Estimation of Transformation Parameters Between Centre-Line Vector Road Maps and High Resolution Satellite Images

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ESTIMATION OF TRANSFORMATION PARAMETERS BETWEEN CENTRE-LINE VECTOR ROAD MAPS AND HIGH RESOLUTION SATELLITE IMAGES

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Abstract

A method for automatically estimating the transformation parameters between road centre-line vector maps and high resolution satellite images is proposed. The advantages of the method are that global image feature extraction is avoided and feature extraction and matching are achieved simultaneously by using the vector data as guidance. The road width, as estimated by the algorithm, together with the road direction are used as constraints to refine the matching results. Arbitrarily chosen road nodes contribute to improving the adjustment. Map-to-image matching has advantages over image-to-image matching and could be a good method for the rapid updating of geographical information system (GIS) data.

Keywords: feature extraction, feature matching, generalised point photogrammetry, multisource data alignment, vector maps and images

Introduction

The objective of this paper is to automatically estimate the transformation parameters between centre-line vector road maps and high resolution satellite images. Other transformation tasks between disparate datasets include image registration (Zitová and Flusser, 2003), absolute orientation in photogrammetry, data conflation (Saalfeld, 1988; Cobb et al., 1998; Doytsher et al., 2001) and data alignment or fusion in geographical information systems (GIS). Registration is posed as the problem of estimating a projective transformation which optimally aligns the image to the object space coordinate system. "Conflation" (Rahimi et al., 2002; Samal et al., 2004; Ruiz et al., 2011a) is a term often used to describe the integration or alignment of different geospatial datasets with different resolutions or of different types. Registration emphasises geocoding the image using ground control information; conflation emphasises reducing the spatial inconsistencies caused by different methods of data collection or differing precisions among multiple datasets. Although distinct to some extent, they all share a common processing step, namely, to accurately identify corresponding spatial features as control points to finish the transformation and optimally align the two datasets. In this paper, which set is taken as the reference dataset (ground truth) is not important; the focus is on finding the correspondence between the map and the image, and ways of using them to estimate the transformation parameters.

Integrating map and image data is important in many applications (Hild and Fritsch, 1998; Zhang, 2004) and can be grouped into the following three categories.

(1) *Geocoding the image*. In the case where the map is taken as the reference data, the image can be oriented after the transformation parameters are estimated. The image can then be used in subsequent analysis such as change detection, mapping, image mosaicking and so on.
(2) *Improving the map data*. In this case, the image (an ortho-image, for example) is taken as the reference data. Recent advances in satellite imaging technology make it possible to capture imagery with ever increasing precision and resolution. For example, once a road network is aligned in a higher accuracy imagery, its relatively poorer map positional accuracy can be improved. Keeping the road network database up to date is important in many GIS applications such as traffic management and mobilising emergency vehicles. Remote sensing imagery is an economic and efficient way of doing this.
(3) *Providing more information*. By combining diverse spatial datasets, a comprehensive set of queries can be supported which could not have been answered by any of these datasets individually. Furthermore, spatial objects in the image can be annotated with detailed attribute information often contained in vector datasets.

However, automatically aligning geospatial data from different data sources remains a challenging task. This is because they are different representations of the same ground objects; there can be remarkable differences between the two representations which makes the matching process even more complicated. Up to now, mainstream methods have included the following four tasks.

(1) *Feature extraction*. Feature points, edges or polygons are extracted from the image.
(2) *Feature matching*. Find a set of corresponding features as control information in two datasets.
(3) *Correspondence checking*. Eliminate inaccurate control point pairs from the set of control points.
(4) *Parameter estimation*. Use the control points to determine the transformation parameters and align the data.

Chen et al. (2006) used road intersections as control points: first a road region classification was executed, and then the system located road intersection points from the road vector dataset. For each intersection point, a template inferred from the vector information (road width and directions) was matched against the localised area around the intersection to find the corresponding intersection in the pre-classified image. Then a vector median filter (VMF) algorithm was used to detect incorrect matches. Finally, rubber-sheeting techniques were used to align the data. Wang et al. (2008) exploited an approach based on a graph-matching scheme that models networks as graphs with embedded invariant attributes. Road networks extracted from both datasets were first transformed into graph structure as input data. The road network was defined by two topological attributes (connectivity and basic loops) and one geometric attribute (relative distance). Graph nodes were then matched to form control points. This method needs both a road classification and the detection of road intersections. Krüger (2001) used a projective transformation which optimally aligned model line segments from a map with data line segments extracted from an image. The transformation was estimated by optimising an objective function which depends on the overlap of the lines and the weighted orthogonal distance between the transformed model segments and data segments. Those line segments with a similar direction and a small separation distance are chosen as the initial correspondences. Feature matching and parameter estimation were solved simultaneously via an iterative procedure. Karjalainen et al. (2006) and Karjalainen (2007) used a scan line method to detect edge points, fitting the equation of a line to the given set of candidate edge points. A goodness-of-fit value was calculated and used as a weighting factor when the orientation parameters were calculated using the coplanarity model.

