A Hierarchical Approach to Automated Registration of High Resolution Satellite Imagery for Change Detection

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Abstract: GIS databases need to undergo frequent updating due to rapid changes in the physical environment. Satellite imagery, with its recently enhanced spatial, spectral and temporal resolution, allows for accurate and reliable detection and characterization of patterns of change. A key factor that dictates the validity and reliability of change detection results is the quality of image registration. There is a need to develop robust registration procedures for multi-temporal, multi-spectral and/or multi-resolution imagery captured from different sensors to facilitate the change detection process. This paper discusses an approach for automated image registration based on a hierarchical image matching strategy. Following an initial feature point extraction phase, the method uses the similarity of grey levels to find homologous point candidates across the images. A hierarchical image pyramid is used to enhance both the success rate and reliability of matching while reducing the computational complexity. The adopted approach also uses contextual information to achieve locally consistent matches. Implementation and testing of the proposed method has involved imagery from different sensors. Here, results are reported for IKONOS and QuickBird data over test sites in Hobart, Australia and Thimphu, Bhutan. The potential of operational automated image registration in the process of change detection is illustrated via these test results.

Keywords: image registration, high-resolution satellite imagery, IKONOS, QuickBird, image matching.

1. Introduction

With the operational deployment of high-resolution imaging satellites, with spatial resolutions of a metre or better, a new source of imagery is available for GIS updating. High-resolution satellite imagery (HRSI) provides global coverage, making available the necessary tools for map revision and production. This is essential in geographic areas undergoing rapid change. Furthermore, the improving spatial, spectral and temporal resolution of imagery allows for reliable, higher-accuracy detection and characterization of ever more detail of the patterns of change. An important component of image-based change detection for GIS updating is image registration. The fact that change detection processes usually involve multi-spectral and/or multi-resolution imagery captured at different times and from different sensors emphasises the need for development of robust registration procedures that can handle these types of images. In addition, the new HRSI sensors usually provide a high-resolution panchromatic image together with lower-resolution multi-spectral images. In order to use these data for efficient change detection and updating, it is necessary to register the images to produce high-resolution multi-spectral imagery through image pansharpening techniques.

The basis of the image registration process is identification of 'control points' that represent precise feature point correspondences. Control points in imagery may be measured manually or by semi- or fully automatic methods. In general, manual selection of control points is a time-consuming and labour-intensive task and the implementation of automatic methods requiring little or no operator supervision is highly desirable.

Comprehensive surveys of automated image registration techniques can be found in [2] and [19]. Existing automated registration methods fall into two categories: area-based and feature-based. In feature-based methods, which are most suited to multi-sensor registration, common features such as curvatures, moments, areas and contour lines or line segments are extracted from images and are used to perform registration ([9], [11], [4], [6]). For example, line segments can be used as primitives in a registration process [6], though this approach generally works well only in cases where the line segments are well presented and preserved.

Various area-based matching methods have also been employed for image registration [8]. In area-based algorithms, a small window of pixels in the first image is compared with windows of the same size in the second image. The matching measure is usually the normalized cross-correlation, and the centres of the matched windows are control points that are then used to solve for the transformation parameters between the two images. For example, feature points have been detected using a Wavelet transform algorithm [8], and then matched across the images. A similar strategy has been used by [18] to register aerial images. In [17] an area-based method involving cross correlation followed by global matching through probability relaxation was applied in image registration to fuse SPOT and LandSat TM imagery. This method was later extended in [10] to register InSAR imagery for DEM generation. Area-based image registration methods are also widely used in computer vision [5] and medical imaging applications [12].

This paper, which is a condensed version of [15], proposes an area-based approach to automated registration of remote sensing images. After image preprocessing, feature points are extracted and the homologous point candidates are located using a similarity measure of correlation coefficients in cross-correlation. The conjugate points across images are finally determined by structural matching. The details of the image registration technique are described in the next section, after which experimental results obtained from HRSI with varying radiometric and geometric properties are presented.

