refinement, aimed at improving the accuracy of the results. So far, the Bias Compensation method is the one that is the most accepted and widely used, but this method has rigorous conditions that limit its use; namely, it can only be used to improve the RPC of images obtained from cameras with a narrow field of view and small attitude errors, such as those used on Ikonos or QuickBird satellites. In many cases, these rigorous conditions may not be satisfied (e.g., cameras with a wide field of view and some satellites with large ephemeris and attitude errors). Therefore, a more robust method that can be used to refine the RPC under a wider range of conditions is desirable. In this paper, a generic method for RPC refinement is proposed. The method first restores the sensor's pseudo position and attitude, then adjusts these parameters using ground control points. Finally a new RPC is generated based on the sensor's adjusted position and attitude. We commence our paper with a review of the previous ten years of research directed toward RPC refinement, and compare the characteristics of different refinement methods that have been proposed to date. We then present a methodology for a proposed generic method for RPC refinement and describe the results of two sets of experiments that compare the proposed Generic method with the Bias Compensation method. The results confirm that the Bias Compensation method works well only when the aforementioned rigorous conditions are met. The accuracy of the RPC refined by the Bias Compensation method decreased rapidly with the sensor's position error and attitude error.

In contrast to this, the Generic method proposed in this paper was found to yield highly accurate results under a variety of different sensor positions and attitudes.

Introduction
The term RPC typically refers to the Rational Polynomial Coefficient, or Rational Polynomial Camera coefficient (Chen *et al.*, 2006). It sometimes has been more generically defined as Rapid Positioning Capability (Dowman and Tao, 2002). RPCs are sometimes also referred to as Rational Function Coefficients (RFCs), or Rational Functional Models (RFM) (Tao and Hu, 2001). RPCs are recommended by the Open GIS Consortium (OGC) and are widely used in the processing of high-resolution satellite images. A RPC model is a mathematical function that relates object space coordinates (latitude, longitude, and height) to image space coordinates (line and sample). It is expressed in the form of a ratio of two cubic functions of object space coordinates. Separate rational functions are used to express the object space to line, and the object space to sample, coordinate relationships (Dial and Grodecki, 2002a).

Because of ephemeris and attitude error, all satellite geometric sensor models, including physical and RPC models, have a definite value of absolute positioning error. For example, the ephemeris and attitude accuracy for Ikonos is about one meter for ephemeris and about one or two arc-seconds for attitude (Grodecki and Dial, 2003). The accuracy for a single stereo pair of Ikonos images, without ground control, is 25.0 m (CE90), and 22.0 m (LE90) (Grodecki, 2001). If the satellite positioning accuracy does not meet the needs of users, the sensor model should be refined by using Ground Control Points (GCPs) or other ancillary data. Before the advent of Ikonos, users of satellite imagery typically made use of physical sensor models. Nowadays, instead of physical parameters, sometimes only a rational polynomial function which consists of 80 coefficients is available. This represents a completely new challenge, because the RPC has a high number of coefficients, and there is no physical interpretation for the order and terms of these coefficients. Many researchers have attempted to address this challenge. Directly calculating a new RPC based on a large number of GCPs (Di *et al.*, 2003) has been proven unfeasible (Grodecki *et al.*, 2003; Hu *et al.*, 2004). The Batch Iterative Least-Squares (BILS) method and the Incremental Discrete Kalman Filtering (IDKF) method each requires a significant number of GCPs and also the covariance matrices of the RFCs which are not available to most users (Hu and Tao, 2002). The Pseudo GCP (PG) method, the Using Parameters Observation Equation (UPOE) method, and the Sequential Least Square Solution (SLSS) method (Bang *et al.*, 2003) all face the problem of how to define the weightings of the coefficients for different observation equations.

In terms of accuracy and computational stability, the Bias Compensation method (Fraser and Hanley, 2003) so far appears to be the best method and has been widely used

Department of Geodesy & Geomatics Engineering, University of New Brunswick, 15 Dineen Drive, PO Box 4400, Fredericton, NB, Canada E3B 5A3 (v009v@unb.ca).

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(Fraser, 2003, 2005; Hu *et al.*, 2002), but this method is effective only when the camera Field Of View (FOV) is narrow and the position and attitude errors are small (Grodecki and Dial, 2003). Some satellites do meet these rigid conditions. For example as noted above, Ikonos imagery has an accuracy of about one meter for ephemeris and about one or two arc-seconds for attitude, and its FOV is less than one degree (Grodecki and Dial, 2003). But many other satellites including some of those launched from China and India probably do not satisfy this condition. As a Generic Sensor Model (GSM), an RPC can accommodate an extremely wide range of images without a need for the satellite ephemeris (Samadzadegan *et al.*, 2005). Therefore, an RPC can be used in a number of different sensors, such as linear push-broom scanners, radar, airborne and space-borne sensors. In these cases, the issue becomes one of how to effectively refine RPC using as few GCPs as possible.

This paper begins with a review of the latest research on RPC refinement. Next, the newly developed Generic method for RPC refinement is presented. We then present a series of experiments that focus on a comparison between the Bias Compensation method, arguably the best technique for sensor refinement currently in use, and the Generic method proposed in this paper. We conclude with some recommendations for future work.

RPC Refinement Methods

On 24 September 1999, Ikonos was launched. Since then, the mapping community has begun to recognize the importance of the RPC: a mathematical function which relates the object space and image space (Equation 1):

$$p = \frac{P_1(\phi, \lambda, h)}{P_2(\phi, \lambda, h)} \tag{1a}$$

$$r = \frac{P_3(\phi, \lambda, h)}{P_4(\phi, \lambda, h)} \tag{1b}$$

$$P(\phi, \lambda, h) = \sum_{i=0}^{m1}\sum_{j=0}^{m2}\sum_{k=0}^{m3} a_{ijk}\phi^i\lambda^j h^k \tag{1c}$$

$$0 \le m_1 \le 3,\ 0 \le m_2 \le 3,\ 0 \le m_3 \le 3,\ m_1 + m_2 + m_3 \le 3 \tag{1d}$$

where (p, r) are the image coordinates, (ϕ, λ, h) are the ground coordinates, and a_{ijk} is the polynomial coefficient. One of the coefficients in the denominator is a constant with a value of 1. In some cases (e.g., Ikonos), the two denominators P_2 and P_4 have the same coefficients.