In order to provide a comprehensive analysis of the various methods, the discussion in the following three sections focuses on questions concerning image feature and auxiliary information requirements.

What Image Features are Used?

This is an important issue that the algorithm needs to address. Points and edges are two of the most frequently used features. Chen et al. (2006) and Ruiz et al. (2011b) prefer road intersections; these are good candidates for control points because road intersections are salient points of road networks and the road shapes around intersections are often well defined. However, good detection of road intersections relies on good classification and accurate template matching. Furthermore, the number of road intersections is far fewer than other features such as arbitrary road nodes and road segments. Like many other researchers, the authors think road segments are better than road intersections as long as the road segments are correctly used (in terms of the mathematical model implemented). Krüger (2001) notes that the advantage of linear features is that they are the main components of a map and thus there is a good chance of finding corresponding features in an image. In addition, correspondences between line segments provide the basis for an objective function which exploits the entire network of extracted line segments in the assessment of the alignment of the map and the image. The optimisation of such objective functions leads to more robust approaches than those that merely use the intersections of adjacent line segments as point features.

Among various linear features, a road network is particularly favoured in the present work for the following reasons:

(1) Unlike points or point-like features, a road network inherently contains substantial semantic information in its structure (topology and geometry) and the road direction can be a guidance in extracting image features.
(2) Roads are relatively regular features which makes them easier to detect.
(3) The position of a road is more likely to remain unchanged, which ensures that corresponding features can be found between datasets collected at different times.
(4) Generalised point photogrammetry (Zhang et al., 2008) can be used to build the orientation model; this means the two points that form an equation in the adjustment are not required to be exactly corresponding points. This makes it possible to use arbitrary road segment nodes as control points thus notably extending the number of control points.

A river is another example of a linear feature, but it is more easily affected by climate and changes over time. Furthermore, mobile road network data from GPS navigation is very popular nowadays and could serve as a good data source.

Is Global Detection of Image Features Needed?

Taking the method based on graph matching as an example (Wang et al., 2008), not only is the extraction of road intersections needed to form the graph nodes, but a good extraction of the whole road network is also required to form graph edges and finally to form graphs. Extracting road segments directly from imagery is a difficult task due to the complexity that characterises natural scenes. The process is error-prone and may require manual intervention. The active contour model called *snake* has been used for semi-automatic road information extraction or road database updating from imagery (Kass et al., 1988; Fortier et al., 2001; Bentabet et al., 2003; Song et al., 2006; 2009). Moreover, processing an image of a large area to extract road information requires a lot of processing time. In urban areas, many networks may share similar patterns; in rural areas, the graphs probably have poor structures. Graph matching itself is both complex and time consuming. Krüger (2001) also extracts line segments from the whole image. A local extraction method is more favourable than a global one since the increasing availability of direct georeferencing information (through global navigation satellite systems and inertial navigation systems) could be exploited to constrain the search space for feature extraction and matching. The existing vector data is also a good guide to image feature extraction.

Is Auxiliary Information Needed?

Auxiliary information includes metadata and attributes about the data sources, such as road width information of vector data. Road width is used in Chen et al. (2006) to generate a road intersection template. In Zhang et al. (2004) the road width is also a problem when constructing the road template; their strategy is to construct a series of road templates with slowly changing road widths and then to try them all in road detection. In this paper, the road is detected by using two road edges, so there is no need to know the road widths; consequently, all roads can be treated in the same way.

In the following sections a fully automatic, efficient and easily implemented method for estimating the transformation parameters between maps and images will be introduced. Global image feature extraction is avoided and feature extraction and feature matching are achieved simultaneously using the vector data as guidance. Although points are apparently extracted, they are essentially used as line segments. No metadata about the vector data is needed; the road widths are instead estimated by the algorithm. In this work, the maps are viewed as the ground truth, and the image has a rational polynomial coefficient (RPC) as its initial orientation parameters. The following is a brief description of the method. Firstly, the vector maps are back-projected onto the image with the help of the initial values of the RPC. Then a search is made for the two road edges, within a given range, along the perpendicular direction to the road vector to find the centre points of the road on the image (the vector road map used represents the road centre lines). In the next stage the matching results are refined with constraints designed from the characteristics of the road; these include the consistency of the road width as well as a condition that the roads extracted should have similar direction to the road vectors that have been back-projected. Finally, the mathematical model for parameter estimation is constructed, based on the principle of generalised point photogrammetry which exploits the relationship between points and line segments. Arbitrary road nodes can contribute to the whole alignment task, thus notably extending the number of control points; they improve the distribution of the observations and the robustness and accuracy of the adjustment.

In the following sections, the proposed algorithm is presented in detail, as well as the experimental results. Conclusions and suggestions for further study are also made.

