AUTOMATED REGISTRATION OF HIGH RESOLUTION SATELLITE IMAGERY FOR CHANGE DETECTION

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ABSTRACT: Change detection is important for an up-to-date GIS database. The ever improving spatial, spectral and temporal resolution of satellite imagery allows for reliable detection and characterization of even more details of the changed patterns with higher accuracy. The quality of registration of the involved imagery is the key factor that dictates the validity and the reliability of the change detection results. The fact that the change detection process usually involves multi-spectral and/or multi-resolution imagery captured at different times and from different sensors emphasises the issue of development of a robust registration procedure that can handle these types of images. This paper introduces a new approach for automated image registration based on a hierarchical image matching strategy. After feature point extraction, the method uses the similarity of the grey levels to find the candidates of the homologous points across the images. To increase success rate and reliability, and reduce computational complexity, a hierarchical image pyramid has been used. Matching then starts from the highest pyramid level with the results being the approximation of the subsequent lower level. The algorithm also uses contextual information to achieve locally consistent matches. The method has been implemented and tested using various remote sensing imagery including IKONOS and QuickBird data over test sites in Melbourne, Australia and Thimphu, Bhutan. The results are promising and reveal the potential for operational automated image registration in the process of change detection.

1. INTRODUCTION

Image registration is an important technique for a great variety of image processing applications where two or more images of the same scene taken at differing times, viewpoints and/or sensors have to be compared. Typically, image registration is required in remote sensing image analysis, cartographic data updating and computer vision for target localization or automatic quality control.

Our specific interest is change detection for GIS database updating from imagery. As a result of recent advances in space sensor technology, high-resolution satellite systems allow the employment of space imagery with 1m or even better ground resolution. Rapid global coverage by these recent high-resolution space sensors brings to us the necessary tools for map revision and production, particularly essential in areas of the Earth's surface 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. 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 sensors usually provide a high-resolution panchromatic image together with low-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 image registration process is based on the identification of control points that precisely locate corresponding pairs of image coordinates. Control points may be measured in imagery manually or by semi- or fully automatic methods. In general, manual selection of control points is a time-consuming and labour-intensive task. Therefore, it is necessary to introduce automatic methods that require little or no operator supervision.

From the last two decades of research, there is a vast body of literature on automated image registration techniques. Comprehensive surveys can be found in Brown (1992) and Zitova & Flusser (2003). Existing automated registration methods fall into two categories: area-based and feature-based. In feature-based methods, common features such as curvatures, moments, areas, contour lines or line segments are extracted from images and are used to perform registration (Li, et al., 1995; Schenk, et al., 1991; Dai & Khorram, 1999; Habib & Alruzouq, 2004). Since most of the proposed features are invariant to the grey scale change, the feature-based methods have shown to be suitable for problems of multi-sensor registration. For instance, in Habib & Alruzouq, 2004 line segments are used as primitives in a registration process. The success of their method depends on the assumption that the line segments are 'rich' in the scene under processing, and common features and feature structures are well preserved. Therefore, their method is efficient and works well only in cases where the line segments are well presented and preserved.

For this reason, area-based methods are still widely used in image registration (Hsieh et al., 1997). 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. The centres of the matched windows are control points that are then used to solve for the transformation parameters between the two images. Various area-based registration approaches have been proposed. Hsieh et al. (1997) detected feature points using a Wavelet transform algorithm; the detected points were then matched across the images. A similar strategy was presented in Zheng & Chellappa (1993) to register aerial images. Zhang et al. (2000) applied an area-based method in image registration to fuse SPOT and LandSat TM imagery. They performed image matching first with cross-correlation.

The correlation coefficients were then used in the next step of global image matching through probability relaxation. This method was later extended by Liao et al. (2004) to register InSAR imagery for DEM generation. Area-based image registration methods are also widely used in computer vision (Georgescu et al., 2004) and medical imaging applications (Thevenaz et al., 1998).

