Effect of the sampling design of ground control points on the geometric correction of remotely sensed imagery

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The acquirement of ground control points (GCPs) is a basic and important step in the geometric correction of remotely sensed imagery. In particular, the spatial distribution of GCPs may affect the accuracy and quality of image correction. In this paper, both a simulation experiment and actual-image analyses are carried out to investigate the effect of the sampling design for selecting GCPs on the geometric correction of remotely sensed imagery. Sampling designs compared are simple random sampling, spatial coverage sampling, and universal kriging model-based sampling. The experiments indicate that the sampling design of GCPs strongly affects the accuracy of the geometric correction. The universal kriging model-based sampling design considers the spatial autocovariance of regression residuals and yields the most accurate correction. This method is highly recommended as a new GCPs sampling design method for geometric correction of remotely sensed imagery.

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1. Introduction

Raw remotely sensed imagery often contains geometric distortions originating mainly from the remote-sensing platform, sensor, atmosphere and Earth (Jensen, 1996). Such imagery cannot be used directly with map-based products in a geographic information system (Toutin, 2004). Consequently, one important procedure that must be carried out prior to analyzing remotely sensed data is geometric correction (image to map) or registration (image to image). This is a prerequisite for a multi-source remote-sensing data fusion, integration, processing and analysis. The main purpose of geometric correction or registration is to determine explicitly the mapping function using ground control points (GCPs) and determine the pixel brightness in the corrected image (Jensen, 1996; Ge et al., 2006). Here, the GCPs are an important data source for aerial photography and remote-sensing geometric correction. No matter which geometric correction model is used, precise GCPs are needed to correct images accurately.

Previous research has indicated that the number, precision and spatial pattern of GCPs affect the accuracy and reliability of the corrected image (Orti, 1981; Labovitz and Marvin, 1986; Mather, 1995; Zhou and Li, 2000; Wang et al., 2005; Zhang et al., 2006; Sertel et al., 2007). The effect of the spatial pattern of GCPs on the estimates of the coefficients of a least-squares bivariate polynomial surface that is used in the correction process has been studied by geographers and geologists (Mather, 1995). Orti (1981) was one of the earliest scholars to explicitly conduct a quantitative investigation on the relationship between the GCP spatial distribution for a Landsat image and geometric correction error. In his experiment, the probability distributions of the location errors at control points were identical and independent, and the spatial distribution of the GCPs was relatively even. It was concluded by Orti (1981) that the accuracy of the positioning of the four corners of a particular image and some areas at the edges depends only marginally on the number of GCPs. Bahadir and Natarajan (1994) presented a trade-off study of a modified bundle adjustment program for the simulation of SPOT geometry vis-a-vis conventional photography with regard to precision for the number of GCPs and the various positions of GCPs in different patterns. The experiment showed that if GCPs were evenly distributed on both sides of the overlapping area along the flight track direction of the satellite, then the correction result was reliable and accurate; if the GCPs were distributed unevenly in the image, then the adjustment accuracy was reduced. Zhang et al. (2006) explored the effect of the spatial distribution of GCPs on the accuracy of imagery rectification. Both area-distributed and linearly distributed GCPs were used to rectify a Landsat Thematic...
Mapper (TM) image of a coastal zone. Rectification accuracy was checked against 99 independent validation points over intertidal mud flats with no ground control. Results indicated that the root mean square error (RMSE) of residuals over these areas was several times larger than its GCP-measured counterpart.

The summary of previous research clearly indicates that the GCPs spatial pattern affects the accuracy of the geometric correction of a remotely sensed image. It is important to select a sufficiently large number of appropriately distributed GCPs. A number of methods to automatically generate GCPs and distribute them evenly in space have been investigated. Chen and Lee (1992) presented an original scheme to generate control point pairs for image rectification automatically using a Voronoi–Delaunay dual diagram. They carried out an experiment on a SPOT image, obtaining highly reliable and accurate results. Similarly, Zhang et al. (2009) proposed the use of a Voronoi tessellation in selecting GCPs and established a relationship between the GCPs spatial pattern and number. The results demonstrated that using a Voronoi tessellation to control the GCP distribution was an effective method for improving the precision of geometric correction.