2. Image Matching

In order to increase the success rate and reliability of image matching results, the proposed method exploits image pixel grey value similarity and geometrical structural information. As illustrated by the overall strategy indicated in Fig. 1, the image matching operation is performed in two steps, where different matching algorithms are employed in each step to achieve the given objectives.

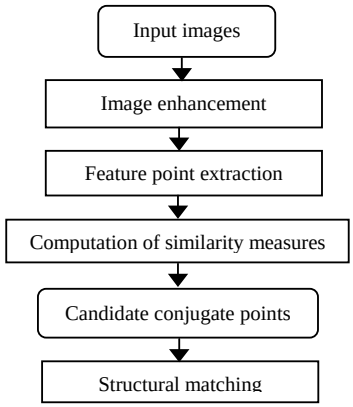

Fig. 1. Image matching strategy.

Image enhancement and feature point extraction forms the first step. Conjugate points are then identified using normalized cross correlation for the similarity measure, which is then used as prior information in the next step, structural matching. The locally consistent matching is achieved through structural matching with probability relaxation. To further ensure the reliability and reduce computational complexity in the matching process, an image pyramid, in which each level is generated by multiplying a generation kernel, is incorporated in the matching strategy. Matching starts from the top level of the pyramid, with results from the higher levels being used as approximations at lower levels. Matching continues until the lowest level of the pyramid is reached, where highest accuracy results are also achieved.

1) Image Preprocessing and Feature Point Extraction

A new version of the Wallis filter [1] is applied in order to optimize the images for subsequent image matching. This filter enhances features in images and therefore enables improved feature point extraction. Furthermore, since the filter is applied in both images using the same parameters, naturally occurring brightness and contrast difference are corrected. The Foerstner operator is used following the image enhancement process to extract well-defined feature points that are suitable for image matching.

2) Computation of Similarity Measures

The normalized cross-correlation coefficient forms the similarity measure of the candidate matching areas. This measure has been shown to be largely independent of differences in brightness and contrast due to normalization with respect to the mean and standard deviation. If (x, y) and (x', y') are the image coordinates of two feature points located in images *f* and *g*, the normalized cross-correlation in a $(2N+1)*(2N+1)$ window is given as

$$\rho = \frac{C_{fg}}{\sqrt{C_{ff} * C_{gg}}} \tag{1}$$

where

$$C_{fg} = \sum_{i=-N}^{N}\sum_{i=-N}^{N}(f(x-i,y-j)-\overline{f})(g(x'-i,y'-j)-\overline{g}) \tag{2}$$

$$C_{ff} = \sum_{i=-N}^{N}\sum_{i=-N}^{N}(f(x-i,y-j)-\overline{f})^2 \tag{3}$$

$$C_{gg} = \sum_{i=-N}^{N}\sum_{i=-N}^{N}(g(x'-i,y'-j)-\overline{g})^2 \tag{4}$$

and $\overline{f}$ and $\overline{g}$ are the local means of the windows in images *f* and *g*, respectively.

3) Structural Matching with Probability Relaxation

A matching pool for candidate conjugate points is constructed with the computed similarity measures and a similarity score is attached to each candidate point pair. Although the correlation coefficient is a good indicator of the similarity between points, problems still exist in determining all correct matches. The existence of image noise, shadows, occlusions, and repeated patterns emphasises these problems. Furthermore, matching using a very local comparison of grey value difference does not necessarily always deliver consistent results in a local neighbourhood. An algorithm for structural matching with probability relaxation for image matching in the registration process has therefore been adopted to overcome these problems. Structural matching seeks the correspondences from the primitives of one structural description to the primitives of a second. Of the several methods of structural matching that have been proposed in the past ([7], [13], [14], [16]), that realised through probability relaxation has been adopted here.