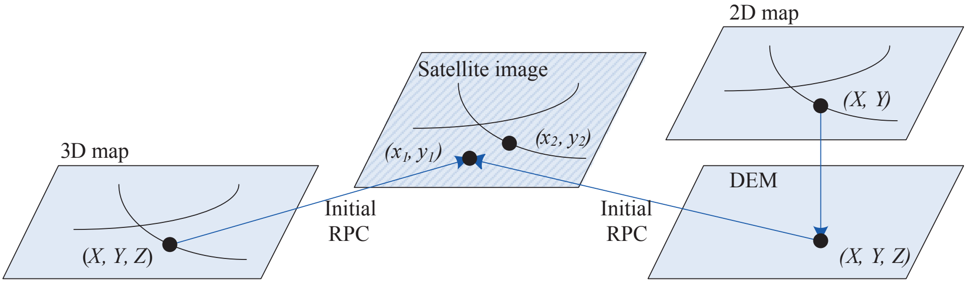


Fig. 1. The principle of registration of the satellite image with the existing vector map.

Method

The general principle of the method is shown in Fig. 1. The vector map is read from the GIS file. These vectors can be 3D lines but usually they are 2D lines, which means that the elevations of the endpoints of the vectors should be obtained from the digital elevation model (DEM). The vectors are then projected onto the image using the initial values of the RPCs. If the initial values are sufficiently accurate then the vectors of the map will be projected correctly onto the image, and perhaps no additional refinement will be needed. However, if the initial values are inaccurate, then the projected positions would have an offset to the correct locations on the image (Fig. 2).

The positions projected with the initial RPC are denoted as (x_1, y_1). Because the initial RPC is not accurate, the object point with ground coordinates (X, Y, Z) and the image point (x_1, y_1) are not corresponding objects; the actual corresponding point is denoted as (x_2, y_2) in Fig. 1. The satellite image can be registered by solving the six parameters a_0, a_1, a_2, b_0, b_1 and b_2 in equation (1). These parameters are used to compensate for the inaccuracy of RPCs (Dial and Grodecki, 2002):

$$\begin{aligned} x_2 &= x_1 + b_0 + b_1 x_1 + b_2 y_1 \\ y_2 &= y_1 + a_0 + a_1 x_1 + a_2 y_1 . \end{aligned} \quad (1)$$

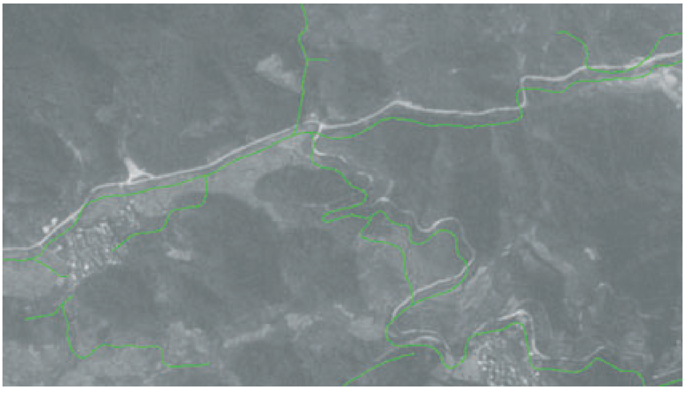


Fig. 2. The projected position of the road map (green lines) with the initial RPC.

Finding the position (x_2, y_2), namely, the corresponding features between the map and the satellite image, is the key procedure in the orientation. In the current method, image feature extraction and feature matching are achieved simultaneously as described in the following three sections.

Feature Extraction and Matching

In medium and small scale maps, the roads depicted represent the roads' centre lines. This means the corresponding image features are the centre points of roads. Two factors should be taken into account when undertaking the extraction of such points: firstly, different roads have different widths; and secondly, brighter roads and darker roads exist simultaneously on the same image (Fig. 3). To deal with the first problem, the detection of road centre points is transformed to the detection of the two road edges, in such a way that all roads can be treated in the same way without needing to consider the influence of different road widths. As long as the two road edges are estimated, the road width and the position of road centre point can be implicitly determined. The algorithm therefore does not need to know road width; instead it is estimated. To solve the second problem, two edge templates are applied to detect the road edges. In one template the grey value increases, in the other the grey value decreases. The method of detecting road edges is to calculate the correlation between the image and the edge templates as shown in Fig. 4.