The RPC may be refined directly or indirectly. Direct refining methods modify the original RPCs themselves, while indirect refining methods introduce complementary or concatenated transformations in image or object space, and do not change the original RPCs directly (Hu *et al.*, 2004).

Indirect Methods

At least three different types of indirect methods have been proposed:

1. The Bias Compensation method proposes a polynomial model defined in image space to correct the RPC (Equation 2), in which Δp and Δr are added to the rational functions to capture the discrepancies between the nominal and the measured image space coordinates (Fraser and Hanley, 2003; Grodecki and Dial, 2003):

$$Line = \Delta p + p(\phi, \lambda, h) \tag{2a}$$

$$Sample = \Delta r + r(\phi, \lambda, h) \tag{2b}$$

$$\Delta p = a_0 + a_s \cdot Sample + a_L \cdot Line + a_{SL} \cdot Sample \cdot Line + a_{L2} \cdot Line^2 + a_{s2} \cdot Samples^2 + \ldots \tag{2c}$$

$$\Delta r = b_0 + b_s \cdot Sample + b_L \cdot Line + b_{LS} \cdot Sample \cdot Line + b_{L2} \cdot Line^2 + b_{s2} \cdot Sample^2 + \ldots \tag{2d}$$

where Δp, Δr are the adjustable functions expressing the differences between the measured and the nominal line and sample coordinates of ground control and (a_i, b_i) are correction coefficients.

For Ikonos, an affine transformation or a translation for the simplest case is often used (Hu *et al*, 2004; Grodecki and Dial, 2003; Fraser and Hanley, 2003):

$$\Delta p = a_0 + a_s \cdot Sample + a_L \cdot Line \tag{3a}$$

$$\Delta r = b_0 + b_s \cdot Sample + b_L \cdot Line \tag{3b}$$

By using an affine transformation to correct the RPC of Ikonos imagery, sub-pixel accuracy is obtained (Fraser and Hanley, 2003; Dial and Grodecki, 2002b; Grodecki and Lutes, 2005), but the Bias Compensation method is effective only when the camera Field Of View (FOV) is narrow and the position and attitude errors are small (Grodecki and Dial, 2003).

2. A polynomial model defined in the domain of object coordinates to correct the RPC is also proposed by Grodecki and Dial (2003) as follows:

$$\Delta p = a_0 + a_P \cdot \phi + a_L \cdot \lambda + a_H \cdot h + a_{P2} \cdot \phi^2 + a_{L2} \cdot \lambda^2 + a_{H2} \cdot h^2 + a_{PL} \cdot \phi \cdot \lambda + a_{PH} \cdot \phi \cdot h + a_{LH} \cdot \lambda \cdot h + \ldots \tag{4a}$$

$$\Delta r = b_0 + b_P \cdot \phi + b_L \cdot \lambda + b_H \cdot h + b_{P2} \cdot \phi^2 + b_{L2} \cdot \lambda^2 + b_{H2} \cdot h^2 + b_{PL} \cdot \phi \cdot \lambda + b_{PH} \cdot \phi \cdot h + b_{LH} \cdot \lambda \cdot h + \ldots \tag{4b}$$

where: (ϕ, λ, h) are ground coordinates, and (a_i, b_i) are correction coefficients.

3. A polynomial model defined in the domain of object coordinates to correct the ground coordinates derived from the vendor-provided RPCs, has been proposed by Di *et al.* (2003). In this method, the polynomial correction parameters are determined by the GCPs:

$$X = a_0 + a_1 X_{RF} + a_2 Y_{RF} + a_3 Z_{RF} \tag{5a}$$

$$Y = b_0 + b_1 X_{RF} + b_2 Y_{RF} + b_3 Z_{RF} \tag{5b}$$

$$Z = c_0 + c_1 X_{RF} + c_2 Y_{RF} + c_3 Z_{RF} \tag{5c}$$

where (X, Y, Z) are the ground coordinates after correction; (X_{RF}, Y_{RF}, Z_{RF}) are ground coordinates derived from the RPC; and (a_i, b_i, c_i) are correction coefficients.

In object space, the ground coordinates do not reflect the satellite sensor's imaging geometry. Therefore, Method 1 is superior to Methods 2 and 3 (Grodecki and Dial, 2003; Gong *et al.*, 2005).

Direct Methods

Sometimes, ground control information is not available at the time of data processing or cannot be supplied for some other reasons (e.g., political sensitivity or confidentiality) (Hu and Tao, 2002). In some cases, it is necessary to avoid changing the existing image transfer format. Therefore, in many cases, a modified RPC is the first choice. Methods that modify the original RPCs are referred to as direct refining methods (Hu *et al.*, 2004). Three such methods are described below:

1. The first direct method is to compute the new rational polynomial coefficients (RPCs) using the vender-provided RPC coefficients as initial values. This method is not stable enough to provide a sufficient accuracy in operational environments, unless a large number of densely distributed

GCPs (about twice the number of unknowns) are available (Toutin, 2004; Tao and Hu, 2001; Di *et al.*, 2003). Therefore, this method is not feasible for RPC refinement (Grodecki *et al.*, 2003; Hu *et al.*, 2004).

