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Mutual information based image registration for remote sensing data

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ABSTRACT

Registration is a fundamental operation in image processing to align images taken at different times, from different sensors or from different viewing angles. Automatic image registration procedures are gaining importance to efficiently register large volumes of remote sensing data available these days. In this Letter, we investigate an automated mutual information based registration technique for remote sensing data. Performance of a number of interpolation algorithms to compute mutual information for registration of multi-sensor and multi-resolution Landsat TM, Radarsat SAR and IRS PAN images is evaluated.

1. INTRODUCTION

Remote sensing images are frequently used for a variety of tasks such as image fusion (Pohl and Van Genderen, 1998), temporal change detection (Lunetta and Elvidge, 1998) and integration of multi-source data in Geographical Information System (GIS). The basis of all these tasks is accurate image registration, though the requirement of registration accuracy may vary from one task to the other. For example, it has been reported that a registration accuracy of less than one-fifth of a pixel is required to achieve a change detection error within 10% (Dai and Khorram, 1998).

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Conventional feature based registration technique via the use of Ground Control Points (GCP) is laborious, tedious, and time intensive. In addition, the use of an automatic registration procedure is important in today's circumstances due to the increasing volumes of remote sensing data and their utilization for a wide range of applications. The process of GCP selection may be made automatic to increase efficiency (Toth and Schenk, 1992, Dai and Khorram, 1999). However, the feature-based approach is subjective as sometimes too few GCPs are selected, the GCPs may be inaccurate and unevenly distributed over the image, which may lead to large registration errors. An automatic intensity based registration approach may, therefore, be more appropriate than the feature-based one, since it is more flexible in the sense that it is image content independent.

The main principle behind any intensity based registration approach is to find a set of transformation parameters that globally optimizes a similarity measure. Two commonly used similarity measures are mean squared difference (MSD) and normalized cross-correlation (NCC) (Brown, 1992). However, these two similarity measures are adequate only for intra-modal registration (i.e., for registration of images taken from the same sensor) (Roche et al., 2000). For multi-modal image registration problems, mutual information (MI) was independently proposed by two groups of researchers to be a suitable similarity measure (Viola and Wells, 1995, Maes et al., 1997). Similar to NCC, the intention is to maximize the mutual information between the two images. Since its introduction, MI has been used widely in many medical image registration problems (e.g., McGarry et al., 1997, Rueckert et al., 1998, Erdi et al., 2000, Zagrodsky et al., 2000), whereas its application in remote sensing image registration has been limited. Only recently, some work has been initiated on registration of remote sensing images using mutual information (e.g., Chen and Varshney, 2000, Johnson et al., 2001, Inglada, 2002).

MI based registration can be implemented through joint histogram estimation using various interpolation algorithms such as nearest neighbour, linear, cubic convolution, and partial volume interpolation. In this Letter, all these algorithms have been implemented and their performance evaluated for the registration of remote sensing images. Registration consistency has been used here as a measure to evaluate the performance of registration (Holden et al., 2000).

2. MUTUAL INFORMATION BASED IMAGE REGISTRATION

Having its roots in information theory, mutual information, $I(A,B)$, of two random variables A and B can be obtained from (Cover and Thomas, 1991),

$$I(A,B) = H(A) + H(B) - H(A,B) \tag{1}$$

where $H(A)$ and $H(B)$ are the entropies of A and B and $H(A,B)$ is their joint entropy. Considering A and B as two images, the MI based registration criterion states that the images shall be registered when $I(A,B)$ is maximal. The entropies and joint entropy can be computed from,

$$H(A) = \sum_{a} - p_A(a) \log p_A(a) \tag{2}$$

$$H(B) = \sum_{b} - p_B(b) \log p_B(b) \tag{3}$$

$$H(A,B) = \sum_{a,b} - p_{A,B}(a,b) \log p_{A,B}(a,b) \tag{4}$$

where $p_A(a)$ and $p_B(b)$ are the marginal probability mass functions, and $p_{A,B}(a,b)$ is the joint probability mass function. These probability mass functions can be obtained from,

$$p_{A,B}(a,b) = \frac{h(a,b)}{\sum_{a,b} h(a,b)} \tag{5}$$

$$p_A(a) = \sum_{b} p_{A,B}(a,b) \tag{6}$$

$$p_B(b) = \sum_a p_{A,B}(a,b) \tag{7}$$

where h is the joint histogram of the image pair. It is a 2D matrix of the following form:

$$h = \begin{bmatrix} h(0,0) & h(0,1) & \dots & h(0,N-1) \\ h(1,0) & h(1,1) & \dots & h(1,N-1) \\ \dots & \dots & & \dots \\ h(M-1,0) & h(M-1,1) & \dots & h(M-1,N-1) \end{bmatrix}$$

assuming the intensity value in the first image varies from 0 to M-1 and in the second image from 0 to N-1. The value $h(a,b)$ is the number of corresponding pairs having intensity value a in the first image and intensity value b in the second image. Thus, it can be seen from equations 1 to 7 that the joint histogram is the only requirement to determine the MI between two images. Different interpolation algorithms such as nearest neighbour (Chen and Varshney, 2000), linear (Holden et al., 2000), cubic convolution (Keys, 1981), and partial volume interpolation (Maes et al., 1997) can be used to estimate the joint histogram of two images. In this paper, the performance of aforementioned interpolation algorithms has been evaluated by means of registration consistency, which is described next.