Following on from the previous research, this paper explores the effects of the method used for selecting GCPs on the accuracy of geometric correction. The selection of GCPs on the ground or in the image space can be regarded as a spatial sampling process. From the perspective of the regression model of geometric correction, the GCPs spatial pattern needs to be such that the selected GCP locations achieve the most accurate geometric correction, which is affected by the estimation errors of the regression coefficients. This can be considered as an issue of GCP sampling optimization. However, there has been little study on improving the accuracy of geometric correction by optimizing the GCPs spatial distribution. This paper uses a spatial sampling optimization technique to optimize the GCPs spatial pattern in the geometric correction process. Currently, there are a number of sampling optimization methods. For example, Brus et al. (2006) proposed a spatial coverage sampling (SCS) method that takes the mean-squared shortest distance as a minimization criterion to ensure that the samples cover the study area as uniformly as possible. Later, Walvoort et al. (2010) developed an R package that implements this sampling technique. However, little work has been done on the optimization of spatial sample configurations when the observations are used to estimate regression coefficients (Heuvelink et al., 2006). Lesch et al. (1995) and Lesch (2005) proposed a site selection algorithm that starts from the sample that is closest to the optimum response surface design calculated from experimental design theory. Lesch’s method (1) selects those sites that optimize the estimation of the regression coefficients and (2) ensures that the spatial separation between sites is large enough. The fitted regression model was then used to predict the target variable at all locations from observations of the auxiliary variables. However, this heuristic method does not use explicitly the spatial correlation in the residual pattern (Lesch, 2005). Moreover, the method is inflexible with regard to the number of sampling points to be selected. Brus and Heuvelink (2007) developed a universal kriging model-based sampling methodology that optimizes the spatial configuration of observations by minimizing the spatially averaged universal kriging variance with the help of exhaustively known covariates. In the following sections, the universal kriging model-based sampling design proposed by Brus and Heuvelink (2007) is referred to as UKMS. This paper adopts both the SCS and UKMS sampling methods to optimize GCPs spatial patterns. In addition, it also considers the commonly used simple random sampling (SRS) method. Both simulation experiments and actual-image analyses are carried out to substantiate the conceptual arguments.

The remainder of this paper is organized as follows. In Section 2, we first briefly describe the principle of geometric correction. Furthermore, the three sampling designs for selecting GCPs are compared on the basis of the accuracy of geometric correction using a set of evaluation criteria. Next, a simulation experiment and an actual case study are presented in Section 3. Finally, the results of the simulation experiment and actual case study are discussed and conclusions are drawn.

2. Principle and methods

2.1. Principle of geometric correction

The geometric correction of a remotely sensed image has three main procedures (Zitov and Flusser, 2003; Toutin, 2004): (1) acquisition of GCPs, (2) estimation of correction model parameters (i.e., computation of the unknown parameters of the mathematical functions used in the geometric correction), and (3) image rectification, which mainly comprises spatial transformation and resampling.

In geometric correction, a model is used to establish the relationship between the position of the image pixel and its actual geographic coordinates. There are numerous geometric correction models in remotely sensed image processing. These models can be divided into two categories (Toutin, 2004): empirical models and physical models. As empirical models do not consider the physical parameters and a priori sensor information, and a mathematical function is directly used to describe the geometric relations between a point on the ground and the corresponding pixel, these models are often adopted in the geometric correction of remotely sensed images. Suppose that a reference image with high precision is available, the reference image coordinates are \( (x, y) \), and the raw or uncorrected image coordinates are \( (u, v) \). The two coordinate systems are related through a pair of mathematical functions \( f(x, y) \) and \( g(x, y) \):

\[
\begin{align*}
\{ f(x, y) \\
g(x, y)
\}
\end{align*}
\]

The precise form of the function in Eq. (1) is usually unknown. Hence, simple first-order, quadratic or cubic polynomials are often chosen. The two-dimensional (2D) polynomial model is most commonly used and has been documented for image rectification since the 1970s (Wong, 1975). Its general expression is

\[
u = \sum_{i=0}^{m} \sum_{j=0}^{n} a_{ij} x^i y^j + \varepsilon_u \quad \text{and} \quad v = \sum_{i=0}^{m} \sum_{j=0}^{n} b_{ij} x^i y^j + \varepsilon_v
\]

where \( a_{ij} \) and \( b_{ij} \) are regression coefficients to be estimated and \( \varepsilon_u \) and \( \varepsilon_v \) are the regression residuals.