2. A Batch Iterative Least-Squares (BILS) method and an Incremental Discrete Kalman Filtering (IDKF) method have been proposed to modify RPCs (Hu and Tao, 2002). It has been found that the prerequisite for obtaining good results using these methods is that the covariance matrices for the RFCs and the image measurements (provided by the data vendor who calculated the RPC initially) are available. Moreover, significant numbers of new GCPs are also required (Hu and Tao, 2002). Experiments have shown that these methods can yield good results for aerial photography, but the accuracy obtained for Ikonos imagery is not sufficient for many users (Hu and Tao, 2002).
3. Bang *et al.*, proposed three methods to modify RPCs: the Pseudo GCP (PG) method, the Using Parameters Observation Equation (UPOE) method, and the Sequential Least Square Solution (SLSS) method (Bang *et al.*, 2003). For the PG method, the RPCs are imported as initial values. The additional GCPs are assigned a large enough weight (compared with the pseudo GCPs) to modify original RPC. This method is similar to Method 1 proposed by Di *et al.* (2003). For the UPOE method, 59 RPC parameter observations are used instead of the pseudo GCPs. The use of each of these three methods involves a question of how to properly assign the weightings for so many different observations, since the order and terms of the RPC coefficients have no physical meaning (Samadzadegan *et al.*, 2005). With regard to their accuracy, an experiment comparing these three methods with the Bias Compensation method showed that the accuracy of SLSS is the best of the three, but is still slightly poorer than that of the Bias Compensation method (Bang *et al.*, 2003).

Limitations of Traditional Methods

The drawbacks, limitations, and relative accuracies of the direct and indirect methods described above are summarized in Table 1, along with a comparison of their accuracies with that of the Bias Compensation method.

Table 1 illustrates that, in terms of accuracy and computational stability, the Bias Compensation method is undoubtedly the best method in current use. Unfortunately, the Bias Compensation method is effective only when the camera field of view is narrow and the attitude errors are small (Grodecki and Dial, 2003). Under these rigorous conditions, the in-track and cross-track errors are equivalent to pitch and roll attitude errors (Figure 1). Thus, it is only necessary to estimate roll and pitch for RPC correction

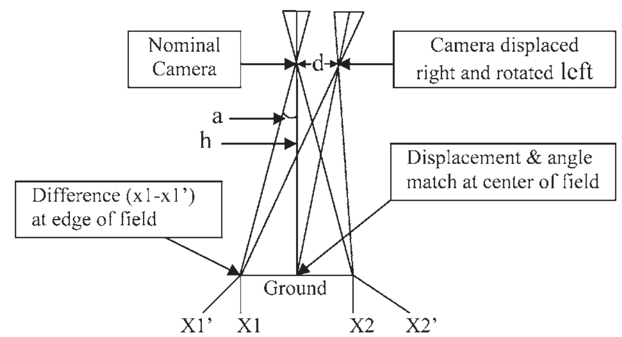

Figure 1. Effect of roll and cross-track errors (Grodecki and Dial, 2003).

TABLE 1. ACCURACIES, LIMITATIONS AND DRAWBACKS OF TRADITIONAL RPC REFINEMENT METHODS

	Method	Accuracy, Limitations and Drawbacks
Indirect Methods	(1) Bias Compensation method	• Accuracy appears to be the best so far. • Effective only when the camera Field Of View (FOV) is narrow and the position and attitude errors are small (Grodecki and Dial, 2003)
	(2) Polynomial model defined in object space to correct the image coordinates	• Accuracy is poorer than Bias Compensation method. • Because the ground coordinates do not reflect the satellite sensor's imaging geometry, this method is not feasible for RPC refinement (Grodecki and Dial, 2003; Gong *et al.*, 2005).
	(3) Polynomial model defined in object space to correct the object coordinates	• Accuracy is poorer than Bias Compensation method. • Because the ground coordinates do not reflect the satellite sensor's imaging geometry, this method is not feasible for RPC refinement (Grodecki and Dial, 2003; Gong *et al.*, 2005).
Direct Methods	(1) Directly compute the new RPCs with a large number of GCPs	• This method is not stable enough and may not provide a sufficient accuracy in operational environments. It is therefore unfeasible for RPC refinement (Grodecki *et al.*, 2003; Hu *et al.*, 2004)
	(2) BILS method and IDKF method	• Accuracy is poorer than Bias Compensation method. • Requires a significant number of GCPs • Requires the covariance matrices of RPC (Hu and Tao, 2002)
	(3) PG Method, UPOE method, and SLSS method	• Accuracy is poorer than Bias Compensation method (Bang *et al.*, 2003). • Difficult to assign weightings for the different observation equations.

(Grodecki and Dial, 2003). But with increasing camera field of view, attitude error, and off-nadir angle, the in-track and cross-track errors are no longer equivalent to pitch and roll attitude errors, and the difference (x1-x1′) at the edge of field (Figure 1) increases according following equations (Grodecki and Dial, 2003; Dial and Grodecki, 2005).

$$d = h^{*}(\tan(c + r) - \tan(c)) \tag{6}$$

$$x1 = -h^{*}\tan(c + a) \tag{7}$$

$$x1' = d - h^{*}\tan(c + a + r) \tag{8}$$

$$difference = x1 - x1' \tag{9}$$

where: h is the flying height, c is the off-nadir angle, r is the attitude error, and a is the half-angle of the camera field of view; Figure 2 shows how the difference (x1-x1′) at the edge of field changes with camera field of view (FOV), off-nadir angle, and attitude error.

Based on Figures 1 and 2, it is evident that the difference (x1-x1′) at the edge of the field of view increases as the width of the camera field of view, the sensor's attitude error, and the off-nadir angle increase. The attitude error is the most important factor affecting the difference (x1-x1′) at the edge of the field.

For Ikonos imagery, with a roll error of 2 seconds, the difference (x1-x1′) is negligible (only 0.000454 m) (Grodecki and Dial, 2003). As a result, only a few parameters are required to effectively model the sensor errors (Grodecki and Dial, 2003). This is why the Bias Compensation method can achieve success in RPC refinement for Ikonos and QuickBird images. It is the desire to obtain a RPC refinement method that will be effective under a wider variety of image conditions and sensor platforms that lead us to develop the Generic Method for RPC refinement.