This paper proposes an area-based approach to automated registration of remote sensing images. After image preprocessing, feature points are extracted and the candidates of homologous points are located using a similarity measure of correlation coefficients in cross-correlation. The conjugate points across images are finally determined by structural matching. In the next section, the details of the image registration technique developed in this work are described. Afterwards, experimental results using high-resolution satellite imagery with varying radiometric and geometric properties are presented. Finally, conclusions are drawn and recommendations for future work are presented.

2. IMAGE MATCHING

Image matching has been an active topic in photogrammetry and computer vision for decades, and still remains a difficult task. In order to increase success rate and reliability of results, our method exploits image pixel grey value similarity and geometrical structural information. We perform image matching in registration in two steps where in each step different matching algorithms are employed on a given objective. The general strategy is outlined in Figure 1.

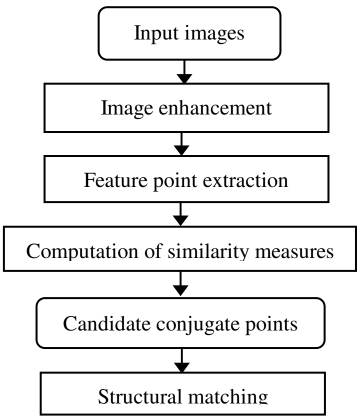

Figure 1. Image matching strategy.

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

2.1 Image Preprocessing and Feature Point Extraction

In order to optimize the images for the subsequent image matching process, we applied a new version of the Wallis filter (Baltsavias, 1991) to process images. The filter enhances features in images and therefore facilitates feature point extraction. Furthermore, since the filter is applied in both images using the same parameters, the naturally occurring brightness and contrast difference are corrected. After image enhancement, the Foerstner operator is used to extract well-defined feature points that are suitable for image matching.

2.2 Computation of Similarity Measure

We use the normalized cross-correlation coefficient as the similarity measure of the candidate matching areas. It has been shown that this estimate is independent of differences in brightness and contrast due to the normalization with respect to the mean and standard deviation.

Let (x, y) and (x', y') be the image coordinates of two feature points located, respectively, in images f and g, the normalized cross-correlation in a (2N+1)*(2N+1) window is then given as:

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

where

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

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

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

Here, $\bar{f}$ and $\bar{g}$ are the local means of the windows in image f and g, respectively.

2.3 Structural Matching with Probability Relaxation

After performing similarity measurement computation, we construct a matching pool for candidate conjugate points and attach a similarity score 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. Firstly, there is the difficulty of how to decide on a threshold in correlation coefficients to select the correct matches. The existence of image noise, shadows, occlusions, and repeated patterns emphasises these difficulties. Furthermore, matching using a very local comparison of grey value difference does not necessarily always deliver consistent results in a local neighbourhood. In order to overcome these problems, we employ an algorithm of structural matching with probability relaxation for image matching in the registration process.

Structural matching seeks the correspondences from the primitives of one structural description to the primitives of a second structural description. Several methods of structural matching have been proposed in the past for various applications (Haralick & Shapiro, 1993; Vosselman, 1992; Zhang & Baltsavias, 2000; Zhang & Gruen, 2003). In this paper, structural matching is realized through probability relaxation.

Let the feature points in the first image be a set *L*, *L*={*li*}, *i=1, 2, … n*, and the feature points in the second image be a set *R*, *R*={*rj*}, *j=1,2,… 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* | T}. Note here the equal sign means "match to". The computation of the conditional probability can be achieved by an iterative scheme (Christmas et al., 1995; Zhang & Baltsavias, 2000) as:

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

where

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

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 $p\{T(l_i, r_j; l_h, r_k) | l_i = r_j, l_h = r_k\}$ 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*). If two pairs of potential matches share the same type of relation, they are defined as compatible since they structurally support each other. Otherwise, if two pairs violate some basic matching constraints, like uniqueness, relative position, etc., they are considered as incompatible.

