Optimal Ground Control Points for Geometric Correction Using Genetic Algorithm with Global Accuracy

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Abstract
Establishing the ground control point (GCP) network is a pre-requisite for georeferencing raw image data. Given current typical digital spatial database quality, much interest among users is about the accuracy of the geometric correction model that yields the final product. This paper reports an approach to optimizing GCP assembly using a genetic/evolution algorithm. The paper also suggests an optimal criterion for accuracy assessment through appraisal of global accuracy of the transformation, which is computed at each point of the image space. Experimental results demonstrate that the proposed approach has a great potential for selection of the best GCPs, and considerable improvement to the accuracy of geometric correction models can be expected when it is implemented.

Keywords: Geometric correction, georeferencing, ground control point, global accuracy, genetic algorithm, Voronoi diagram.

Introduction
The geometric processing of remote sensing images is a key issue in multi-source data integration, management and analysis for many geomatic applications. During the satellite imaging process, the projection, tilt angle, scanner, atmospheric condition, earth curvature and the undulation will cause the satellite images to be distorted. The quantitative use of these images requires the geometric distortions in them to be corrected, or rectified, to a desired map projection. Geometric correction, also known as georeferencing and image rectification, is necessary when the output products of image analysis are overlayed on a map or merged into a geographic database [Fontinovo et al., 2012; Gianinetto, 2012; Yan et al., 2012; Wang et al., 2012; Arun and Katiyar, 2013]. Sertel et al. [2007] and Topan and Kutoglu [2009] introduced the figure condition method to analyze the accuracy of geometric correction. Through this method, a more rigorous analysis of accuracy of georeferencing models can be conducted.

The most widely used model relies on the use of ground control points (GCPs) located in the image and the corresponding map in order to empirically determine a mathematical
coordinate transformation to correct the geometry. Theoretically, raw satellite images can be geometrically corrected through deployment of such a model. However, this requires a large number of well-spread GCPs to be identified prior to use of the coordinate transformation function. This is an obvious limitation because the identification of plausible GCPs is a time consuming task. Furthermore, the number of places where it is possible to identify GCPs may be small due to the characteristics of the study areas and other hazards in GCP selection.

Many techniques have been devised and applied for automating GCP selection. A review of these methods is presented in the next section. All of these automatic GCP extraction/identification/selection/location/determination techniques provide the mapping profession with the means to assemble a large number of original GCPs without inordinate manual labour.

Indeed, from these prolific, automatically-derived results, users need to select a set of GCPs that offers the transformation accuracy level required by the project accuracy specifications.

Traditionally, to make the best transformation model (according to the previously-determined criteria) from the set of \( n \) original GCPs, we need a traverse of all of associated abilities among them under the condition of minimum limitation \( m \) of GCPs. This leads to the large number of trials:

\[
N = C_n^m + C_n^{m-1} + \ldots + C_n^1 \quad [1]
\]

For instance, the minimum of points required to perform the transformation of order \( t \) polynomial transformation is equal to \( \frac{(t+1)(t+2)}{2} \). With a certain \( n \), the minimum of \( m \) leads to maximum of \( N \), approximated to \( 2^n \). This computing complexity cannot be normally overcome by deployment of sequential searching algorithms. In such a case, alternate optimizing computer algorithms (e.g. “evolution algorithms”) need to be investigated and applied.

Evolution algorithms have been around since the early sixties. They apply the rules of nature: evolution through selection of the fittest individuals, but in this case the individuals represent solutions to a mathematical problem. Genetic algorithms (GAs) are generally the best and most robust kind of evolutionary algorithms so far [Schmitt, 2001]. These genetic algorithms offer a heuristic, population-based, evolutionary optimization method whereby defined populations evolve over generations using the Darwinian principle of survival of the fittest. GAs have the capability to tackle objective functions that are non-differentiable, non-continuous, non-linear, noisy, flat, multidimensional, or have many local minima or constraints. If these characteristics are strongly present, GAs offer an effective approach to solve optimization problems including those in applied remote sensing and spatial science [Cui et al., 2013; Pedergnana et al., 2013; Wang et al., 2014].