The Proposed Method

The Generic method proposed in this paper can be classified as a direct method for RPC refinement because it directly modifies the RPC coefficients. It is defined in object space and consists of three components (Figure 3): (a) Restore the sensor's position and attitude: This involves restoring the pseudo light ray that existed when the image was acquired. The sensor's pseudo position and attitude (equivalent to camera Exterior Parameters (EPs)) are obtained; (b) Adjust the sensor's position and attitude. The GCPs are used to refine the EPs; and (c) Generate a new RPC. The new RPC is generated using a grid of image points.

Restoring the Sensor's Position and Attitude

Step 1

From a point on the image P(I, J), given an elevation value (H1), the corresponding ground position P1(x1, y1) of the point P(I, J) can be obtained by an iterative process. For the same image point P(I, J), given another elevation value (H2), H2 > H1, another ground point P2(x2, y2) is obtained. Then for the point P(I, J) on the image, two corresponding ground points P1(x1, y1, H1) and P2(x2, y2, H2) are obtained. A vector $\overrightarrow{n12}$ from point P1(x1, y1, h1) to point P2(x2, y2, H2) can be calculated (Figure 4). If this vector were the light ray used by the sensor in acquiring the image point P(I, J), the sensor position Ps1(Xs1, Ys1, Hs1) can be obtained from the extension of this vector. The sensor height Hs is a fixed value. For a satellite, Hs will be large, e.g., 600 km. If the height is low, small discrepancies in x and y (ε_x, ε_y) will lead to a large correction to the two rotation angles ψ_x and ψ_y. For an airborne remote sensing system, this height may be only several thousand meters.

Of course, this vector is not the actual light ray by which the image point P(I, J) was acquired. Instead, it is a pseudo light ray and the sensor position Ps1(Xs1, Ys1, Hs1)

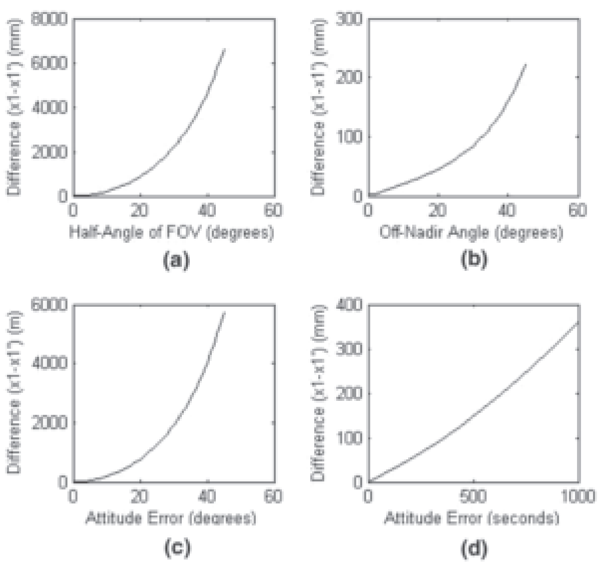

Figure 2. (a) the difference (x1-x1′) changes with FOV (attitude error = 2 seconds, (b) off-nadir angle = 0), (c) off-nadir angle (attitude error = 2 seconds, FOV = 0.93 degrees), and (d) attitude error (off-nadir angle = 0, FOV = 0.93 degrees).

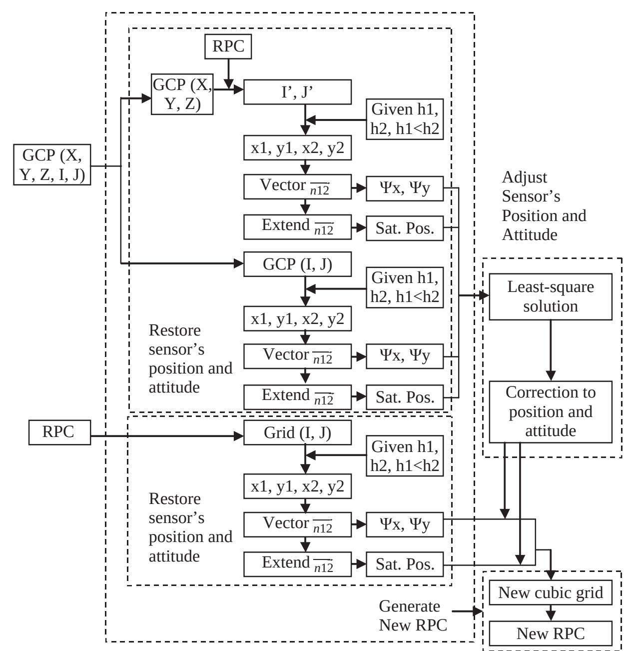

Figure 3. Flowchart of RPC Refinement Using the Generic Method.

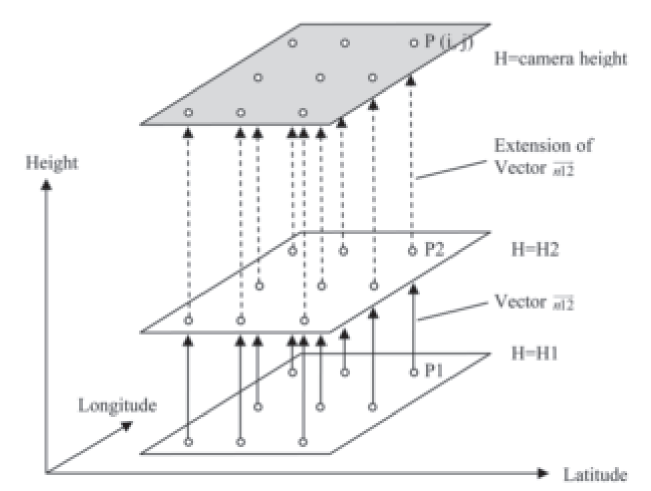

Figure 4. Restoration of camera's pseudo light ray.

is pseudo sensor position. Fortunately, it does not matter whether the light ray and sensor position are actual or not. Even a pseudo light ray and pseudo sensor position are effective for RPC refinement in the proposed Generic method.