The vector maps are used as guidance for feature extraction. Firstly, the image area located within a scan line is resampled; the scan line is a line perpendicular to the road lines with a certain width (in this research this is 15 pixels on either side, but the value should be adjusted to the precision of the initial parameters). Then the correlation of each position in the scan line with the edge templates is calculated; the two positions that have the greatest correlation are taken as the position of the two edges, and then they are interpolated to a more precise sub-pixel position. The result of feature extraction is shown in Fig. 5. The

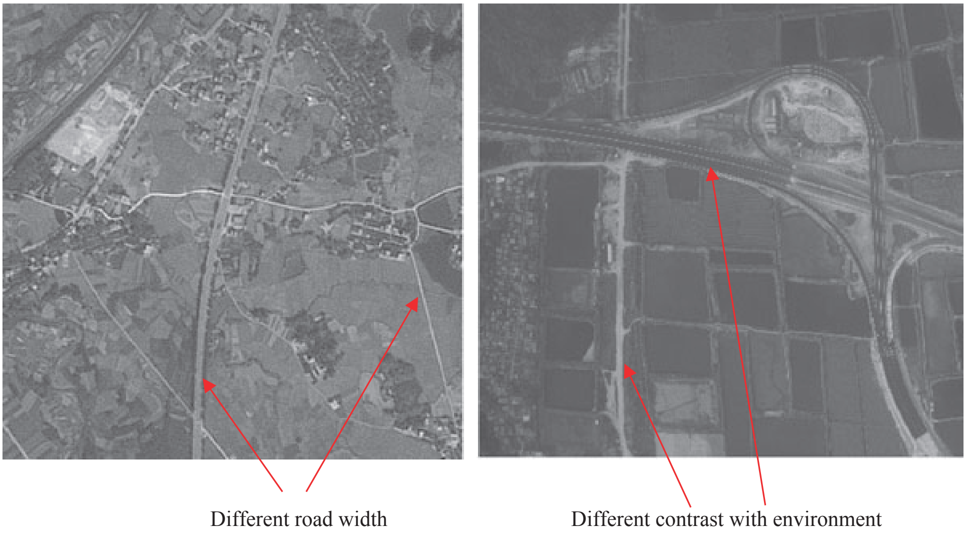


FIG. 3. Different road widths (left) and different road contrasts (right) should be considered.

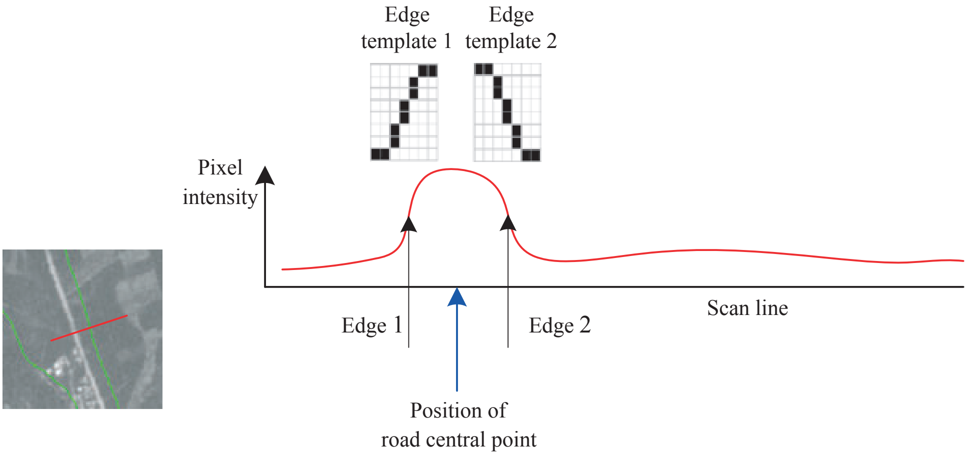


Fig. 4. The method of road centre point detection with two edge templates. The green lines indicate the initial projected roads. The red line indicates the scan line within which the road edges and road's centre point are to be found.

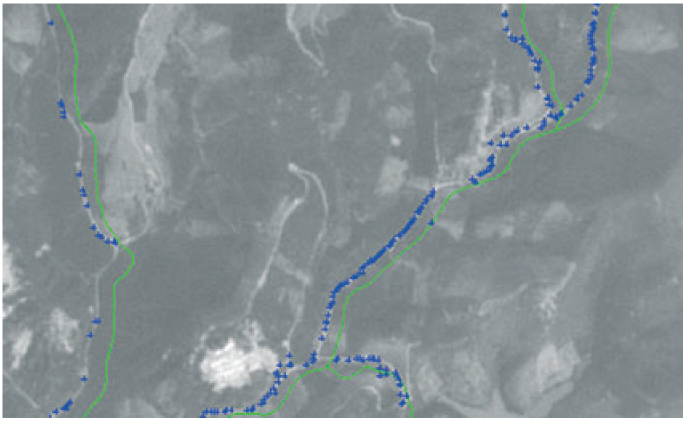


Fig. 5. Road centre point extraction result. The green lines indicate the initial projected roads. The blue crosses indicate the extracted road centre points.

main advantage of the scan line method is that there is no need to carry out separate edge detection prior to the feature matching because the road nodes that the scan lines pass through, and the road centre points extracted by this scan line, can be viewed as potential correspondences. In practice it is difficult to state the two are true correspondences because a "points to lines" transformation has poor localisation, but this does not influence the parameters' estimation, as explained later.