The 2D polynomial function model of first order (6 parameters) allows for only correcting by means of a translation along both axes, a rotation, scaling along both axes and an oblique transformation. A quadratic polynomial function (12 parameters) allows, in addition to the previous transformations, for correction of the torsion and convexity along both axes. A cubic polynomial function (20 parameters) further increases the correction flexibility, in a way that does not necessarily correspond to any physical reality of the image acquisition system. A quadratic polynomial function is often sufficient for actual image geometric correction, and it is used in this work. Its concrete form is

\[
\begin{align*}
\{ u = a_{00} + a_{01} x + a_{02} y + a_{11} x y + a_{20} x^2 + a_{02} y^2 + \varepsilon_u \\
v = b_{00} + b_{01} x + b_{02} y + b_{11} x y + b_{20} x^2 + b_{02} y^2 + \varepsilon_v
\}
\end{align*}
\]

2.2. Sampling designs for selecting GCPs

To investigate the effect of spatial sampling designs for selecting GCPs on the accuracy of the geometric correction, three sampling designs are adopted here.
2.2.1. Simple random sampling (SRS)

SRS is a commonly used sampling design for selecting GCP locations in an image. It is a probability sampling design in which locations are selected with equal probability and independently from each other. It needs no prior information in the sampling process. As a result, it is easy to implement in practice and is widely adopted in GCP collection. However, the spatial pattern of GCPs obtained with SRS does not ensure an accurate or optimal geometric correction.

2.2.2. Spatial coverage sampling (SCS)

SCS is a sampling method that provides the optimal dispersion of sampling points in geographical space (Royer and Nykha, 1998). Brus et al. (1999) proposed to use the mean of the squared shortest distance (MSSD) as an optimization criterion and to use the well-known k-means clustering algorithm as an optimization algorithm. This method partitions the area in compact geographical strata, from which a location can be selected. For mapping purposes, Brus et al. (2006) proposed to select the centers of the strata, and this is the approach taken in the present paper. SCS has been implemented in the package splot (Walvoort et al., 2010) and is available at the Comprehensive R Archive Network (CRAN, http://cran.r-project.org/). The advantage of SCS is that it does not need any prior or auxiliary information. Hence, it is easy to apply in practice.

2.2.3. Universal kriging model-based sampling (UKMS)

When the residuals in the regression model are spatially auto-correlated, ordinary least squares (OLS) estimation of the regression coefficients is not optimal (Lesch, 2005). Therefore, this will affect the accuracy of geometric correction. To overcome this weakness, we adopt the method of UKMS proposed by Heuvelink et al. (2006) and Brus and Heuvelink (2007) to optimize the spatial patterns of GCPs. UKMS takes a universal kriging model of reality as prior information and optimizes the sampling scheme on the basis of the minimization of the mean universal kriging variance (MUKV). For the geometric correction model described in Eq. (3), the target variable is not stationary but has a spatial trend in the image. The relationship between the target variable and the spatial coordinates or explanatory variables is described by a (multiple) linear regression model. Furthermore, a variogram for the regression residuals is required. We can then optimize the sampling locations by spatial simulated annealing (SSA), using the MUKV as a criterion. In the case of universal kriging, the locations of samples are optimized in both feature space and geographic space. That is because estimation of the relationship between the target variable and the explanatory variables profits from a large spread of the observations in the feature space, while interpolation of the residuals gains from a uniform spreading of the observations in geographic space (Brus and Heuvelink, 2007). The details of the UKMS algorithm are described in Heuvelink et al. (2006) and Brus and Heuvelink (2007). The specific issues of how to combine UKMS into the optimization of GCPs spatial patterns are discussed below.

First, the relationship between the target variable and explanatory variables is determined. UKMS assumes that the relationship between the target variable and explanatory variables takes the form of a linear regression equation with known structure but unknown coefficients. In the quadratic polynomial model (Eq. (3)), \( u \) or \( v \) are the target variables and \( x \) and \( y \) and their quadratic forms are the explanatory variables. Therefore, the trend form in the UKMS is known.