From vector $\overrightarrow{n12}$, vector $\overrightarrow{n21}$ can be obtained. From vector $\overrightarrow{n21}$, two tilted angles in *x* and *y* directions Ψx and Ψy can be obtained (Figure 5). For high-resolution satellite images, the azimuth accuracy is very high, so the rotation angle Ψz is very small (Grodecki and Dial, 2003). Therefore, its initial value can be set to "0." For airborne sensors, the azimuth angle should be estimated according to GCPs and other assistant information.

For an image point P(I, J), the preceding calculations have provided corresponding pseudo sensor position Ps1(Xs1, Ys1, Hs1) and three rotation angles around the *x*, *y*, and *z* axis, Ψy, Ψx and Ψz.

Adjusting the Sensor's Position and Attitude

Step 2

For every GCP, its corresponding pseudo sensor position (*Xs, Ys, Hs*) and three rotation angles Ψy, Ψx and Ψz are calculated.

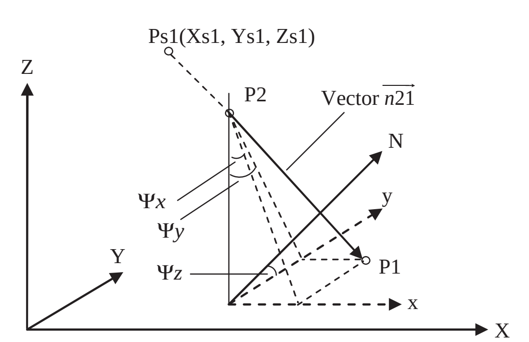

Figure 5. Restoration of sensor's position and attitude.

Step 3

The RPC adjustment observation equations for each GCP are constructed as follows.

$$(\hat{X}s + (\hat{H}s - h_i)\ \tan(\hat{\psi}_x))\ \cos(\hat{\psi}_z) + (\hat{Y}s + (\hat{H}s - h_i)\ \tan(\hat{\psi}_y))\ \sin(\hat{\psi}_z) - x_i + \varepsilon x_i = 0 \tag{10}$$

$$-(\hat{X}s + (\hat{H}s - h_i)\ \tan(\hat{\psi}_x))\ \sin(\hat{\psi}_z) + (\hat{Y}s + (\hat{H}s - h_i)\ \tan(\hat{\psi}_y))\ \cos(\hat{\psi}_z) - y_i + \varepsilon y_i = 0 \tag{11}$$

$$\hat{X}s = Xs + \Delta Xs \tag{12}$$

$$\hat{Y}s = Ys + \Delta Ys \tag{13}$$

$$\hat{H}s = Hs + \Delta Hs \tag{14}$$

$$\hat{\psi}_x = \psi_x + \Delta\psi_x \tag{15}$$

$$\hat{\psi}_y = \psi_y + \Delta\psi_y \tag{16}$$

$$\hat{\psi}_z = \psi_z + \Delta\psi_z \tag{17}$$

where *Xs, Ys, Hs* are the pseudo sensor position, x_i, y_i, h_i are ground coordinates of i^{th} GCP, and ψ_x, ψ_y, and ψ_z are rotation angles of the vector corresponding to the i^{th} GCP.

In these observation equations, the sensor position (*Xs, Ys, Hs*) and three rotation angles (ψ_x, ψ_y, ψ_z) are adjustable parameters.

Because the sensor's position and attitude change with the time in a pushbroom remote sensing system, we are proposing to use a polynomial model defined in the domain of image coordinates to represent the adjustable functions ΔXs, ΔYs, ΔHs, $\Delta\psi_x$, $\Delta\psi_y$, and $\Delta\psi_z$.

Although a higher order polynomial may achieve higher internal accuracy, this higher internal accuracy may not lead to a more accurate RPC, because the RPC is a mathematical function that is only an approximation of a rigorous physical model. Our experiments have shown that the higher the order of the polynomial model, the greater the amount of the accuracy that will be lost after the approximation of the new RPC generation. We are therefore proposing to use a linear polynomial model for RPC refinement:

$$\Delta Xs = a_0 + a_S\ Sample + a_L\ Line \tag{18}$$

$$\Delta Ys = b_0 + b_S\ Sample + b_L\ Line \tag{19}$$

$$\Delta Hs = c_0 + c_S\ Sample + c_L\ Line \tag{20}$$

$$\Delta\psi_x = d_0 + d_S\ Sample + d_L\ Line \tag{21}$$

$$\Delta\psi_y = e_0 + e_S\ Sample + e_L\ Line \tag{22}$$

$$\Delta\psi_z = f_0 + f_S\ Sample + f_L\ Line \tag{23}$$

For high-resolution images obtained from satellites such as Ikonos and QuickBird, the errors in satellite height and yaw angle are very small (Grodecki and Dial, 2003), therefore, ΔXs, ΔYs, $\Delta\psi_x$, and $\Delta\psi_y$ provide enough information to accurately correct the satellite's position and attitude. In this research, when fewer than three GCPs are used for RPC refinement, only the translations a_0, b_0, d_0, e_0 are considered. When three or more GCPs are used, a_i, b_i, d_i, and e_i, are considered. According to our experiments, for Ikonos and QuickBird, all 12 parameters are considered only when: (a) the GCP's number is large enough (50 or more), (b) the GCPs are distributed uniformly, and (c) the GCP's accuracy is good enough (at least sub-pixel). Otherwise, too many parameters may be generated with a resultant loss of accuracy. We solved these parameters in the following order: (d_i, e_i, f_i) for $\Delta\psi_x$, $\Delta\psi_y$ and $\Delta\psi_z$; (a_i, b_i, c_i) for ΔXs, ΔYs, and ΔHs.