The compatibility function plays an important role in the process of structural matching. In Zhang et al. (2000) the correlation between image segments was used to evaluate the compatibility function. In our investigation, we adapted the function defined in Zhang & Gruen (2003) as

$$T / \exp((\Delta p_x^2 + \Delta p_y^2)/\beta)$$

where

$$\Delta p_x = (x_h - x_i) - (x_k - x_j)$$

$$\Delta p_y = (y_h - y_i) - (y_k - y_j)$$

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 horizontal, vertical and two main diagonal directions at the window around the point *li*. β is a constant value.

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

The method described in the paper has been implemented, and tests have been conducted using several high-resolution satellite images to illustrate the feasibility and the robustness of the suggested image matching technique. Recent tests were performed on stereo IKONOS and QuickBird imagery with various terrain types and landcover. In addition, image matching was also carried out between high-resolution panchromatic and low-resolution multispectral imagery.

The first test site was over Hobart, Australia, encompassing a total area of $120km^2$. The IKONOS Geo image pair employed covered a variety of landcover types, including mountainous forest areas, and hilly neighbourhoods, parks and city buildings. The images were acquired towards the end of the southern hemisphere summer. Both images were collected on the same orbital pass in reverse scan mode. The height difference in the site is around 1200m.

Figure 2 illustrates a portion of image matching results in the registration of the stereo images. The first and second images are presented at the top of, and below the figure, respectively. The matched points are shown by white crosses. In this small area, more than a hundred conjugate points are automatically found, although some parts of the second image are highly saturated (see the top of the second image).

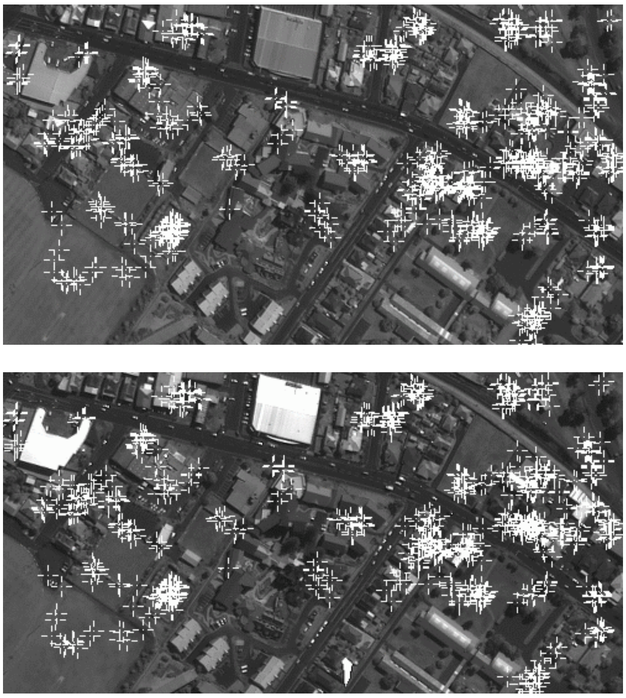

Figure 2. Image matching for the registration of IKONOS stereo images of Hobart, Australia.

Figure 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 which only very few are not correct.