Second, the variogram of regression residuals is needed in UKMS optimization. After estimating the coefficients of the geometric correction model using the GCPs derived from SCS, the \( u \) and \( v \) coordinates of the validation points and their residuals can be calculated from Eq. (3). Therefore, the variogram for the UKMS is obtained by calculating the semivariance of the residuals in each coordinate direction.

Finally, an objective function is constructed. For a geometric correction model, two variables \((u \text{ and } v)\) need to be estimated. Likewise, two objective functions, the mean universal kriging variances in the \( u \) and \( v \)-coordinates (MUKV\(_u\) and MUKV\(_v\)) need to be optimized. To combine them, the sum of the two mean universal kriging variances MUKV = MUKV\(_u\) + MUKV\(_v\) is introduced into UKMS optimization. Therefore, an optimal GCPs spatial pattern is obtained by SSA, using MUKV as a criterion measure.

2.3. Accuracy evaluation of geometric correction

The positional accuracy of the geometric correction refers to the accuracy of the geometrically rectified image. Hold-out validation is a widely used method for accuracy assessment (Brovelli et al., 2008). This method divides the dataset into two subsets: GCPs and validation points (VPs). The GCPs are used to rectify the image and the VPs to validate the accuracy of the correction. The restriction on such a selection is that both GCPs and VPs are sufficiently well-distributed throughout the whole image. Also the optimal sampling design of the GCPs is different from that of the VPs. Here, we collected the VPs independently from the GCPs. The VPs were selected by stratified simple random sampling (SSRS) (Brus et al., 2011).

After optimization of the sampling pattern, the \( u \) and \( v \)-coordinates can be predicted at the VPs, as well as the prediction errors. On this basis, a common criterion to assess the accuracy of geometric correction is to calculate the root mean square error (RMSE) of the VPs (Jensen, 1996). The RMSE is defined as

\[
\text{RMSE} = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (e_{ui}^2 + e_{vi}^2)},
\]

where \( n \) is the number of VPs, \( e_{ui} \) and \( e_{vi} \) represent the residuals of the \( i \)-th VP in the \( u \) and \( v \)-coordinates, respectively. Moreover, \( \text{RMSE}_u \) and \( \text{RMSE}_v \), which represent the root mean square errors in the \( u \) and \( v \)-coordinate, can be calculated in the similar way.

Furthermore, the prediction errors at the VPs can be used to estimate the population (entire image) error statistics. Let us denote the sum of the two squared errors by \( z_i = e_{ui}^2 + e_{vi}^2 \), \( i = 1, 2, \ldots, n \), then from a stratified simple random sample the spatial mean (population mean) of \( z \) can be estimated by (de Grujter et al., 2006):

\[
\hat{z} = \frac{1}{H} \sum_{h=1}^{H} n_h \bar{z}_h,
\]

where \( H \) is the number of strata, \( n \) is the number of sampling units in the area, \( n_h \) is the number of sampling units in stratum \( h \), and \( \bar{z}_h \) is the sample mean of the sum of the squared errors in stratum \( h \).

The sampling variance of the estimated population mean of \( \hat{z} \) can be estimated as

\[
\hat{\text{V}}(\hat{z}) = \sum_{h=1}^{H} \left( \frac{n_h}{n} \right)^2 \hat{\text{V}}(\bar{z}_h),
\]

where \( \hat{\text{V}}(\bar{z}_h) \) is the estimated sampling variance of \( \bar{z}_h \):

\[
\hat{\text{V}}(\bar{z}_h) = \frac{1}{n_h(n_h - 1)} \sum_{i=1}^{n_h} (z_{ih} - \bar{z}_h)^2.
\]

The standard error of the estimated mean is estimated as \( \sqrt{\hat{\text{V}}(\hat{z})} \). The 100(1 - \( \alpha \))% confidence intervals for \( \hat{z} \) is given by:

\[
\hat{z} \pm t_{1 - \alpha/2} \times \sqrt{\hat{\text{V}}(\hat{z})},
\]
where $t_{1−α/2}$ is the $(1 − α/2)$ quantile of the Student distribution with $(n − H)$ degrees of freedom (Cochran, 1977). This confidence interval is based on the assumption that $z$, and therefore $\hat{z}$, is normally distributed. If the distribution deviates clearly from normality, the data should be first transformed to normality, for instance by taking the logarithm. The interval boundaries thus found are then back-transformed to the original scale.