Generating the New RPC

Step 4

In order to generate a new RPC, a grid of image points is used to calculate corresponding pseudo sensor positions and attitude angles. These are adjusted according to Equations 18 through 23.

Step 5

After the sensor positions and attitude angles corresponding to a grid of image points have been adjusted with Equations 18 through 23, a set of cubic points are generated with these new vectors. The new RPC is generated using these cubic points.

Because the Generic method is defined in object space, it can simulate the camera's exterior parameters, such as the camera's position and attitude. Therefore, it can theoretically be used in any geometric situation and does not have any limitations on the camera, regardless of the field of view, position error, or attitude error.

Experiments

In order to evaluate the Generic method, we designed two sets of experiments. First, we used SPOT5 and Ikonos image data to test the Generic method and compare the results with those of the Bias Compensation method under the condition of narrow field view and small ephemeris and attitude errors. We then designed another set of experiments using simulated SPOT5 data generated by adding errors to the ephemeris and attitude data. We used this simulated data to compare the Generic method and the Bias Compensation method, and to determine the Generic method's capability under a variety of different conditions.

Experiment Set 1

In this set of experiments, SPOT5 and Ikonos image data were used to test the capability of the Generic method under the conditions of narrow field of view and small attitude error.

In the SPOT5 image, there were a total of 37 GCPs. We used one, three, and seven GCPs to refine the RPC, respectively. The other 36, 34, and 30 ground control points were used as checkpoints. Figure 6 shows the distributions of GCPs and checkpoints (CHK) on the SPOT5 image in three of the test cases. Table 2 and Figure 7 show the test results.

Table 2 and Figure 7 indicate that the accuracy of the Generic method and the Bias Compensation method are quite similar when the field of view is narrow and the attitude error is small. The largest difference is less than 0.1 pixels.

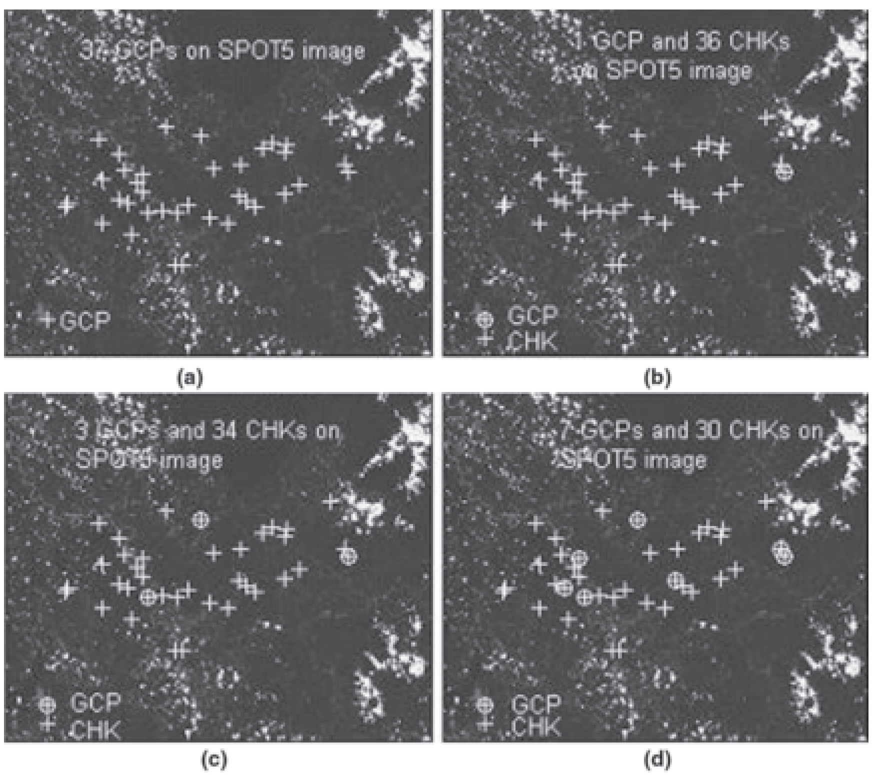

Figure 6. Distribution of GCPs and CHK points on SPOT5 image: (a) 37 GCPs, (b) one GCP and 36 CHKs, (c) three GCPs and 34 CHKs, and (d) seven GCPs and 30 CHKs.

Table 2. Accuracy Comparison between the Bias Compensation Method and Generic Method using SPOT5 Image Data in Five Cases

Case	GCP and CHK Points	Generic method Col. RMSE (pixels)	Generic method Row RMSE (pixels)	Bias method Col. RMSE (pixels)	Bias method Row RMSE (pixels)
0	0 GCP, 37 CHK Points	2.12	19.65	2.12	19.65
1	1 GCP, 36 CHK Points	4.28	5.57	4.38	5.54
2	3 GCPs, 34 CHK Points	1.13	0.86	1.13	0.87
3	7 GCPs, 30 CHK Points	1.15	0.95	1.15	0.95
4	37 GCPs are also CHKs	0.91	0.70	0.99	0.76

Note: Col. = Column; RMSE = Root Mean Square Error

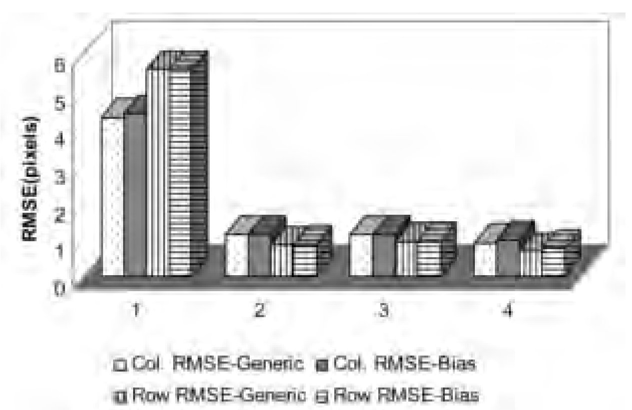

Figure 7. Accuracy comparison between the Bias Compensation method and Generic method using SPOT5 image data in cases 1, 2, 3, and 4 (Note: Col. = Column; RMSE = Root Mean Square Error).