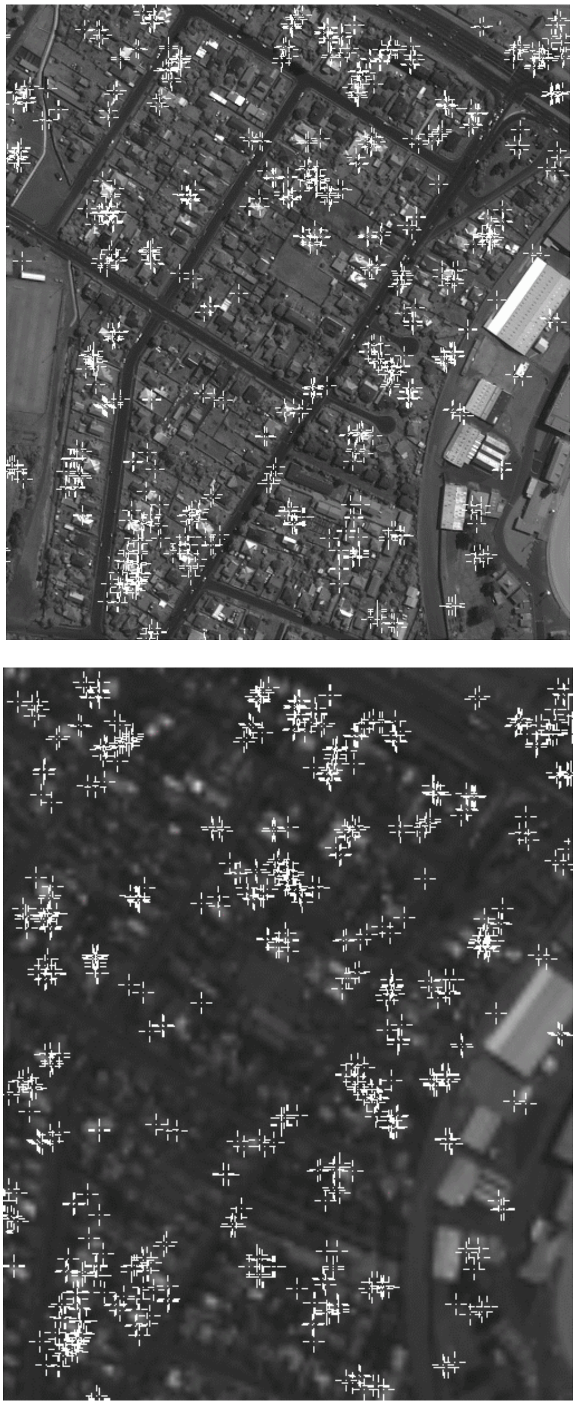

Figure 3. Example of matching 1m resolution IKONOS imagery (above) with 4m resolution imagery (below).

The second test site was Thimphu, Bhutan. The QuickBird images were taken in December, 2004. The terrain height ranges from 2100 to 4300m. Again, similar to the Hobart test site, image matching was performed between stereo images (Figure 4) and between the high-resolution panchromatic image and low-resolution multispectral image (Figure 5). It is again observed that good performance was achieved, even when large radiometric and geometrical differences are present.

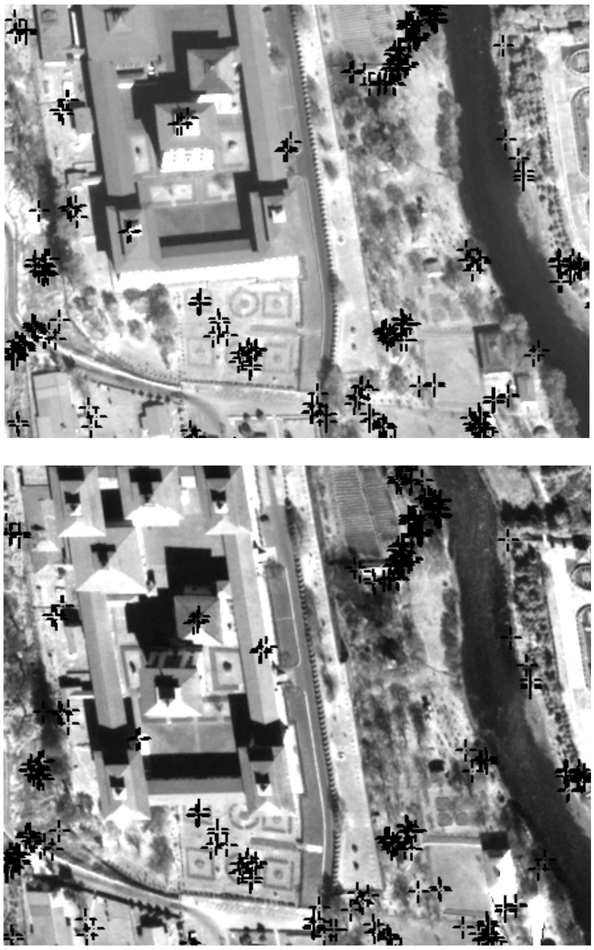

Figure 4. Example of matching QuickBird stereo images. The matched points are labelled by black crosses.