3. Experiments

3.1. Simulation experiments

3.1.1. Generation of simulation data

To understand thoroughly the effect of the sampling designs for selecting the GCPs on the accuracy of the geometric correction and to reduce the matching error in collecting pairs of control points from a reference image and uncorrected image, a series of gray images was simulated. In the simulation experiments, with the help of Arc/Info Grid module software (Kreis, 1995) and Interactive Data Language (Bowman, 2006), a $512 \times 512$ pixel thematic raster map with three classes was simulated. According to category characteristics defined in advance, each pixel was randomly classified as belonging to one of the three classes, and the proportions of the classes were 1:1:1. Next, a focal majority function was used, with its radius determined as $15 \times 15$, to express the degree of clustering. To enhance the contrast of the images, the pixel values of the three classes were individually set at 50, 150, and 250, as shown in Fig. 1a.

The image given in Fig. 1a is called the reference image while the image with positional distortion is referred to as the uncorrected or distorted image. The simulated distorted image was obtained by adding a simulation error to the reference image, which is referred to as processing “pollution” (such as shift, scaling, rotation, polynomial transformation, and other processes). Here, in the simulation experiments, a quadratic polynomial transformation was added to the reference image to simulate distortion effects (Fig. 1b). However, actual images often have very complex spatial distortion characteristics. Quadratic polynomial distortion was used here for two reasons: (1) it is easy to add distortions to the image and avoid the effect of resampling and interpolation on image registration (Dai and Khorram, 1998) and (2) it allows selection of a suitable geometric correction model to confirm the rectification process and compare the corrected result with the simulated ideal image.

3.1.2. Sampling designs for selecting GCPs

The first step in geometric correction is to obtain the control points on a map or in a reference image. Accurate identification of GCPs is a prerequisite for obtaining accurate correction. In the simulation experiments, after studying the effect of GCP numbers on the geometric correction, 16 GCPs were determined as a proper number to select and participate in the correction process (Labovitz and Marvin, 1986). In addition, the 16 points were selected three times, by different sampling designs viz. SRS, SCS, and UKMS. In SRS, the GCPs are selected fully randomly, i.e., with equal probabilities and independently from each other. While in SCS and UKMS, the GCPs are not selected randomly but purposefully by minimizing the MSSD or MUKV criterion. If SRS of GCPs would have been repeated than this would have led to different SRS samples. We selected only one SRS, and assumed that the accuracy of the geometric correction obtained with this SRS sample is sufficiently representative for all other samples that could have been selected by SRS. This was verified by repeating the SRS several times, although the result of just one of these is reported here. The three spatial samples of GCPs selected by these three designs and their corresponding Voronoi tessellations (Shi and Pang, 2000) are shown in Fig. 2.

3.1.3. Selection of VPs

To evaluate the accuracy of the geometric corrections based on the three sampling designs, a fixed set of VPs were selected by SSSR from the entire image. This was achieved by a reference image being divided into $5 \times 5 = 25$ smaller squares and two locations being selected at random within each square. Thus, 50 VPs were collected from the reference image, as shown in Fig. 3.

For each sample of VPs, the RMSE in the $u$-coordinates ($\text{RMSE}_u$), the RMSE in the $v$-coordinates ($\text{RMSE}_v$), and the total RMSE were estimated to evaluate the accuracy of the geometric correction. Furthermore, statistical inference results for SSSR were used to assess the accuracy of the entire image. The mean, variance, and confidence interval of the sum of the two squared errors for the entire image were estimated using Eqs. (5), (6), and (8), respectively.

3.2. Experiments using actual remotely sensed imagery

Compared with actual remotely sensed imagery, the simulated image has the advantage that it is convenient to control the characteristics of the image to obtain GCPs and VPs. For example, it is easy to identify the GCPs or VPs at the intersection of three classes in the simulation image (see Fig. 1). However, the feature points in

Fig. 1. Simulated images with three thematic classes. (a) Reference image with no geometric deformation. (b) Quadratic polynomial deformation of reference image.
actual images, especially in low-resolution images, are often difficult to identify clearly (see Fig. 4). This will reduce the accuracy of locating GCPs or VPs, and consequently affect the calibration and validation of geometric correction. However, the geometric distortion of actual remotely sensed data is more complex, and some related issues require further attention. Therefore, we use actual images as experimental objects to illustrate the problem and further investigate the effect of the GCPs spatial pattern on the accuracy of geometric correction.