This paper reports the result of using a GA for choosing the best subset of GCPs with respect to the optimal criterion: global accuracy of the transformation. The global accuracy expression, which is built using the least squares method, is computed at each point of the image space for a given set of GCPs. As the role of Root Mean Square Error (RMSE) has been criticised deficient in geo-transformation [Morad et al., 1996], employment of the global accuracy is an appealing point of the paper.
A review of automatic GCP selection

There have been various approaches proposed in the literature for automating GCPs for geometric correction goals. Motrena and Rebordao [1998] identified GCPs automatically based on the characteristics of GCPs and their neighbourhood, invariant with respect to rotation and contrast change. This method used the autocorrelation function of an azimuthal projection around the GCP and Euclidean minimum distance classifier to characterize GCPs.

On the other hand, Lisaka and Sakurai-Amano [1996] used road intersections as very good GCPs in a SAR image. Information fusion and Hough transform based approaches were applied to determine GCPs automatically from multi-look SAR imagery. Alternatively, Kim and Im [2003] applied automated matching based on normalized cross correlation for automated control point generation. The matching technique was improved by determining the size and shape of match windows according to incidence and scene orientation angles. Then, the robust estimation of mapping functions from control points can be used to automate satellite image registration.

Likewise, Couloigner et al. [2002] developed a method and wrote software for automatic identification of high quality GCPs in RADARSAT images using data from a topographic database. Two approaches are used to match the two data sources: vector and raster approach. Then GCPs are extracted from the category “stretches of water” or “water bodies”. Carrion et al. [2002], Chirici et al. [2004] and Gianinetto et al. [2004, 2008] proposed a new approach to high resolution orthoimage generation, based on the use of automatic GCPs extraction by means of a multi-resolution least squares matching routine. The implementation of GEOREF software has been completed and its operational application to upgrade spatial databases of satellite images has become possible.

Hong et al. [2006] in another approach introduced an inverse geolocation method for GCP extraction by synthetic aperture radar (SAR) simulation. This method improves the accuracy of extracted GCPs by accommodating topographic effects, and requires a high-resolution digital elevation model (DEM) and SAR with precise orbit data. Fornaciai et al. [2008] used the SITOGEO-GIS tool to acquire the GCPs for an orthorectification procedure of Landsat 7 ETM+ images.

More recently, Gill et al. [2010] also used over 1600 GCPs created from field measurements for geometric correction of Landsat images throughout Queensland, Australia from 1988 to 2007. Koppe et al. [2012] investigated the optimized stereo constellation for the GCP retrieval procedure. The quality of GCPs retrieved from TerraSAR-X and TanDEM-X imagery is assessed to be dependent to the input image parameters.

Advanced geometric correction model

The geometric distortions in satellite images can be geometrically corrected using models and mathematical functions. Whatever the mathematical function used, the geometric correction method and processing steps are more or less the same. The processing steps are as follows:

- Acquisition of image(s) and pre-processing of metadata;
- Acquisition of ground points with image coordinates and map coordinate X, Y, (Z);
- Computation of unknown parameters of mathematical functions used for the geometric correction model for one or more images; and
- Image(s) rectification with (differential) or without DEM.
GCP acquisition is an important step as the accuracy of the GCP positioning affects the accuracy of the geometric correction. Practically no algorithm can achieve good geometric correction results by using poorly-positioned GCPs. An efficient geo-correction system demands positioning sharply-definable ground points on the image: quality in these terms is more important than the quantity of GCPs [Katiyar et al., 2003]. The number of excellent GCPs used on the geometric correction model varies with the method of collection, sensor type and resolution, image spacing, geometric model, study site, physical environment, GCP definition and the final expected accuracy [Toutin, 2004].