An Ikonos image was also used in this research. There were a total of 113 GCPs in this test field. Initially, we used only one GCP to refine the RPC. The other 112 ground control points were used as checkpoints. In the second test, nine GCPs were used to refine the RPC, and the other 104 ground control points were used as checkpoints. Plate 1 shows the distribution of GCPs and checkpoints on the Ikonos image in two cases. Table 3 and Figure 8 shows the test results.

Table 3 and Figure 8 show that the accuracies of the Generic method and the Bias Compensation method are again similar. Once again, the largest difference in accuracy between the two methods is less than 0.1 pixels.

This experiment set showed that the Generic method has the same capability as the Bias Compensation method to process images having a narrow field of view and small attitude error.

Experiment Set 2

In this set of experiments, SPOT5 image data was used to produce nine cases of simulated data (Table 4) to test the capability of the Generic method to process images under a variety of different ephemeris and attitude errors. Tables 5, 6, and 7 and Figures 9, 10, and 11 show the test results.

From Tables 5, 6, and 7 and Figures 9, 10, and 11, it is evident that the Bias Compensation method is very good at detecting ephemeris data error and can work well under a variety of different ephemeris errors, but with increasing attitude error, use of the Bias Compensation method becomes progressively less effective. This is particularly obvious in case three and case nine when the attitude error is greater than 0.01 radius (Tables 6 and 7 and Figures 10 and 11) where the RMSE of column and row error for the Bias Compensation method ranges from about four to seven pixels. In contrast to this, the Generic method is very stable in that the RMSE remains about one pixel under a variety of different cases.

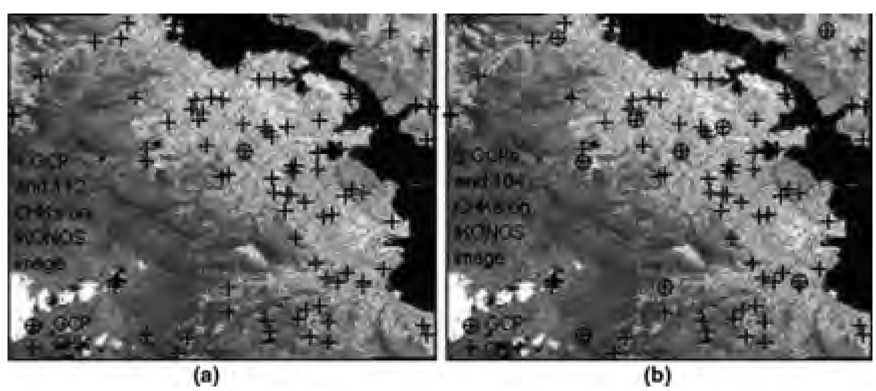

Plate 1. Distribution of GCPs and CHK points in the Ikonos image: (a) one GPC and 112 CHKs, and (b) nine GCPs and 104 CHKs.

Table 3. Accuracy Comparison between the Bias Compensation Method and the Generic Method using the Ikonos Image Data in Four Cases

		Generic method		Bias method	
Case	GCP and CHK Points	Col. RMSE (pixels)	Row RMSE (pixels)	Col. RMSE (pixels)	Row RMSE (pixels)
0	0 GCP, 113 CHK Points	5.09	3.41	5.09	3.41
1	1 GCP, 112 CHK Points	0.90	0.79	0.90	0.79
2	9 GCPs, 104 CHK Points	0.76	0.83	0.76	0.83
3	114 GCPs are also CHKs	0.62	0.70	0.68	0.71

Note: Col. = Column; RMSE = Root Mean Square Error

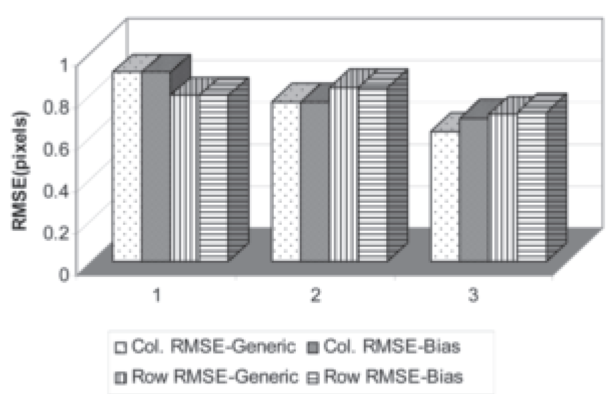

Figure 8. Accuracy comparison between the Bias Compensation method and Generic method using Ikonos image data in three cases (Note: Col. = Column; RMSE = Root Mean Square Error).

Table 4. Nine Cases of Simulated SPOT5 Data Obtained by Adding Different Errors to Satellite Position and Attitude Data

Case	Δx (m)	Δy (m)	Δz (m)	$\Delta\Psi x$ (rad)	$\Delta\Psi y$ (rad)	$\Delta\Psi z$ (rad)
1	10	10	10	0.001	0.001	0.001
2	100	100	100	0.01	0.01	0.01
3	1000	1000	1000	0.1	0.1	0.1
4	10	10	10	0	0	0
5	100	100	100	0	0	0
6	1000	1000	1000	0	0	0
7	0	0	0	0.001	0.001	0.001
8	0	0	0	0.01	0.01	0.01
9	0	0	0	0.1	0.1	0.1

Table 5. Accuracy Comparison between the Bias Compensation Method and Generic Method using One GCP and 36 CHK Points in Nine Cases

