MATCHING CONJUGATE POINTS BETWEEN MULTI RESOLUTION SATELLITE IMAGES USING GEOMETRIC AND RADIOMETRIC PROPERTIES

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ABSTRACT:

Remotely sensed images are the main source for a variety of mapping and change detection applications. Images from different satellites are employed in several of these applications. However, each type of these images has different resolution and orientation. Hence, they need to be co-registered before any meaningful utilization. The first step in the registration process is to find conjugate points between the images. This paper presents a modified approach of Scott and Longuet-Higgins approach to find conjugate points between different remotely sensed images. In such an algorithm, initially , corner points are extracted automatically in two images, and for each pair of points a cost value is computed. The cost of corresponding any two points is computed using image coordinates and pixel intensities. The cost values are then used to fill a cost matrix, and its SVD is used to find correspondent points. The algorithm is tested on three pairs of satellite images with different resolutions and orientations. Result shows that the presented approach succeeded in finding more than 96% of conjugate points between two different satellite images using only the image coordinates. Moreover, result shows that including the image intensities in the matching procedure does not improve the results significantly.

1. INTRODUCTION

Recent progress in remote sensing systems started a new mapping era. Satellite images such as; Landsat, SPOT, IRS, IKONOS, and QuickBird images are used in; topographic mapping, land management and monitoring, urban and coastal planning, and site development. In addition, they are used in a variety of change detection applications. The aim of any change detection application is to recognize and identify temporal variations at a given location (Habib, et al., 2004). These applications are implemented using satellite images with different orientations and resolutions. Thus, these images have to be registered before they are employed in any change detection process. The quality of the image registration process affects the results and outcomes of the change detection process dramatically (Li et al., 2002). Moreover, finding correct conjugate points between satellite images is essential for any high quality image registration process. Image registration can be accomplished either manually or semi-automatically. In a manual image registration system, the operator identifies each point and its correspondences in other images on the computer screen. However, this process needs an expert operator and consumes time and money. On the other hand, in a semi-automatic system, the operator open each image separately and identify well defined tie points, then a point corresponding algorithm is used to find matched points. Several studies have been conducted on automatic and semi-automatic image registration. Recent image registration techniques are either time consuming, satellite dependent, or semi-automated. This necessitates the development of a fully automated algorithm for satellite image registration.

Habib and Al-Ruzouq (2005) used the Modified Iterative Hough Transformation (MIHT), presented in Habib and Kelley (2001), to register a dataset of different satellite images. The dataset includes; IKONOS, SPOT-5, Landsat-7, Quickbird, Orbview, and EROS-A1 satellite images. Linear features were used as the primitive registration features. The 2D affine and similarity transformations were used to establish the mathematical model between the features. The algorithm generates all possible matching hypotheses between the registration primitives for a given image pair. For each hypothesis, the transformation parameters are computed. Each hypothesis then votes in its corresponding cell in an accumulator array of the transformation parameters. Matching hypothesises that contribute to the peak cell are used to establish corresponding primitives (Habib, 2000). Such approach is time consuming and requires intensive effort in selecting the accumulator cell size, searching, optimum sequence for the parameter estimation (Al-Razuq, 2004).

Sui et al. (2006) presented an algorithm to register remote sensing images with GIS data. The algorithm is based on extracting and recognizing water surfaces in the images and the GIS data. Therefore, these surfaces are used to extract bridges. Unchanged features are then extracted and a shape matrix, Flusser (1992), is established and solved to define corresponding features using the technique presented in (Zhao, 2004). However, such technique requires a high quality and reliable GIS database. Wavelet-based feature extraction is used in Hong et al. (2004) to extract image features for the registration process. First pyramid images were produced using the multi-resolution property of the wavelet. Feature points were obtained through finding the maximum of the wavelet coefficients of the detailed images. Feature correspondence was then established using the probability relaxation method. These points were used as an initial set for the next level of matching. A threshold value is used at this step to get the required sets of feature points. In the next step, least squares matching technique is employed to refine the initial set. The authors observed that this technique is time consuming and is affected severely by terrain relief.