Correspondence Checking

This process aims at guaranteeing the quality of the control points which are prepared for the final estimation of transformation parameters.

TABLE I. Parameters used for feature extraction and checking.

Description of parameter	*Value*
Number of road nodes limit	10
Node distance limit	5 pixels
Correlation limit	0·5
Valid ratio limit	0·8
Direction difference limit	5°
Width difference limit	2 pixels

(1) Firstly, there is a limitation on the number of road nodes in each road; only those roads with a sufficient number of nodes are used in feature extraction. It is reasonable to assume that roads with more nodes have a longer length and are more reliable.
(2) When generating the scan line which passes through road node $N(i)$, the previous node $N(i - 1)$ and the next node $N(i + 1)$ are only used if the distance between $N(i - 1)$ and $N(i + 1)$ is large enough. The scan line is then constructed in a direction perpendicular to the vector line formed by $N(i - 1)$ and $N(i + 1)$. It is very common that road nodes are sparser when the road direction changes slowly and denser otherwise. In other words, when the distance between road nodes is large, it can be inferred that the road is stable in this location and is better suited to be used for feature extraction.
(3) When searching for the two road edges, the two positions with maximum correlation are viewed as the road edges; only if the two correlations are high enough can the position be counted as a successful feature extraction. The positions are then interpolated into more precise locations by fitting a curve about the correlation value. The position of road centre points is then calculated and the road node is marked as valid. If the percentage of valid nodes to the total number of nodes for a road is low, this road is viewed as invalid.
(4) Since feature extraction is essentially a 1D search, it is easily influenced by noise. Two constraints designed from the characteristics of the road are therefore added to further refine the feature extraction result. One is that the direction of image features should be similar to the direction of the road vector, so the difference between their directions can be a constrained. The other is the width of an individual road rarely changes significantly, so statistical evaluation is conducted concerning the width of a road, such as its median width. Those points with a large difference in the median are eliminated. Curve fitting of road centre points was also tried in the algorithm but was found to be unnecessary when the two constraints above were used.

A summary of the above conditions are listed in Table I.

Transformation Parameters Estimation

It was noted earlier that points on line "correspondences" are not very likely to be exact because they have poor localisation. Traditional methods cannot tolerate such discrepancies as they are based on point-to-point correspondence. In order to gain the full benefit from using linear features, a different mathematical model is needed to the one used in point-based methods. There has been a substantial body of work dealing with the use of linear features that can be represented by analytical functions (such as straight lines and conic curves) or free-form linear features in photogrammetric orientation (Mulawa and Mikhail, 1988; Kubik, 1991; Habib et al., 2004). The coplanarity model is often used in line photogrammetry and requires three directional vectors. The definition of the three vectors is different depending on the particular method and options include: the vector defining the ground control line (GCL); the vector from any point on the GCL in the image to the perspective centre; and the vector from a fixed point on the GCL to the perspective centre. At least three non-parallel GCLs are required to determine the exterior orientation of the image. The transformation function implemented in this paper is the affine transformation in image space.

Generalised point photogrammetry (Zhang et al., 2008) is used in this paper. The advantage of this approach is that it is unnecessary for a certain set of correspondences to be rigorously correct. This makes it possible to use line segment nodes as control points, thus notably extending the number of control points, improving the distribution of observations and the robustness and accuracy of the adjustment. The method is termed "generalised point" because it unifies the point primitives and linear primitives; it is a way of building error equations from the corresponding point pairs discussed in the previous section of this paper. In each such point pair, one point is the position of the road vector node back-projected onto the image (x_1, y_1), whilst the other point is the image road centre point (x_2, y_2) based on the road vector node. As shown in Fig. 6, the blue points on either side of (x_2, y_2) are extracted image road centre points based on other road vector nodes near (x_1, y_1). The horizontal axis is the x direction, the vertical axis is the y direction, and θ represents the angle between the horizontal axis and the image line segment. For every pair of corresponding points, only one equation, depending on the direction of the image line segment, is used. When the direction of the image line segment is closer to the y axis (Fig. 6(a)), dx is treated as the error and only an x equation is constructed (see equation (2)), determining how far the point (x_1, y_1) should be moved parallel to the x axis. Similarly, when the direction of the image line segment is closer to the x axis (Fig. 6(b)), dy is treated as the error and only a y equation is constructed, determining how far the point (x_1, y_1) should be moved parallel to the y axis. Once completed for all corresponding pairs, the transformation parameters can then be solved:

$$\begin{aligned} x_2 - x_1 &= b_0 + b_1x_1 + b_2y_1; \text{when } |\theta| \geq 45^\circ. \\ y_2 - y_1 &= a_0 + a_1x_1 + a_2y_1; \text{when } |\theta| < 45^\circ \end{aligned} \tag{2}$$