	1 GCP, 36 CHKs			
	Generic method		Bias method	
Case	Column RMSE (pixel)	Row RMSE (pixel)	Column RMSE (pixel)	Row RMSE (pixel)
1	14.79	3.32	15.86	4.58
2	98.33	5.45	109.06	7.59
3	959.91	17.22	1040.90	166.77
4	5.54	4.30	5.53	4.42
5	5.34	4.45	5.52	4.68
6	3.41	5.94	5.40	7.36
7	14.81	3.31	15.86	4.55
8	98.55	5.62	109.07	7.27
9	961.33	19.70	1040.75	160.96

Note: RMSE = Root Mean Square Error

Table 6. Accuracy Comparison between the Bias Compensation Method and Generic Method using Three GCPs and 34 CHK Points in Nine Cases

	3 GCP, 34 CHKs			
	Generic method		Bias method	
Case	Column RMSE (pixels)	Row RMSE (pixels)	Column RMSE (pixels)	Row RMSE (pixels)
1	0.87	1.13	0.86	1.15
2	0.88	1.13	0.85	1.50
3	0.86	1.29	4.22	7.88
4	0.86	1.13	0.87	1.13
5	0.87	1.13	0.87	1.13
6	0.87	1.14	0.87	1.13
7	0.87	1.13	0.86	1.15
8	0.88	1.13	0.85	1.51
9	0.86	1.21	4.20	7.97

Note: RMSE = Root Mean Square Error

Conclusions

Unlike the Bias Compensation method which is defined in image space, the proposed Generic method is defined in object space. It directly modifies the RPC coefficients, but it does not require any assistant information about RPC, such as the covariance matrices, like other direct methods.

The Generic method simulates the sensor's imaging geometry and can be used to adjust the camera's position and attitude. Therefore, it can effectively refine the RPC under a variety of different conditions. As position and attitude errors increase, the Bias Compensation method becomes less effective. Especially when the attitude error is greater than 0.01 radiuses, the RMSE of column and row error for the Bias Compensation method ranges from about four to seven pixels. In contrast to this, the Generic method described in this paper is very stable under a variety of different conditions. Even when the attitude error is greater than 0.01 radiuses, the RMSE always remains about one pixel. In fact, it appears that the Generic method completely overcomes the drawbacks and limitations of the Bias

Table 7. Accuracy Comparison between the Bias Compensation Method and Generic Method using Seven GCPs and 30 CHK Points in Nine Cases

7 GCP, 30 CHKs				
Case	Generic method		Bias method	
	Column RMSE (pixel)	Row RMSE (pixel)	Column RMSE (pixel)	Row RMSE (pixel)
1	0.95	1.15	0.95	1.15
2	0.97	1.15	0.95	1.39
3	0.97	1.25	4.02	6.71
4	0.95	1.15	0.95	1.15
5	0.95	1.15	0.95	1.15
6	0.95	1.15	0.95	1.16
7	0.95	1.15	0.95	1.15
8	0.97	1.15	0.95	1.39
9	0.98	1.18	3.99	6.79

Note: RMSE = Root Mean Square Error

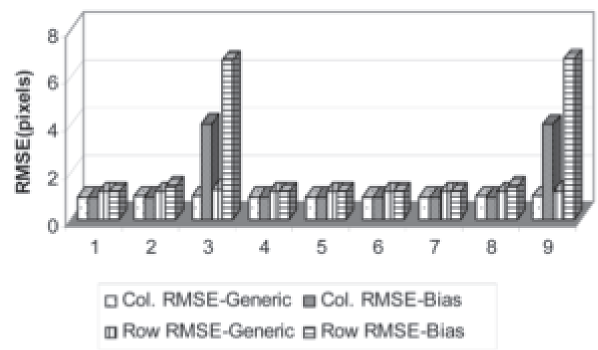

Figure 11. Accuracy comparison between the Bias Compensation method and Generic method using simulated SPOT5 data in nine cases (seven GCPs, 30 CHK points) (Note: Col. = Column; RMSE = Root Mean Square Error).

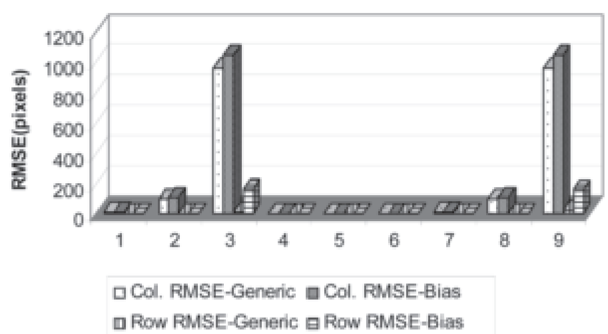

Figure 9. Accuracy comparison between the Bias Compensation method and Generic method using simulated SPOT5 data in nine cases (one GCPs, 36 CHK points) (Note: Col. = Column; RMSE = Root Mean Square Error).

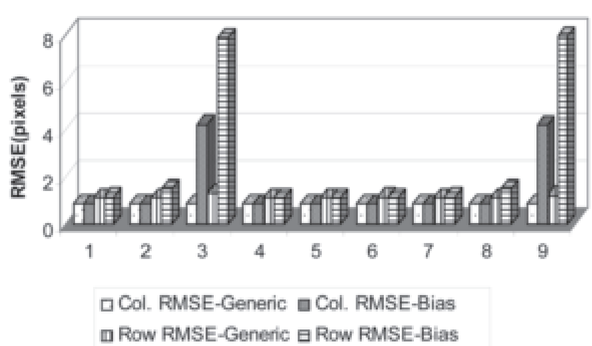

Figure 10. Accuracy comparison between the Bias Compensation method and Generic method using simulated SPOT5 data in nine cases (three GCPs, 34 CHK points) (Note: Col. = Column; RMSE = Root Mean Square Error).

Compensation method. It can be used regardless of the sensor's field of view, attitude error or position error.

We hope this Generic method can be used to refine not only the RPCs of high-resolution satellite images, but also other generic sensor models. In the future, we plan to test this method under a wider variety of different conditions and sensors, such as airborne wide angle cameras, large off-nadir angles, and different satellite data.

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