Conventionally, to assess the accuracy of the resultant geometric correction, Root Squared Error (RSE) is calculated based on the resultant vector from residuals in x and y axes of independent check points (ICPs) $RSE = \sqrt{u^2 + v^2}$ where $u$, residual in the x axis; $v$, residual in the y axis. The total RMSE is then derived as $Total\_RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (u^2 + v^2)}$ where $n$ is the number of ICPs.

As several authors have demonstrated, removing those GCPs that lead to a great increase of total RMSE improves quality (reduces RMSE) of the georeferencing model [Gibson and Power, 2000; Rocchini and Di Rita, 2005]. Nevertheless, error reduction by removal of points, which have high value of residual, does not necessarily yield commensurate improvement in the geometric correction [Morad et al., 1996]. In order to avoid this disadvantage, we suggest the use of global accuracy instead of RMSE for measuring geometric correction performance.

![Advanced geometric correction model using genetic algorithms.](image-url)
Our advanced geometric correction model (Fig. 1) proposes a method, in which a genetic algorithm approach is applied to extract the best set of GCPs from the set of original GCPs. Original GCPs can be manually or automatically collected, and the methods can refer to a number of sources: for instance, global positioning system (GPS) survey, air photo surveys, paper or digital maps, chip data base.

The automatic GCP extraction techniques mentioned above are amenable to implementation via the genetic approach. Clearly, the efficiency of automating in this way is worth an investigation.

**Optimal criterion: Global accuracy**

To implement and test the model, we focused on the empirical geometric correction where the unknown transformation coefficients are estimated by a least-squares adjustment technique. However, this advanced model can be applied for any geometric correction models where a set of GCPs is involved and the accuracy is identified and quantified numerically.

In the least square transformation approach, the image distortion is modelled empirically as a mapping transformation from the acquired image coordinates to the desired map projection coordinates. The mapping function is generally chosen to be a bivariate polynomial. Denoting the image coordinates by \( r = (x, y) \) and the mapped coordinates by, \( r' = (x', y') \) the mapping functions are given by:

\[
x' = f_1(x, y) = \sum_{j=0}^{q} \sum_{k=0}^{q-1} a_{jk} x^j y^k \quad [2]
\]

\[
y' = f_2(x, y) = \sum_{j=0}^{q} \sum_{k=0}^{q-1} b_{jk} x^j y^k \quad [3]
\]

where \( q \) is the mathematical order of the polynomial equation and \( \{a_{jk}\} \) and \( \{b_{jk}\} \) are empirically-derived coefficients. The choice of \( q \) is dependent on the degree of non-linearity of the distortion. The degree \( q \) must be large enough to correct highly localized distortion, is at the expense of an increase in the sensitivity to modelling errors. This model can be expressed generally in the form:

\[
r' = \Phi \alpha \quad [4]
\]

where \( r' \) is a \( n \times 1 \) vector of the map coordinates, \( \Phi \) is a \( n \times p \) matrix of polynomial functions of the image coordinates, and \( \alpha \) is a \( p \times 1 \) vector of unknown coefficients. This is one of the least-squares problems, where the estimated transformation coefficient vector, \( \alpha \), is given by:

\[
\alpha = \left( \Phi^T \Phi \right)^{-1} \Phi^T r' \quad [5]
\]

with the variance-covariance matrix:

\[
K_{\alpha \alpha} = m_0^2 \left( \Phi^T \Phi \right)^{-1} \quad [6]
\]
where $m^2_0$ is the root mean square error of unit weight. The error of the transformation is propagated from the estimated coefficients and the image coordinates. The first differential is derived from [4] as follows:

$$\delta r' = \Phi \delta \alpha + \alpha \delta \Phi \quad [7]$$

The variances of the map coordinates $\nu_{r'}$ are identified by taking the square of [7]:

$$\nu_{r'} = \Phi \nu_{\alpha \alpha} \Phi^T + \alpha \nu_{\Phi \Phi} \alpha^T \quad [8]$$

This expression provides an estimate of the error variance at any point in the image space for a specific set of GCP observations.