Lavigne (2006) described an image registration algorithm based on detecting features that are invariant in translation and rotational transformations, invariant in illumination, and identify the ones that remain persistent through scale changes (Lowe, 2004) ?????. Classified translation, rotational, illumination, and locally scale-invariant features are then validated through a decimation process. Selected features are expressed as descriptors, which are used to establish feature correspondences. The relationship between descriptor sets was established by estimation of an affine transformation model, used subsequently in the final image warping and resampling phase of the system. Results were evaluated and showed an average feature correspondence rate of about 80%. The algorithm was only tested on small patches of satellite images with relative spatial resolution of 1.0/1.0 and 0.64/1.0. A survey of other image registration techniques is presented in Zitova and Flusser (1998).

This paper presents a modified and efficient method to automatically solve the point correspondence problem between a pair of satellite images based on the Scott and Longuet-Higgins algorithm. The method has been used before in close range environment. In its original implementation, it depends on computing the proximity matrix between all pairs of point using the Euclidean distance between the points regarding they lay on the same plane. However, this research shows that this implementation is not suitable for satellite images due to the variations in image resolutions and orientations. Hence, a modified version was adapted based on the four-parameters similarity transformation model. The modified version showed reliable and high quality results with IKONOS, QuickBird, SPOT images.

In addition, another implementation that incorporates both geometric and radiometric attributes is presented. The remaining of the paper is organized as follows. First, image registration using only geometric properties is introduced. Then image registration using radiometric and geometric properties is proposed. Experimental results using SPOT, IKONOS, and QuickBird images are then discussed and analysed . Conclusions are then stated.

2. IMAGE REGISTRATION USING GEOMETRIC PROPERTIES ONLY

In this section the use of geometric properties only to match conjugate points will be discussed. This is accomplished via a modified version of the Scott and Longuet-Higgins algorithm. The algorithm utilizes a main property of the singular value decomposition (SVD) to satisfy both exclusion and proximity principles. The advantage of the algorithm is its straightforward implementation founded on a well conditioned eigenvector solution which involves no explicit iterations. In order to describe the algorithm, as an assumption N and M are two patterns, containing n features N_i (i = 1 : n) and m features M_j (j = 1: m), respectively. The end result is to find a one-to-one correspondence matrix between the features of the two patterns. The algorithm is implemented as follows:

- First, a proximity matrix G of the two sets of features is constructed. Each element G_{ij} is a Gaussian-weighted distance between two features N_i and M_j as shown in equation (1), (Scott and Longuet-Higgins, 1999).
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$$G_{ij} = e^{-r_{ij}^2 / 2\sigma^2} \tag{1}$$

where $i = 1,2,\dots,n$, $j = 1,2,\dots,m$,
r_{ij} is the Euclidean distance between the two features (i and j) assuming that they are lying on the same plane,
σ controls the degree of interaction between the two sets of features: a small value enforces local interactions, while a larger value permits more global interactions.

- Second, perform the SVD of G: G = TDUT.
- Third, convert D to a new matrix E obtained by replacing every diagonal element D_{ii} with 1 and then compute the product: P = TEUT.
- Finaly, the new matrix P has the same shape as the proximity matrix G and has the interesting property of amplifying good pairings and attenuating bad ones. Hence, if Pij is both the greatest element in its row and the greatest element in its column, then those two different features I and J are regarded as being in 1:1 correspondence.

In this research a modified geometric cost is used to build the proximity matrices in Equation 1. The new cost is computed using the (four-parameters) similarity transformation model. The model is based on using four transformation parameters to relate the transformation between any two images and is computed as follows. Assume two features I and J in the 1st and 2nd image respectively. Given the coordinates of the start point in each image, the resolution of each image, and the orientations of both images, a similarity equation could be driven between the coordinates of both images as shown in equation 2.

$$r_{ij} = \mathbf{D}_{ij}^T \otimes \mathbf{D}_{ij}$$

where (2)

$$\mathbf{D}_{ij} = \begin{bmatrix} x_i \\ y_i \end{bmatrix} - S \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \begin{bmatrix} u_j \\ v_j \end{bmatrix} + \begin{bmatrix} t_x \\ t_y \end{bmatrix}$$

where S : is the scale factor between the two images,
θ :is the rotation angle between the two images,
t_x,t_y: are the shift values between the two images,
x_i, y_i : are the coordinates of point (i) in the first image,
u_j, v_j : are coordinates of point (j) in the second image.