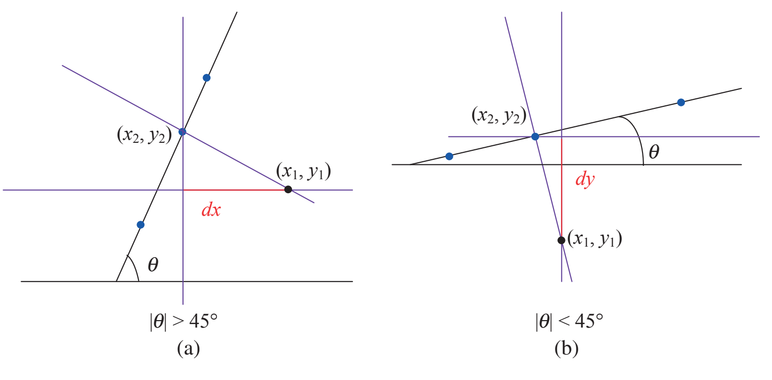


Fig. 6. The principle of generalised point photogrammetry (equations based on the direction of the line segment).

Experiment

In this section, the results of applying the approach proposed in this paper are presented. The image in the experiment is a SPOT-5 PAN image with a 2·5 m ground sampling distance (GSD) and an image size of 24 000 × 24 000 pixels, located in the mountainous Zhaoqing area of Guangdong province, China. The horizontal positional accuracy of the initial RPC parameter is about 40 m (16 pixels). The SPOT image was taken in 2007 and the vector maps were collected in 2006. The vector road maps are from the 1:10 000 topographic road database. The horizontal positional accuracy of the map is better than 5 m in flat areas and 7·5 m in mountainous areas. The DEM used is a contemporary product and the height accuracy satisfies 1:10 000 map accuracy requirements (3 m in flat areas, 7 m in very mountainous areas). Fig. 9 provides a general view of the data.

Feature Extraction and Data Alignment Results

Road centre point extraction results are presented in Fig. 7. The top picture of Fig. 7 provides the extraction result without using the *direction difference limit* and *width difference limit* constraints (Table I). It can be seen that many incorrect points are detected under the influence of noise. The bottom picture shows the result when the two constraints are added where almost all the erroneous points are eliminated. The efficiency of the

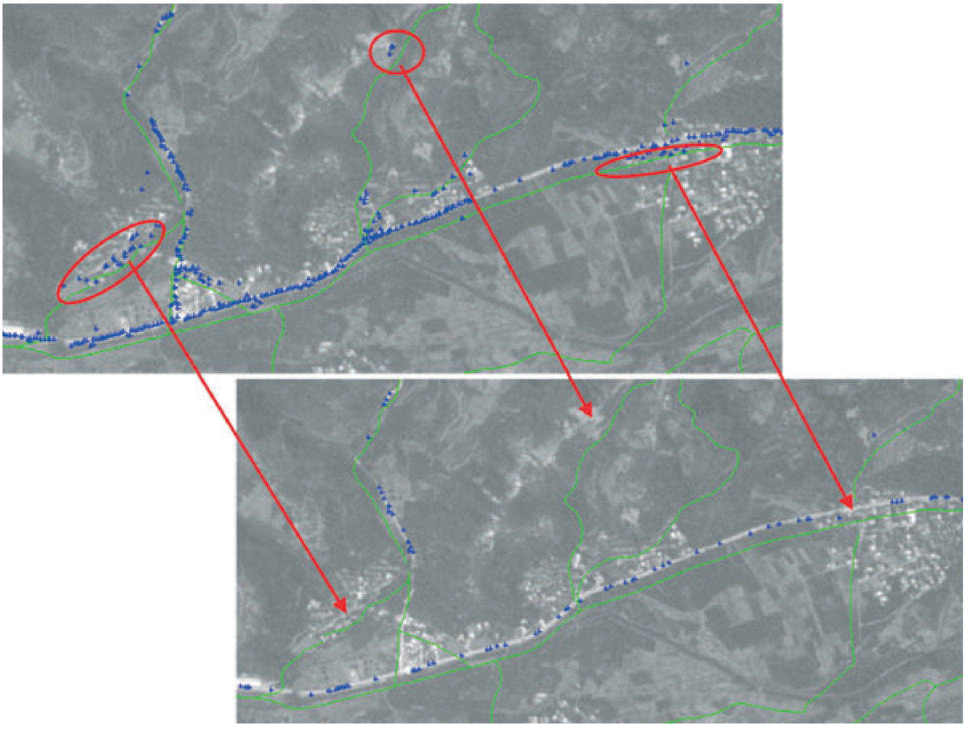
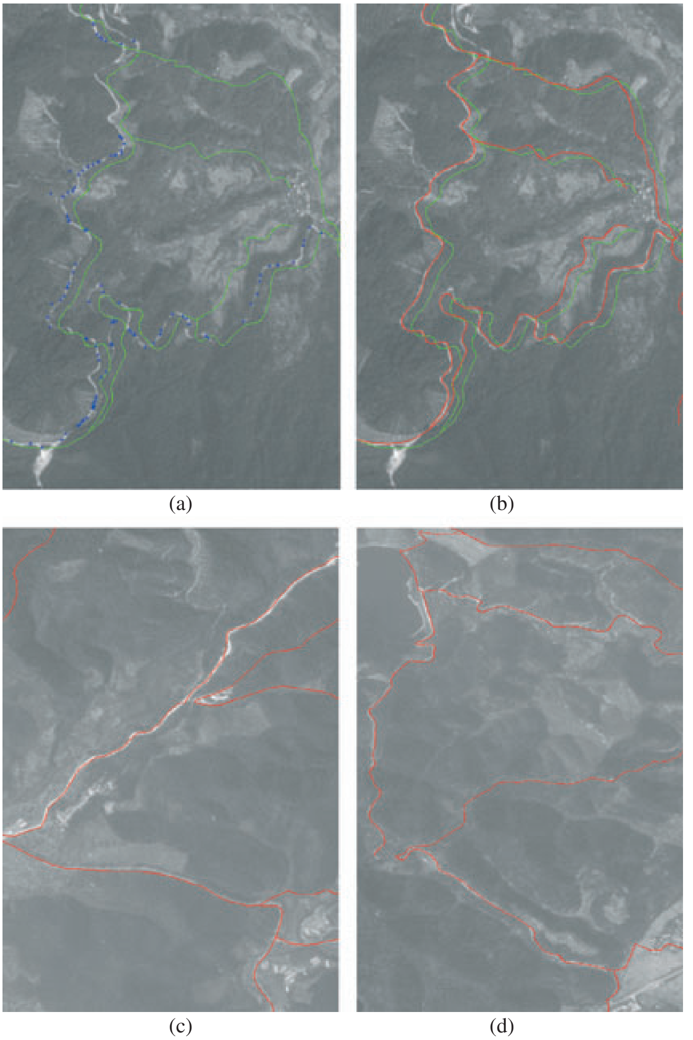