Let the feature points in the first image be a set *L*, $L=\{li\}$, $i=1, 2, \ldots n$, and the feature points in the second image be a set *R*, $R=\{rj\}$, $j=1,2,\ldots m$. The mapping from the first image to the second image is represented as *T*. Assuming the right type of mapping *T*, we seek the probability that *li* matches *rj*, i.e. the matching problem becomes the computation of a conditional probability $P\{li = rj \mid T\}$ (the '=' sign means 'match to'). The computation of the conditional probability is via an iterative scheme ([3], [14]):

$$P^{(t+1)}\{l_i = r_j|R\} = \frac{P^{(t)}\{l_i = r_j\}Q^{(t)}(l_i = r_j)}{\sum_{h} P^{(t)}\{l_i = r_h\}Q^{(t)}(l_i = r_h)} \tag{5}$$

where

$$Q^{(t)}(l_i = r_j) = \prod_{h=1,\, h\neq i}^{n}\ \sum_{k=1}^{m} P\{T(l_i, r_j; l_h, r_k)|l_i = r_j, l_h = r_k\}P^{(t)}\{l_h = r_k\} \tag{6}$$

The value of *Q* expresses the support that is given to the hypothesis match ($li = rj$) from neighbouring points taking into consideration the relations between them.

The function $p\{T(l_i, r_j; l_h, r_k) \mid l_i = r_j, l_h = r_k\}$ is called the "compatibility function". Its value is in the range between 0 and 1 and it quantifies the compatibility between the match ($li = rj$) and a neighbouring match ($lh = rk$). This compatibility function plays an important role in the process of structural matching. In [17] the correlation between image segments was used to evaluate the compatibility function. In this investigation, we adapted the function defined in [16] as

$$T / \exp((\Delta p_x^2 + \Delta p_y^2)/\beta) \tag{7}$$

$$\Delta p_x = (x_h - x_i) - (x_k - x_j) \tag{8}$$

$$\Delta p_y = (y_h - y_i) - (y_k - y_j) \tag{9}$$

where *T* is a value quantified by the texture information and it is defined as inversely proportional to the minimum of four grey value variances in the horizontal, vertical and two main diagonal directions at the window around the point *li*. β is a constant. The iteration scheme is then initialised by assigning the previously computed normalized correlation coefficient to $p^0\{l_i = r_j\}$ for a possible matched pair *li* and *rj*. When the iterative procedure is terminated, the point pair which receives the highest probability is selected as the actual match.

3. Experimental Results

Testing of the proposed method has been conducted using HRSI to illustrate the feasibility and robustness of the suggested image matching technique. These tests have centred upon stereo IKONOS and QuickBird images covering various terrain types and land cover, and have included image matching between high-resolution panchromatic and lower-resolution multi-spectral imagery.

The first test data comprised an IKONOS Geo image pair of the city of Hobart, Australia. The 120km^2 scene covered a variety of land cover types, including mountainous forest areas (to a height of 1200m above sea level), hilly neighbourhoods, parks, suburban housing and city buildings. Both images were collected on the same orbital pass in reverse scan mode.

Fig. 2 illustrates a portion of the image matching results in the registration of the stereo images. The matched points are shown by white crosses. In this small area, more than a hundred conjugate points were automatically found, even though some parts of the second image (right-hand image in the figure) are highly saturated.

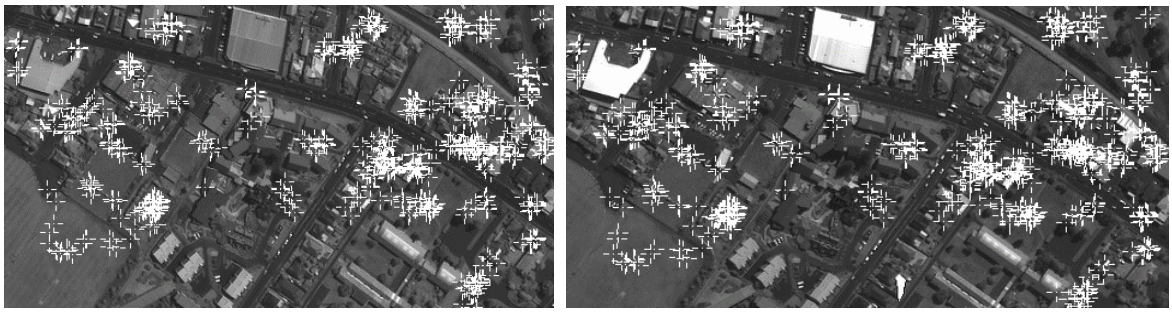

Fig. 2. Image matching for the registration of IKONOS stereo images of Hobart, Australia.