The values of r_{ij} are then used to fill the proximity matrix. There are several reasons stand behind using this form. First, the scale difference between the satellite images is usually larger than the scale difference between normal close range images. Furthermore, the orientation and other geometric parameters are usually affordable in the header files of the satellite images. Even if the header files are not available these parameters could be computed easily given the approximate orientations of the satellite images.

3. IMAGE REGISTRATION USING RADIOMETRIC AND GEOMETRIC PROPERTIES

The use of radiometric and geometric properties of image points to build the proximity matrix was introduced by (Delponte et al.,2006; Zhao, 2004, Pilu, 1997) with different formation of the proximity matrix. In all these research, only close range images taken from approximately the same distance and with approximately the same pixel size were used. Hence, they used Euclidean distance to compute the geometric cost. In addition, the normalized image intensity correlation was used in these researches. However, the normalized image intensity correlation fails to give reliable results with multi-resolution images. Therefore, the following approach is used:

- Given two images I(x, y) and J(x, y) with respectively two different pixel sizes S_i and S_j, where $S_j > S_i$.
- Convolve the finest resolution image ($I(x, y)$) with a Gaussian filter as follows:

  $I_\sigma(x, y) = G_\sigma \otimes I(x, y)$

Where $I_\sigma(x, y)$ is the convolution of the image $I(x, y)$, G_σ *is the* Gaussian filter of size 3 by 3, $I(x, y)$ is the image with the finest resolution.

- Compute a new image (II_σ (x, y)) by up-sampling the image I_σ (x, y) from Si to Sj using bilinear interpolation. Hence, the resolution of II_σ (x, y) is the same as the resolution of J(x, y).
- Compute the normalized image intensity correlation using the two images $II_\sigma(x, y)$ and $J(x, y)$ as shown in equation 3.

$$C_{ij} = \frac{\sum_{k=1}^{n}(G_{k1} - G_1)(G_{k2} - G_2)}{\sqrt{\sum_{k=1}^{n}(G_{k1} - G_2)^2 \bullet \sum_{k=1}^{n}(G_{k2} - G_2)^2}} \quad (3)$$

where C_{ij} = correlation coefficient for a pair of image points in images 1 and 2,
n = total number of points in the window,
G_1, G_2 = mean intensity values for the windows in images 1 and 2 respectively,
G_{k1}, G_{k2} = intensity values at position k in the windows in image 1 and 2 respectively.

- The new proximity matrix is computed as shown in equation 4.

$$G_{ij} = [e^{-(C_{ij}-1)^2/2\gamma^2}][e^{-r_{ij}^2/2\sigma^2}] \quad (4)$$

where C_{ij} = normalized image intensity correlation between the two features (i and j),
γ = rate of decrease for C_{ij},

other parameters are presented in Equation 1.

4. EXPERIMENT RESULTS AND ANALYSIS

4.1 Dataset description

The dataset used in this research consists of three satellite images covering West Lafayette city, IN, USA. The first image is an SPOT3 panchromatic image, with a pixel size of 10 meters. The second image is an IKONOS panchromatic image, with a pixel size of 1 meter. The third image is a QuickBird multispectral image, with a pixel size of 2.4 meters. Harris corner detection (Harris and Stephens, 1998) was used to automatically extract corner points in all images. Figure 1 shows the point distribution over the QuickBird image.

Figure 1. Point distribution over the QuickBird image

4.2 Experiment

Experiment was divided into two parts; using only the geometric property and using the geometric and radiometric properties. For each part, six experiments are conducted using either the Euclidean distance or the four-parameters transformation model. Different values for the σ ranging from 0.05 to 1.0 are used. In the implementation steps, the values of the proximity matrices were normalized by dividing them by the maximum cost. For the four-parameters transformation, approximate values for the transformation parameters are used to find the correspondence points. The scale (S) is computed as the ratio between the resolutions of the images. The translations (t_x and t_y) are computed as the differences between the image coordinates of a given point. The rotation angle between the two images is approximately measured given the coordinates of two points. Hence, these approximate values are used as the initial values for the computation of the condition equation of the four-parameter transformation model without computing the adjusted values. Table 1 shows the approximate transformation parameters.