3.2.1. Data description

As an example of real uncorrected remotely sensed data we consider a TM multispectral image acquired over Beijing, China, on May 22, 2002. The resolution of this image is 30 m. A 573 × 615 pixel subset of the source image was used in this experiment (see Fig. 4a). The image includes Beijing Capital International Airport and its surrounding areas to the north-east of Beijing. A precise geocorrected SPOT image obtained over the same area on April 24, 2002 was taken as a 6876 × 7378 pixel reference image (Fig. 4b). The RMSE of the reference image is 2.0 m, which is less than the image resolution of 2.5 m. Therefore, this high-resolution SPOT image can be regarded as a precise reference image for correcting the TM image in the following experiments.
Fig. 4. Actual remotely sensed image: (a) the uncorrected TM image, and (b) reference SPOT image.

Fig. 5. The sampling designs for selecting GCPs in actual remotely sensed image: (a) SRS, (b) SCS, and (c) UKMS. The hollow triangle represents the ideal GCPs location in the reference image, while the filled triangle represents the real GCPs location after adjustment.
3.2.2. Geometric correction of remotely sensed data

Similar to the case of the simulation experiments, the process of geometric correction of a TM image mainly comprises the following four steps. The first step is the selection of an appropriate geometric correction model. According to the deformation characteristics shown in Fig. 4, a quadratic polynomial model, which is described by Eq. (3), was adopted to correct geometric deformation of the TM image. Second, sets of 16 GCPs were selected using different designs, namely SRS, SCS, and UKMS, were selected to determine the coefficients of the regression model. Besides, 50 VPs were selected by SSRS to assess the accuracy of geometric correction. Third, we performed geometric correction using a quadratic polynomial model with 16 GCPs and resampled the corrected image employing the cubic convolution resampling. Finally, the accuracy of geometric correction was assessed using the VPs.

3.2.3. Sampling designs for selecting GCPs

The effect of the spatial sampling design for selecting GCPs on the geometric correction of a TM image was thus investigated. To avoid matching error in the geometric correction, the matching error was controlled within 0.2 pixels in the TM image. Therefore, it was assumed that the accuracy of correction was only affected by the spatial pattern of the GCPs. These three samples of GCPs spatial patterns and their corresponding Voronoi tessellations are shown in Fig. 5. Here, the prior information in UKMS, namely the trend function and residual variogram, was based on the SCS correction results.

4. Results and discussion

4.1. Simulation experiment results

For geometric correction of the second-order polynomial distorted simulation image, the quadratic polynomial model parameters required were estimated by least-squares adjustment using the GCPs generated above. There were 16 GCPs for calibration and 50 VPs for validation in each geometric correction experiment. As described in Section 3.1, GCPs spatial patterns for SRS, SCS, and UKMS were designed in the simulation experiments. Here, SRS and SCS did not require prior information. The prior information of UKMS was provided by the SCS geometric correction. (1) The trend function was determined by the geometric correction model employing SCS. (2) The variogram was modeled by an exponential model using 50 VPs residuals in SCS. The variogram for the u-coordinate is shown in Fig. 6a, with a nugget of 0.015, sill of 0.053, and range of 420 pixels. The variogram for the v-coordinate is shown in Fig. 6b, with a nugget of 0.008, sill of 0.043, and range of 385 pixels. Using this prior information, the UKMS GCPs spatial pattern was obtained. Furthermore, it is important to note that GCPs and VPs must be located at ground or image characteristic points, such as the crossing of roads or the corner of a building, which are clearly identified in practice. Therefore, if the control points are not located as such, a small adjustment is needed to ensure GCPs are located at feature points around the sample points. For example, in the cases of SCS and UKMS shown in Figs. 2 and 5, the hollow triangle represents the ideal GCPs location in the reference image, while the filled triangle represents the real GCPs location after adjustment.