To assess the global accuracy of the transformation, we define the average uncertainty as:

$$s = \frac{1}{m} \sum_{i=1}^{m} \left( \nu^2_{x_i} + \nu^2_{y_i} \right)^{1/2} \quad [9]$$

where $m$ is the total of pixels in image space and $\nu^2_{x_i}, \nu^2_{y_i}$ are derived from [8] and calculated only at pixel $i$.

Equation [9] will be used as the optimal GA criterion (fitness function). The lower the average uncertainty, the higher is the global accuracy.

The first and second-order polynomial functions were applied for running experiments reported in this research paper. Polynomials with higher orders were not applied, because this could produce large image distortions [Rocchini, 2004]. Increasing the degree of transformation results in a decrease in the residual error between the observed and estimated GCPs. However, due to the uncertainties of the higher order coefficients, it does not necessarily describe the actual errors between the observed and true GCPs [Ford and Zanelli, 1985]. The first and second-order transformations are represented in detail as follows:

The 1st-order transformation:

$$r' = \begin{bmatrix} 1 & x & y \end{bmatrix} \begin{bmatrix} \alpha_0 & \ldots & \alpha_2 \end{bmatrix}^T \quad [10]$$

$$\delta r' = \begin{bmatrix} 1 & x & y \end{bmatrix} \begin{bmatrix} \delta \alpha_0 & \ldots & \delta \alpha_2 \end{bmatrix}^T + \begin{bmatrix} \alpha_0 & \ldots & \alpha_2 \end{bmatrix} \begin{bmatrix} \delta 1 & \delta x & \delta y \end{bmatrix}^T \quad [11]$$

$$\delta r' = \Phi \delta \alpha + \alpha \delta \Phi \quad [12]$$

The 2nd-order transformation:

$$r' = \begin{bmatrix} 1 & x & y & x^2 & y^2 \end{bmatrix} \begin{bmatrix} \alpha_0 & \ldots & \alpha_5 \end{bmatrix}^T \quad [13]$$

$$\delta r' = \begin{bmatrix} 1 & x & y & x^2 & y^2 \end{bmatrix} \begin{bmatrix} \delta \alpha_0 & \ldots & \delta \alpha_5 \end{bmatrix}^T + \begin{bmatrix} \alpha_0 & \ldots & \alpha_5 \end{bmatrix} \begin{bmatrix} \delta 1 & \delta x & \delta y & \delta xy & \delta x^2 & \delta y^2 \end{bmatrix}^T \quad [14]$$
\[ \delta r' = \Phi \delta \alpha + \alpha \delta \Phi \quad [15] \]

By indicating \( \Phi \) and \( \alpha \) for the first-order [12] and second-order [15] transformations as above, the variances of map coordinates can be calculated at any pixel using [8].

**GCPs selection methods**

*Proposed genetic algorithm approach*

A genetic algorithm is an unorthodox search or optimization technique operated on a population of \( n \) artificial individuals [Reeves and Rowe, 2002]. Individuals are characterized by chromosomes (or genomes) \( S_k, k = \{1, \cdots, n\} \). The chromosome is a string of symbols, which are called genes, \( S_k = (S_{k1}, \cdots, S_{kN}) \), and \( N \) is a string length. Individuals are evaluated via calculation of a fitness function. To evolve through successive generations, GAs perform three basic genetic operators: selection, mutation and crossover. Through chromosomes’ evolution, GAs search for the best solution(s) in the sense of the given fitness function.

![Flowchart](image)

*Figure 2 - Genetic approach for making the best GCPs from original GCPs.*
Application of the GA approach in geometric correction is illustrated in Figure 2. The first generation has ten individuals (chromosomes). Each individual is a binary string, which encodes $N$ original GCPs by 0, 1 digits. Equation [9] is used as the goodness of fit function corresponding to the optimal solution. A roulette wheel selection method is used to select the individuals that produce an intermediate population. Parents are selected based on their fitness. Chromosomes have more chances to be selected if they are better (have higher fitness) than the others. Imagine all chromosomes in the population are placed on a roulette wheel; everyone has its place big according to its fitness function (Fig. 3).