4. CONCLUSIONS AND RECOMMENDATIONS

With the rapid advancement of space sensor technology and the availability of high-resolution satellite data, there is an increasing need for developments in robust image registration. This paper has presented a method for image matching in automated registration of high-resolution satellite imagery. The method exploits image pixel grey value similarity and geometrical structural information. Image matching was performed in two steps. After feature point extraction, cross correlation was used to find the candidate conjugate points across images. The correlation coefficients were then taken as the initial probability in a structural matching through probability relaxation. In order to increase the success rate and reliability of the results, and reduce the computational complexity, a hierarchical pyramid strategy was employed.

Test results using IKONOS and QuickBird imagery over various terrain types and landcovers have been presented. The matching was performed between stereo images and between high-resolution panchromatic and low-resolution multi-spectral imagery. The results show good performance has been achieved in both cases, in both test sites. More tests are planned in the near future when new data becomes available. The new tests will be performed to match images from different sensors and/or taken at different times.

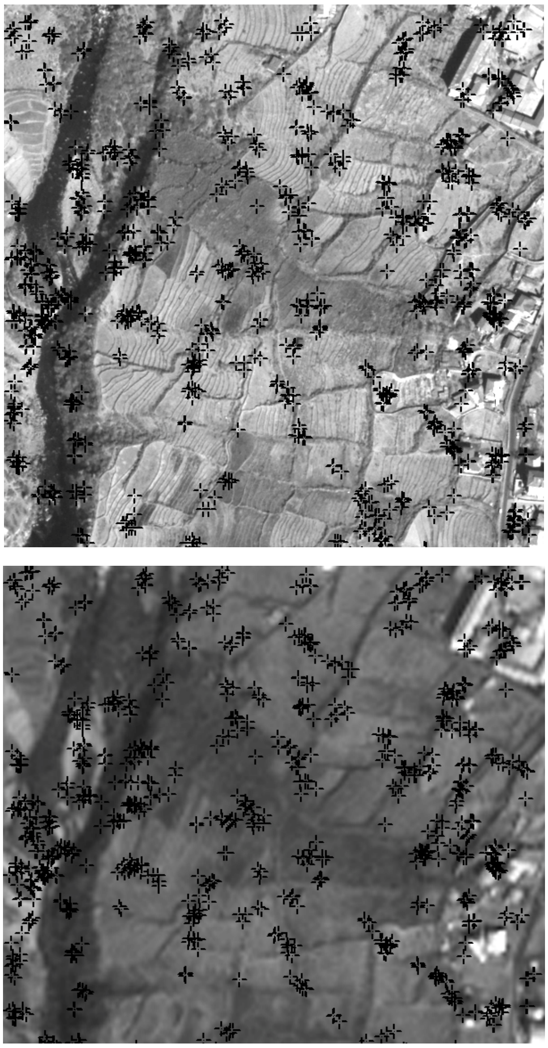

Figure 5. Example of matching between 60cm QuickBird panchromatic (above) and 2.4m multispectral imagery (below). The matched points are labelled by black crosses.

The current research focus is on extending the capability of the developed method. Firstly, we are improving the method to handle images with large orientation differences. In order to achieve even higher reliability, other features apart from points, such as lines and regions, can be used in the image matching. In addition, the techniques developed in Baltsavias (1991) will be employed in post processing of the image matching to achieve higher registration accuracy. This is especially useful in some applications such as InSAR image registration for DEM generation.

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