Using the framework of the simulation experiment discussed in section 3.1, three sampling design for selecting GCPs (i.e., SRS, SCS, and UKMS), the corresponding VP RMSE statistics (i.e., RMSEu, RMSEv, RMSE) and the sum of the two square errors statistical inference results (i.e., the mean, variance, t-value, lower confidence and upper confidence of z) were calculated as listed in Table 1. In the case of the SRS GCPs spatial sampling design (see Fig. 2a), the GCPs were distributed randomly throughout the image. The RMSE and the mean of z were 0.5413 and 0.2930, respectively, which were the largest values among the three sampling design. In the case

Fig. 6. The variogram of residuals in simulation experiments: (a) u-coordinate SCS residual variogram, (b) v-coordinate SCS residual variogram, and (c) UKMS residual variogram.
of the SCS GCPs design (Fig. 2b), the whole image was partitioned into 16 compact strata, from which the centers of the strata were selected as GCPs. The RMSE and the mean of z were 0.4417 and 0.2411, respectively. Compared with SRS, the SCS was far more accurate. The UKMS GCPs design (Fig. 2c) was optimized with prior information of SCS. GCPs were distributed more dispersedly than in SCS throughout the image. The outer GCPs were closer than those of the other spatial sampling designs to the boundary. The RMSE and the mean of z were 0.4089 and 0.1674, respectively, which were the smallest values among the three spatial sampling designs. This result indicates that the UKMS GCPs sampling design provided the most accurate geometric correction. In comparing the criterion of the RMSE, UKMS was 24.5% and 7.43% more accurate than SRS and SCS, respectively. The variogram of total residuals in UKMS is given in Fig. 6c. This figure shows that for the UKMS, the residuals of the geometric correction model do not have an autocorrelated structure after GCP optimization.

In addition, SRS statistical inference results were also calculated to infer the geometric accuracy of population. Taking UKMS GCPs spatial sampling design as an example, the mean and standard deviation of the sum of two square errors z for each pixel in the corrected image were 0.1674 and 0.1519, respectively. The \( t \) value was 7.794, indicating that the estimation for the entire image was significant. In a two-tailed test, at a 95% confidence interval of the difference, the geometric error of z for each pixel in the corrected image was between 0.1243 and 0.2106 pixels. The upper confidence interval of z is less than 0.5 pixels. The UKMS thus provides an accurate geometric corrected image.

### 4.2. Results of actual-image experiments

The geometric correction process for an actual image is similar to that for a simulated image. The quadratic polynomial model was adopted to correct unknown deformations of the TM image using the GCPs generated above. The GCPs spatial sampling designs were those of SRS, SCS, and UKMS. The prior information in UKMS was provided by SCS geometric correction. The variogram for the \( u \)-coordinate is shown in Fig. 7a, with nugget, sill and range parameters of 0, 32.0 and 4850.0 m, respectively. The variogram for the \( v \)-coordinate is shown in Fig. 7b, with nugget, sill and range parameters of 29.5, 79.5 and 10,500 m, respectively. It is concluded from Fig. 7a and b that the residuals for the \( u \) and \( v \)-coordinates are spatially autocorrelated, which would lead to inaccurate estimation of coefficients in the geometric correction model. Therefore, UKMS methods that attempt to optimize the GCP spatial pattern were adopted here.

![Fig. 7](image-url) **Fig. 7.** The variogram of residuals in actual image experiments: (a) \( u \)-coordinate SCS residual variogram, (b) \( v \)-coordinate SCS residual variogram, and (c) UKMS residual variogram.
Using the framework discussed in Section 3.2, the effect of the sampling design for selecting GCPs on the geometric correction of actual remotely sensed imagery is further investigated here. The RMSE statistics and the statistical inference results for were calculated from 50 stratified random sampled VPs as listed in Table 2. In the case of the SRS GCPs spatial sampling design (Fig. 5a), GCPs were distributed unevenly and not dispersedly enough in the reference image. The RMSE and the mean of were 20.98 and 440.0, respectively, which were the largest values among the three GCP sampling designs. In the case of SCS GCPs spatial sampling design (Fig. 5b), GCPs were distributed evenly in the reference image. However, they were not dispersed sufficiently compared with the case for UKMS. The RMSE and the mean of were 15.59 and 243.1, respectively. This is a 26% improvement in the criterion of the RMSE for the SRS. Fig. 5c shows the UKMS GCPs spatial distribution after optimizing the GCPs spatial pattern. The UKMS GCPs spatial pattern performs the best among these three GCP sampling designs. The RMSE and the mean of were 14.46 and 214.2, respectively.