The wheel is rotated and the selection point will indicate which chromosome is selected when the wheel is stopped. It is obvious that the chromosome with bigger fitness will be selected more times (competing rule in the evolutionary theory).

The crossover operator selects random pairs from the intermediate population and performs 1-point crossover. Genes from parent chromosomes are selected to create new offsprings. A crossover point is selected randomly and genes before this point are copied from the first parent and everything after a crossover point is copied from the second parent (Fig. 4).
Finally, individuals are mutated and they form the new population. The mutation prevents falling all solutions in the population into a local optimum. A few randomly chosen bits are switched from 1 to 0 or from 0 to 1 as illustrated in Figure 5.

The evolution process will end when a suitable solution has been founded (converged) or a certain number of generations have passed, depending on the needs of the user.

**Competitive method based on Voronoi diagram**

For comparisons, we also implemented in this paper a competitive method based on the Voronoi diagram proposed by Li and Cheng [2008]. The approach considers the accuracy as well as the distribution factor using the concept of “important value” to control the uniformity of the distribution of GCPs. The following summarizes basic steps of the Li and Cheng’s method.

1. Load the geographic coordinates and image coordinates of GCPs.
2. Compute the position error for each GCP based on polynomial geometric correction model in accordance with the principle of least-squares method. Let us define \( E_i = \sqrt{\varepsilon_{x_i}^2 + \varepsilon_{y_i}^2} \) as the position error of the \( i \)-th GCP where \( \varepsilon_{x_i} \) and \( \varepsilon_{y_i} \) are errors on the x and y axes respectively.
3. Construct Voronoi diagram using the point vector layer of GCP taking the border of ROI as the map boundary.
4. Calculate the “importance value” to judge the importance of GCP by: \( inv_i = S_i / S_{ROI} = S_i / \sum_{i=1}^{n} S_i \) where \( S_i \) is the area of polygon containing the \( i \)-th GCP.
5. Normalize the important value by the following formula:

\[
\overline{inv_i} = \frac{inv_i}{(inv_i)_{max}} \quad [16]
\]

where \( \overline{inv_i} = 1 - \overline{inv_i} \).
6. Combine error and important value via the function \( f \) to evaluate GCPs:

\[
f_i = w \cdot \overline{\text{error}_i} + (1 - w) \cdot \overline{\text{inv}_i} \quad [17]
\]

where \( w \) is the weighting coefficient and \( \overline{\text{error}_i} \) is the normalized position error of the \( i \)-th
GCP: \( \text{error}_i = E_i / E_{\text{max}} \). In Li and Cheng [2008], \( w \) is set equal to 0.2 and this is also the value we utilized in this paper for comparisons.

(7) Ranking GCPs using their \( f \) values and eliminate GCPs having the greatest \( f \) values. It also means that the smaller the value of \( f \), the better (in terms of less error and more even distribution) is the GCP. For unbiased comparisons with our proposed GA approach, we retain a number of GCPs that is equal to the number of GCPs selected by GA.

**Experiments and discussions**

Aerial photographs (Figs. 6 and 7) of two study areas are chosen in this research: Shepparton and Mildura, Victoria, Australia. The Shepparton and Mildura photos were captured on 4 March 1993 and 31 December 1992 respectively. The master source used in geometric correction is the road network in Victorian Spatial Data Infrastructure (VSDI). The highway/street intersections were selected/located as GCPs using ArcGIS software. Experiments reported here include a municipal, i.e. the Shepparton case study, and a rural area, i.e. the Mildura case study. Locating the positions of GCPs for the municipal area is easier and more accurate positioning can be expected than for the GCP assembly for the rural area. We originally collect 47 and 55 GCPs in the Shepparton case study for the first and second order geo-references respectively. In the Mildura case, the number of GCPs is 30 and 39 for first and second order geo-references respectively.