Fig. 7. Road centre point extraction results. Top: without constraints. Bottom: with constraints. Green lines indicate the initial projected roads; blue crosses indicate the extracted road centre points.

constraints can be explained by the fact that the direction and the width of erroneous points are usually without regularity and are not satisfied by the characteristics of a road. Some correct points are also deleted, but since there are an enormous number of detected points, the loss of some correct points has little effect on the parameter estimation process.

Occlusions from buildings and vegetation are troublesome when trying to extract road information from very high resolution images such as aerial photographs; however, such occlusions are less problematic when dealing with satellite imagery. With regard to the satellite image registration problem, not all roads need to be extracted. Since the area covered by one scene satellite image is usually very large, although some roads cannot be extracted, there are a sufficient number that can be used to solve the registration problem. In



(a) (b) (c) (d)

Fig. 8. Data alignment results. The red lines indicate the final position of roads.

the experiment shown in Fig. 7, some roads are affected by buildings and others are occluded by vegetation and are invisible in the image, but there are still many features that can be extracted successfully.

Clouds, blur and low contrast are some of the common issues affecting image quality. The algorithm presented here would fail if the satellite image is covered by a large amount of cloud and image blur would affect the precision of the feature extraction. The low contrast problem can be handled, to some extent, by image pre-processing algorithms.

Fig. 8(a) shows another road centre point extraction result and Fig. 8(b) is the corresponding data alignment. Further alignment results are shown in Figs. 8(c) and (d).

Comparison of Map-to-Image and Image-to-Image Matching

Fig. 9(a) shows a general view of the map-to-image matching data where 15 250 road vectors are involved. Fig. 9(b) shows a general view of the image-to-image matching data where the large rectangle represents the area covered by the SPOT-5 image, and each small quadrangle represents a 1:10 000 scale ortho-image covering 6594 × 4849 pixels. There are 166 ortho-images in total. The image-to-image matching method is based on image correlation, and a pyramid strategy is employed as well. Harris feature points are first extracted from the ortho-images and then matched to the SPOT image with the help of initial RPC values from pyramidal images. Then the matching result is delivered layer by layer from the coarser pyramid to the finer pyramid. After finding the corresponding points, the point from the ortho-image is used as a control point to register the satellite image. Comparative statistics

TABLE II. A comparison between map-to-image and image-to-image registration.