5. Discussion

Three different GCPs spatial sampling designs, those relating to SRS, SCS, and UKMS, were designed for geometric correction. In a SRS sampling design, the GCPs are selected randomly, which is often required by geometric correction models for the inference. However, SRS may lead to an uneven cover of the image space, therefore, this GCPs spatial sampling design might be potentially inefficient. At the opposite extreme, the SCS GCPs spatial sampling design achieves even coverage of the entire reference image. Under the condition that we have no information about the geometric correction model parameters, which are almost invariably unknown in advance, it will usually be appropriate to consider the SCS GCPs sampling design. SCS can be regard as a model-independent sample design, defined in terms of the geometry of the sample location (Royle and Nychka, 1998). The resulting design of SCS tends to be spatially regular in appearance, as shown in Figs. 2b and 5b. Likewise, the reference image in the simulation or actual image experiment is square. Therefore, the optimal SCS of 16 GCPs from a regular square takes the midpoints of 16 subsquares of equal area. Nevertheless, in practical applications, the references or incorrect images are irregular and it is difficult to equally divide the image artificially. In these situations, SCS can be used to provide an optimal way for obtaining the GCPs.

Compared with SCS, UKMS can be regarded as a model-dependent approach. It achieves two purposes, which are the efficient estimation of geometric correction model parameters and the efficient prediction of the spatial distribution of residuals. These two purposes are balanced by minimizing the universal kriging prediction error variance. Brus and Heuvelink (2007) showed that the universal kriging variance incorporates both the estimation error variance of the trend and the prediction error variance of the residual. After minimizing the mean (or sum) of the universal kriging variance for the entire image, one automatically obtains the right balance between optimization of the sample pattern in geographic and feature spaces. From Figs. 6 and 7, it was demonstrated that the UKMS design, which considered the spatial autocovariance of regression residuals, was efficient to estimate the parameters of geometric correction models. Hence, UKMS performs best in both simulation and actual-image geometric correction experiments.

As in the UKMS GCPs optimization, the quality measure of MUKV does not depend on the data values themselves but merely on the spatial pattern of the predictors and the covariance structure of the residuals. This allows us to compute the MUKV before collecting the GCP coordinates. However, the UKMS needs the variogram of regression residuals to calculate the covariance of samples and predictors before samples optimization. In this paper, the variogram was provided by the SCS geometric correction. Therefore, it needs to collect GCPs for twice: the first time is to collect the GCPs for SCS geometric correction which in order to obtain the regression form and regression residual variogram; the second time is to collect GCPs for UKMS geometric correction based on the results of SCS. As a result, this method becomes less efficient, even though UKMS achieves the most accurate geometric correction. Besides this, the variogram of regression residuals always contains uncertainty, which will propagate into UKMS optimization and affect the GCP configuration. Hence, dealing with the situation that no prior variogram is known or the variogram has uncertainty is a key problem in UKMS optimization. Diggle and Ribeiro (2007) proposed a way to solve this problem through utilizing a model-based geostatistical approach. In this approach, the residual variogram can be modeled from expert judgment or empirical experience. Then one treats the variogram as being uncertain and estimates its parameters using a Bayesian approach (Diggle and Ribeiro, 2006; Diggle and Ribeiro, 2007). Therefore, this model-based geostatistical method can be adopted in the GCPs spatial pattern optimization when no variogram is known or variogram has uncertainty.

6. Conclusion

In this paper, the effect of the sampling design for selecting GCPs on the accuracy of geometric correction was studied in a simulation and an actual-image experiment. In the experiment, sets of 16 feature points were selected as GCPs with SRS, SCS, and UKMS spatial sampling design, and 50 stratified random sampled VPs were adopted to evaluate the accuracy of image geometric correction. From the experiments, it was demonstrated that the spatial pattern of GCPs greatly influences the accuracy of image correction. The UKMS GCPs optimization produces the best result in both simulation and actual-image experiments. Both simulation experiments and actual-image experiments show that the more disperse and the distribution of GCPs, the higher the geometric correction precision. According to the experiments, it can be found that SCS and UKMS GCP sampling method is able to improve the accuracy of geometric correction considerably. These are highly recommended as a new GCPs optimization method in the geometric correction of remotely sensed imagery.
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