![Figure 6 - The road network (VSDI) overlays on the aerial photographs of Shepparton.](image)
Table 1 reports results obtained by the applications of original GCPs, GCPs based on Voronoi diagram, and GCPs selected by GA approach for geometric correction models. It is obvious that the results of comparisons demonstrate the dominance of the optimized GCPs against original GCPs and GCPs selected by the Voronoi diagram approach in both areas. The global accuracy of optimized transformation is significantly improved (displayed by blacker colour on the right panel in Figs. 10, 14, 18 and 22). The accuracy is higher at the areas where the GCP distribution intensifies (blacker areas). The 2nd-order transformation spends more time in processing than the 1st-order transformation due to its higher matrix dimensions. However, it is more effective in cases of highly localized distortion. The global accuracy of 2nd-order transformation is higher than 1st-order one (manifested via the lower uncertainty).

For each experiment, the competitive method of Li and Cheng using Voronoi diagram is implemented to filter GCPs. In the 1st-order transformation of the Shepparton case study, 47 original GCPs are reduced to 24 GCPs as equal to the number of GCPs retained by GA (see Tab. 1). Figure 8 shows the Voronoi diagrams constructed using 47 original GCPs and 24 retained GCPs using the Voronoi diagram approach. GCPs having the largest $f$ values calculated by Equation [17] are eliminated.

Figure 7 - The road network overlays on the aerial photographs of Mildura.
| Aerial photograph of | Shepparton – Victoria, Australia (municipal area) | Mildura – Victoria, Australia (rural area) |
|---------------------|--------------------------------------------------|-------------------------------------------|
| Master source       | VSDI                                             | VSDI                                      |
| Master projection   | UTM GDA 1994 Zone 55                             | UTM GDA 1994 Zone 54                      |
| Transformation order| 1\textsuperscript{st}                             | 2\textsuperscript{nd}                     |
| The number of generations in GA | 100 | 75 | 80 | 50 |
| The number of original GCPs | 47 | 55 | 30 | 39 |
| The number of optimized GCPs by GA | 24 | 27 | 8  | 18 |
| Average uncertainty using original GCPs | 0.924 | 0.815 | 1.789 | 1.005 |
| Average uncertainty based on Voronoi diagram GCPs | 1.030 | 1.053 | 1.526 | 1.115 |
| Average uncertainty based on optimal GCPs by GA | 0.835 | 0.404 | 0.874 | 0.782 |
| Illustrated by      | Figs. 8-11                                       | Figs. 12-13                               |

The error surface based on 24 Voronoi diagram GCPs are exhibited in Figure 9. On the other hand, Figure 10 displays the error surfaces using 47 original GCPs on the left and 24 GA GCPs on the right respectively.

The comparisons between the error surface using the GCPs extracted by GA and those based on two random sets of GCPs are also accomplished (see Fig. 11). Each random set of GCPs also comprises 24 GCPs that is the same number with the GCPs set extracted by GA.

![Image](image_url)

**Figure 8** - Shepparton case study, 1\textsuperscript{st}-order transformation. Voronoi diagrams based on 47 original GCPs and 24 retained GCPs.
Figure 9 - Shepparton case study, 1st-order transformation. Error surface using 24 Voronoi diagram GCPs.

Figure 10 - Shepparton case study, 1st-order transformation. Error surfaces based on original GCPs and optimized GA GCPs.
The above procedures are replicated for the 2nd-order transformation in the Shepparton case study and also for the 1st-order and 2nd-order transformation in the Mildura case study. The following figures (Figs. 12-17) graphically demonstrate the results of these experiments.
Figure 13 - Shepparton case study, 2nd-order transformation. Error surfaces based on original GCPs and optimized GA GCPs.