Comparison aspects	*Map-to-image*	*Image-to-image*
Processing time	1·5 min	47 min
Data volume involved	70 megabyte	5063 megabyte
Precision	1·55 pixels	0·94 pixels
Features extracted	62 755 pairs	25 862 pairs

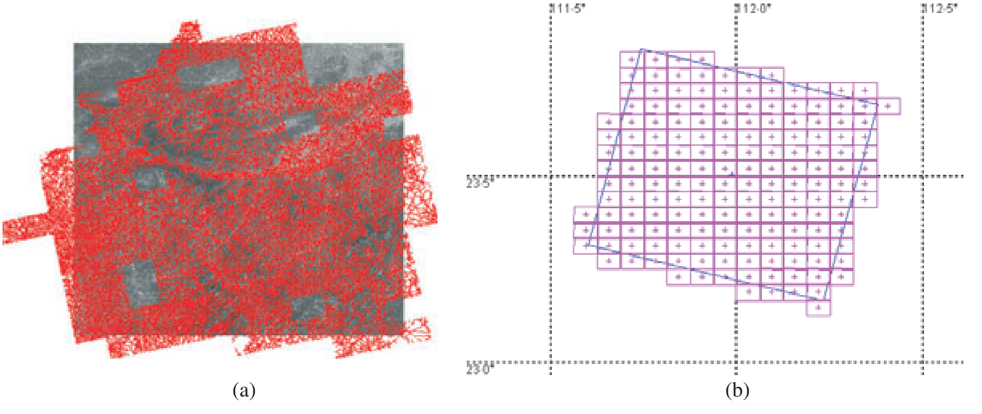


FIG. 9. A general view of the experimental data. (a) SPOT-5 satellite image superimposed with road vectors in red. (b) Ortho-image quadrangle with the SPOT-5 image boundary superimposed.

for the map-to-image and image-to-image methods are shown in Table II. The distribution of the features are quite balanced over the whole image in both cases, so the adjustment result is quite reliable. The map-to-image registration precision is a little inferior to the image-to-image registration since the map data is collected manually and has a little loss of precision. Other than this, Table II demonstrates that the map-to-image registration has great advantages in terms of processing time and data volume.

Conclusion

In this paper, a fully automatic and efficient method for estimating transformation parameters between vector road maps and images has been introduced. Global image feature extraction is avoided and the feature extraction and matching are achieved simultaneously by using the vector data as guidance. No metadata about the vector data is needed. By using two edge templates to detect road centre points, roads with different widths can be treated in the same manner; furthermore, the position of centre points and the width of the road can be obtained at the same time. The matching results are refined using constraints designed using general characteristics of roads, such as the consistency of road widths and that the roads extracted should have a similar direction to the back-projected road vectors. By building the mathematical model based on the principle of generalised point photogrammetry, correspondences do not have to be rigorously correct, so arbitrary road nodes can contribute to the whole alignment task which notably extends the number of control points, thus improving the distribution of observations and the robustness and accuracy of the adjustment. The map-to-image registration has great advantages in terms of lower processing time and data volume, and so could be a good method for fast GIS data updating. For future work, further tests will be carried out and larger scale road maps, where highways are represented by parallel lines, will be considered.

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Résumé

Une méthode est proposée pour estimer automatiquement les paramètres de transformation entre des cartes routières en mode vecteur et des images satellitales à haute résolution. Les avantages de cette méthode sont qu'elle n'a pas besoin d'extraction globale d'objets dans les images, et que l'extraction et l'appariement se font simultanément en s'appuyant sur les données vectorielles. La largeur des routes, qui est estimée par l'algorithme, ainsi que leur direction, sont utilisées comme contraintes pour affiner les résultats de l'appariement. Des nœuds routiers choisis arbitrairement contribuent à améliorer le recalage. Le recalage de la carte sur l'image présente des avantages par rapport au recalage entre images, et pourrait être un moyen approprié pour une mise à jour rapide des données dans les systèmes d'information géographique.

Zusammenfassung

Dieser Beitrag stellt eine Methode zur automatischen Bestimmung der Transformationsparameter zwischen Straßenachsen aus vektoriellen Kartendaten und hochauflösenden Satellitenbilddaten vor. Merkmalsextraktion *und -zuordnung werden, gesteuert durch die Vektordaten, simultan gelöst. Straßenbreite und -richtung werden durch den Algorithmus bestimmt und dienen als Bedingungen, um die Zuordnungsergebnisse zu verbessern. Beliebige Straßenkreuzungen können für die Ausgleichung unterstützend wirken. Die Zuordnung von Karte zu Bild hat Vorteile gegenüber einer Bild zu Bildzuordnung und könnte somit für eine zügige Fortführung von GIS Daten vorteilhaft sein.*

Resumen

Se propone un método para estimar de forma automática la transformación entre la linea central de carretera en mapas vectoriales e imágenes de satélite de alta resolución. Las ventajas del método son que se evita la extracción global de características de la imagen y la extracción de características y su correspondencia se realizan simultáneamente usando el mapa vectorial como guía. El ancho de la vía, estimada por el algoritmo, conjuntamente con la dirección de la carretera son usados como restricciones para refinar el resultado de la correspondencia. Los nodos arbitrarios de la carretera contribuyen a mejorar el ajuste. La correspondencia mapa a imagen tiene ventajas frente a la correspondencia imagen a imagen y puede ser un buen método para la actualización rápida de datos SIG.