Fig. 3 shows image matching results between the 1m ground resolution panchromatic image and a grey scale 4m resolution image produced from the IKONOS RGB multi-spectral bands. During matching, the low resolution image was enlarged four times using bicubic interpolation. As expected, many fine structures in the high-resolution image are not present in the low-resolution image. However, a hundred or so conjugate points were nevertheless located in this small image patch. Of these, all but a small number are correct.

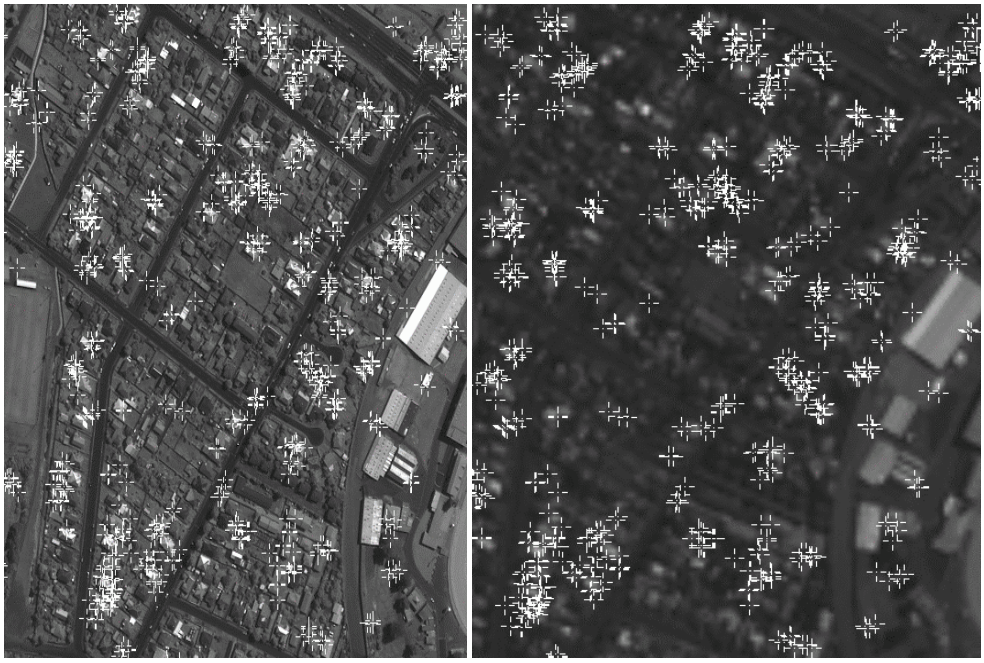

Fig. 3. Example of matching 1m resolution IKONOS imagery (left) with 4m resolution imagery (right).

A QuickBird stereo image pair of Thimphu, Bhutan formed the second test data set. The terrain height in this data set ranged from 2100 to 4300m. Image matching was again performed between stereo images (Fig. 4) and between the high-resolution panchromatic image and lower-resolution multi-spectral image (Fig. 5). A reliable matching performance was again achieved, even though large radiometric and geometrical differences were present.