Figure 14 - Mildura case study, 1st-order transformation. Error surface based on 8 Voronoi diagram GCPs.
Figure 15 - Mildura case study, 1st-order transformation. Error surfaces based on original GCPs and optimized GA GCPs.

Figure 16 - Mildura case study, 2nd-order transformation. Error surface based on 18 Voronoi diagram GCPs.
Through four experiments, it is convinced that GCPs sets filtered by GA dominate those driven by the Voronoi diagram approach although both sets have the same number of GCPs. GCPs chosen by GA also lead to superior results compared to original GCPs. In addition, random sets of GCPs are inferior to the original set of GCPs. Therefore, they are also significantly dominated by the set of GCPs extracted by the proposed GA approach.

More specifically, in the 1st order geo-transformation of the Shepparton case study, both random sets of GCPs yield the average uncertainty at 1.068 and 1.109 respectively (Fig. 11) whilst the original set of GCPs obtains the lower average uncertainty at 0.924 (Fig. 10). With 24 GCPs extracted by GA, the proposed approach obtains the lowest average uncertainty at 0.835 (Fig. 10). This is smaller than the average uncertainty at 1.030 of the Voronoi diagram method (see Fig. 9). Obviously, GCPs acquired by GA outperform those picked by the Voronoi diagram approach.

The more significant outcomes are found in the 2nd order transformation of the Shepparton case study (Figs. 12 and 13). The best result comes from the set of 27 GCPs extracted by GA with the average uncertainty of 0.404, which is much lower than 0.815 of the original set of 55 GCPs (Fig. 13) and 1.053 of the Voronoi diagram GCPs set (Fig. 12). Two random sets of 27 GCPs produce the average uncertainty at 1.097 and 1.387 respectively.

In the Mildura case study, the 1st order geo-reference demonstrates a more remarkable improvement of the GCPs extracted from the proposed GA approach compared to the original set and both random sets of GCPs. The gap between the best average uncertainty (0.874 of the GA GCPs) and the worst average uncertainty (3.237 of one random set) is very large (see Fig. 15). On the other hand, the Voronoi diagram GCPs generate a mediocre performance in this case study with the average uncertainty of 1.526 (see Fig. 14). Alternatively, the 2nd order geo-transformation of the Mildura case study also illustrates the superiority of the GCPs taken by GA compared to the original GCPs, Voronoi diagram...
GCPs (Figs. 16 and 17) and both random sets of GCPs. The darker the image, the higher is the accuracy (also meant the lower is the average uncertainty) of the geo-transformation.

Conclusions and future work

Instead of using conventional criterion (the low total RMSE value based on GCPs for estimating parameters and ICPs for model checking), this paper assesses the accuracy of geometric correction by global accuracy that is calculated at any point in the image space for a specific GCPs set. The employment of global accuracy guarantees the distribution of GCPs in the image space. The best GCPs are selected, via the GA approach, from the original GCP list in according to this criterion. The comparisons are organized between the optimized GCPs with GCPs selected by the Voronoi diagram approach and also with two GCPs random sets. All of the test results showed the power of GA although it is computationally demanding. It requires as many transformations to be calculated as there are GCPs. However, historical computational limits have practically vanished in the face of modern processing capabilities.

This model is useful as it saves the time consuming human task of removing/adding the GCPs, which have high/low value of RMSE residuals. GCP acquisition is now conveniently extracted by many automatic techniques (a review of these techniques has been presented extensively in this paper). These techniques can provide a large number of GCPs. These prolific, automatically-derived GCPs then need to be filtered and selected, aiming to build the most accurate geometric correction model. For these circumstances, our proposed GA approach will be much effective and useful when combined with an automatic GCP extraction method.

A shortcoming in experimental results of this study is that the model is only applied to airborne images although it can be used for various satellite images and scanned paper maps where GCPs are utilized for georeferencing. It is likely worth to apply and verify the proposed model with various satellite images and/or paper maps (if accessed) in further works.

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