	SPOT-IKONOS	SPOT-QuciBird	IKONOS-QuickBird
S	10	4	0.4
θ^o	13	12	-0.8
t_x(pixels)	3589	3870	281
t_y(pixels)	759	1872	1068

Table 1. Approximate transformation parameters between the SPOT, IKONOS, and QuickBird satellite images

4.3 Results and analysis

Results are represented in figures 2 and 3. Figure 2 shows the percentage of correctly matched points using only the geometric properties. Figure 3 shows the percentage of correctly matched points using the geometric and radiometric properties. Several remarks are observed from the two figures. The Euclidean distance result varies dramatically with the value of sigma for both cases. Consequently a correlation is highly noticed between the match and the sigma value specially when sigma ranges from zero to 0.5. The percentage of correctly matched points for the Euclidean distance reaches its maximum (90%) only for the IKONOS/QuickBird case. The percentage for the IKONOS/SPOT and the QuickBird/SPOT are below 70%.. The decrease in the matching can be related to the low resolution of the spot images. Including the image correlation did not improve the results.

On the other hand, for the four-parameter case, the percentage of correctly matched points are within the range of 96% to 100%. The results for the four-parameters are independent of the values of sigma. The results are stable regardless the image pair used. Moreover, incorporating the image correlation did not affect the results. The four parameters transformation model have several advantage. The scale, rotation, and two translation parameters are easy to compute. No real parameters are required, however, only approximate values can provide high quality matching results. In addition, the model represents the geometry of the images more realistically than the Euclidean distance measure. The quality of the results of the four parameters transformation model are not affected by large scale differences, i.e. SPOT-IKONOS and SPOT-QuickBird. Moreover, the results using this model are independent on the value of σ.

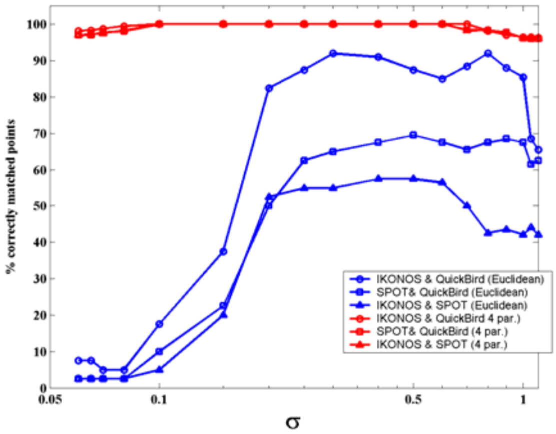

Figure 2. Percentage of correctly matched points using geometric properties only

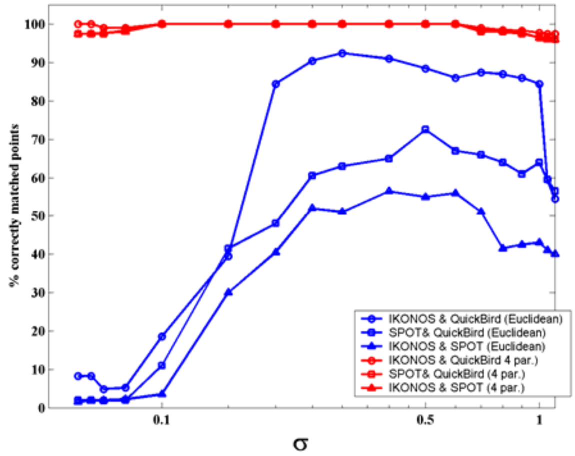

Figure 3. Percentage of correctly matched points using geometric and radiometric properties

5. CONCLUSIONS

This paper presented a modified method to solve the point correspondence problem between different satellite images. The method is based on the Scott and Longuet-Higgins algorithm. This algorithm was utilized to solve the point correspondence problem between close range images in a previous work. The original algorithm, based on the Euclidean distance, was investigated. However, due to the rigorous transformation between satellite images, it fails to provide high quality results. Thus, a modified algorithm based on using the four-parameters transformation model was proposed and tested. Results showed that the modified algorithm provides a comprehensive solution for the point correspondence problem between satellite images. In addition, it is stable regardless of the values of the orientation of the satellite images, the scale ratio between the images, or the translation values between the images. Therefore, the presented method could be used to solve the point correspondence problem between any pair of satellite images. This will provide high quality inputs for a variety of change detection applications. Future work will focus on testing the proposed algorithm with other datasets. The effect of the distribution control points on the quality of the results will also be addressed.