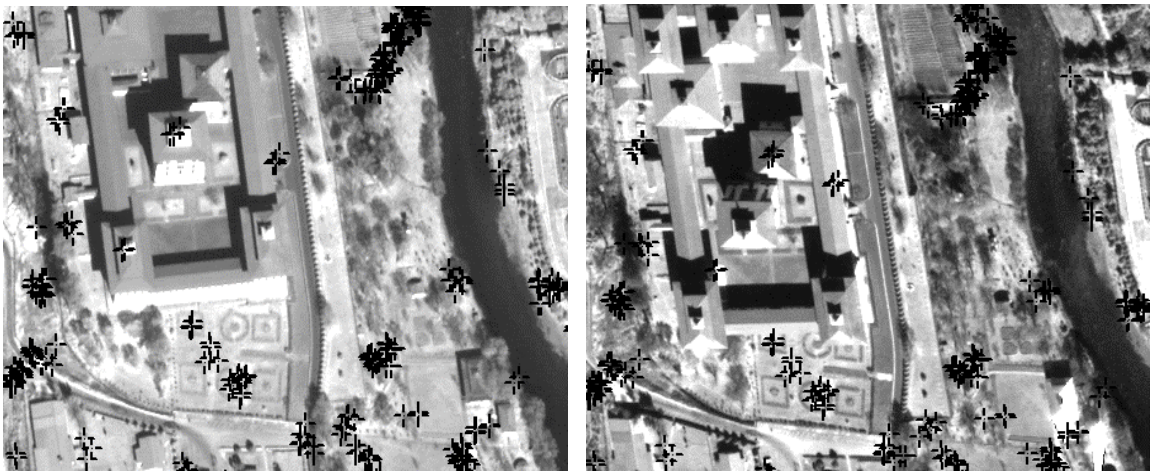

Fig. 4. Example of matching QuickBird stereo images. The matched points are labelled by black crosses.

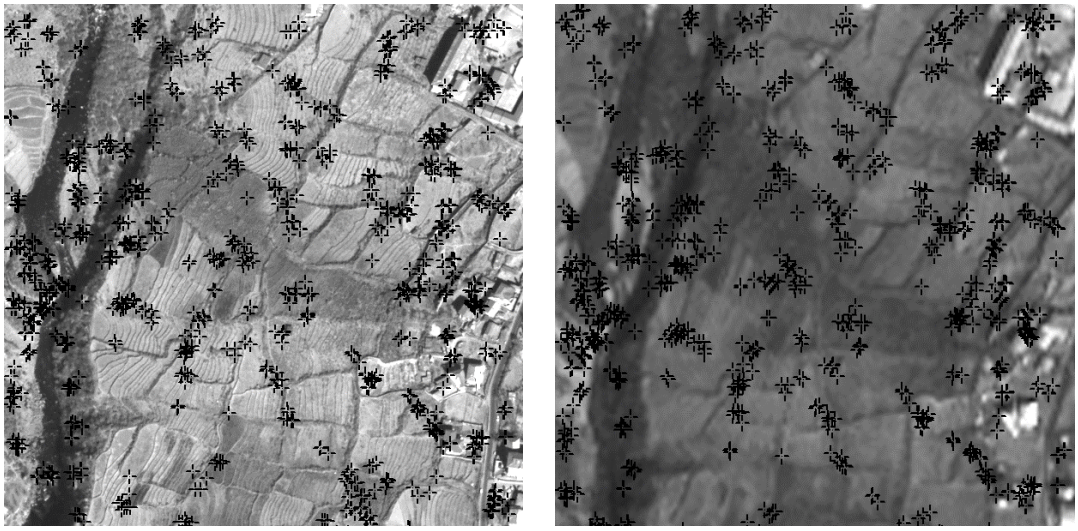

Fig. 5. Example of matching between 60cm QuickBird panchromatic (left) and 2.4m multi-spectral imagery (right). The matched points are labelled by black crosses.

4. Conclusions

With the increasing availability of HRSI, there is a growing need for further developments in robust automated image registration. This paper has presented a method for image matching in support of automated registration of HRSI. The method exploits image pixel grey value similarity and geometrical structural information. Image matching is performed in two steps. After feature point extraction, cross correlation is used to find the candidate conjugate points across images. The correlation coefficients are then taken as the initial probability in a structural matching through probability relaxation.

Test results using IKONOS and QuickBird stereo imagery have been presented. The matching was performed between stereo images and between high-resolution panchromatic and low-resolution multi-spectral images. Results show robust

and reliable performance in both test data sets. Additional tests are currently underway, with these concentrating upon matching images from different sensors and/or images recorded at different times.

The current research focus remains on enhancing the capability of the developed approach, with special attention being given both to improving the method of handling images with large orientation differences, and to utilising features other than points, such as lines and regions.

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