REFERENCES

Al-Razuq, R., 2004. *Semi-automatic registration of multi-source satellite image with varying geometric resolutions*. PhD thesis, Calgary University, Calgary, Alberta.

Delponte, E., Isgr, F., Odone, F., and Verri, A., 2006. SVD-matching using SIFT features. *Graphical Models*, Vol. 68(5-6), pp. 415-431.

Flusser, J., 1992. Invariant shape matrix description and measure of object similarity. *Proceedings of 4th IEE International Conference of Image Processing and its Applications*, Maastricht, The Netherlands, pp. 139 - 142.

Habib A., and Al-Ruzouq, R., 2005. Semi-automatic registration and change detection using multisource image with varying geometric and radiometric properties. *Photogrammetric Engineering and Remote Sensing*, Vol. 71(3), pp. 325-332.

Habib, A., 2000. New approach to solving matching problems in photogrammetry. *The International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences*, Amsterdam, The Netherlands, Vol. XXXIII, Part B2, pp. 257 – 264.

Habib, A., Al-Ruzouq, R. and Kim, C.J., 2004. Semi-automatic registration and change detection using multisource image with varying geometric and radiometric properties", *The International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences*, Istanbul, Turkey, Vol. XXXV, Part B2, pp. 445 - 450.

Habib, A., and Kelley, D., 2001. Automatic relative orientation of large scale image over urban areas using modified iterated Hough transform. *International Journal of Photogrammetry and Remote Sensing*, Vol., pp. 56: 29–41.

Harris, C. and Stephens, M., 1998. A combined corner and edge detector. *Proceedings of the 4th Alvey Vision Conference*, Manchester, England, pp. 147-151.

Hong, G., Zhang, Y., and Fraser, D., 2004. A new image registration technique in urban change detection. *Proceeding of the 2004 ASPRS Annual Conference*, Denver, Colorado.

Lavigne, D., 2006. AMIR: A new automated multisensor image registration system. *Proceeding of the 2006 ASPRS Annual Conference*, Reno, Nevada.

Li, D., Haigang, S., and Ping, X., 2002. Automatic change detection of geospatial data from image. *The International Archives of Photogrammetry, Remote Sensing, and Spatial Information Sciences*, Xian, China, Vol. XXXIV, Part 2, pp. 245-252.

Lowe, D.G., 2004. Distinctive features from scale-invariant keypoints. *International Journal of Computer Vision*, Vol. 60(2), pp. 91-110.

Pilu, M., 1997. Uncalibrated stereo correspondence by singular value decomposition. *Proceedings of the Computer Vision & Pattern Recognition Conference*, Puerto Rico, USA, pp. 261-266.

Scott, G., and Longuet-Higgins, H.C., 1991. An algorithm for associating the features of two images. *Proceedings of the Royal Society London*, Vol. B244, pp. 21-26.

Sui, H., Gong, J., Xiao, J., and Li, M., 2006. Automatic recognition of bridges over water and registration in remotely sensed images with GIS data. *Proceedings of the ISPRS Commission VII Mid-term Symposium,* Enschede, The Netherlands, Vol. XXXVI, Part 7.

Zhang, Z.H., 2004. An automatic procedure for SAR-optical satellite image registration based on multi-layer feature matching strategy. *Proceedings of Intelligent Signal Processing and Communication Systems*, Seoul, Korea, pp. 574 –580.

Zhao, F., 2004. Image matching based on singular value decomposition. *Proceedings of the 5th Pacific Rim Conference on Multimedia*, Tokyo, Japan, pp. 119-126.

Zitova, B. and Flusser, J., 2003. Image registration methods: a survey. *Image and Vision Computing,* Vol. 21, pp. 977-1000.