3. REGISTRATION CONSISTENCY

In the absence of proper registration ground data, registration consistency (Holden et al., 2000) can be used as a measure to evaluate the performance of registration algorithms implemented. Defining $T_{A,B}$ as the transformation found by using image A as the floating image and image B as the reference image, the registration consistency (dp) of $T_{A,B}$ and $T_{B,A}$ over the images A and B can be formulated as,

$$\langle dp \rangle = (1/N_A) \cdot \sum_{(x,y)\in(I_A \cap I)} \left\| (x,y) - T_{B,A} \circ T_{A,B}(x,y) \right\| \quad 8a$$

$$\cong (1/N_B) \cdot \sum_{(x,y)\in(I_B \cap I)} \left\| (x,y) - T_{A,B} \circ T_{B,A}(x,y) \right\| \quad 8b$$

where (x,y) is the coordinate of a pixel in an image, the composition $T_{A,B} \circ T_{B,A}$ represents the transformation that applies $T_{B,A}$ first and then $T_{A,B}$. I is the overlap region of images A and B. I_A is the discrete domain of image A, N_A is the number of pixels of image A within the overlap region, I_B is the discrete domain of image B, and N_B is the number of pixels of image B within the overlap region. The registration consistency, dp, in equation 8a, specifies the mean shift of a pixel p in image A resulting from the transformation $T_{A,B}$ and the transformation $T^{-1}{}_{B,A}$. Similarly, equation 8b represents the mean shift of a pixel p in image B resulting from the transformation $T_{B,A}$ and the transformation $T^{-1}{}_{A,B}$. In general, it is expected that the value of dp from equations 8a and 8b will be the same.

4. EXPERIMENTAL RESULTS

Landsat Thematic Mapper (TM), Indian Remote Sensing Satellite (IRS) Panchromatic (PAN), and Radarsat Synthetic Aperture Radar (SAR) images covering a region of the San Francisco Bay, California were used in this study. Experiments consisted of two parts. In the first part, the registration of IRS PAN images and Radarsat SAR images (multi-sensor case) at approximately the same (i.e., 5.8 m of PAN and 6.25 m of SAR) was considered. Two datasets belonging to different portions of the region were selected. The image dimensions of the first dataset were [360×360] pixels for PAN and [360×280] pixels for SAR respectively whereas the image dimensions for the second data sets were [360×360] pixels for both PAN and SAR images. The transformation parameters ($T_{A,B}$) representing rotation (degree), vertical and

horizontal displacements (meter), and the registration consistencies obtained using various interpolation algorithms are shown in tables 1 and 2. The simplex search algorithm (Nelder and Mead, 1965) was used as an optimizer in all the cases. From these tables, it can be observed that the registration results from different interpolation algorithms are very close to each other. However, partial volume interpolation produced the most consistent results, as observed from the registration consistencies shown in the last column of the table. Notice that the nearest neighbour interpolation algorithm yields performance comparable to other algorithms. Hence, the nearest neighbour interpolation may be suitable for joint histogram estimation because of its efficiency in implementation.

[tables 1 and 2 here]

The second experiment consisted of the registration of images acquired from two optical sensors but at different spatial resolutions (multi-resolution case). Landsat TM image at 28.5 m spatial resolution and IRS PAN at 5.8m spatial resolution were considered. The sizes of the images were [1024×1024] pixels for IRS PAN image and [256×256] pixels for Landsat TM image. Table 3 shows the registration consistencies using various interpolation algorithms. The transformation parameters are not shown for this experiment, since they were found to be very close to each other. From table 3, we can observe that partial volume interpolation has again resulted in the highest registration consistency amongst all.

[table 3 here]

4. CONCLUSIONS

An MI based image registration technique for multi-sensor and multi-resolution image registration was investigated in this Letter. Various interpolation algorithms were used to

estimate the joint histogram for the determination of MI. All the algorithms have resulted in similar registration consistencies. Nevertheless, partial volume interpolation produced the most consistent results when either of the two images served as the reference image. The nearest neighbour interpolation performed better than the linear or cubic convolution interpolation. Further, its performance was comparable to partial volume interpolation. Nevertheless, since nearest neighbour interpolation is computationally most efficient, it seems reasonable to adopt this algorithm when registering images of large sizes using an MI based approach. Further investigations are needed to compare the registration accuracies of different interpolation algorithms for the MI based registration technique using actual ground data.

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Table 1 Results from registration of PAN and SAR images (dataset 1). *T* denotes the transformation parameters (rotation (degree), vertical displacement (m) and horizontal displacement (m)

Algorithm	$T_{PAN,\ SAR}$ [degree, m, m]	$T_{SAR,\ PAN}$ [degree, m, m]	Registration consistency (m)
NN Interpolation	[20.73, 11.44, -74.81]	[-20.72, -36.60, 64.66]	1.39
Linear Interpolation	[20.70, 11.87, -75.19]	[-20.60, -38.17, 63.94]	2.49
CC Interpolation	[20.66, 12.70, -74.57]	[-20.59, -38.48, 64.61]	1.09
PV Interpolation	[20.64, 11.49, -73.92]	[-20.71, -37.30, 65.13]	1.05

Table 2 Results from registration of PAN and SAR images (dataset 2). *T* denotes the transformation parameters (rotation (degree), vertical displacement (m) and horizontal displacement (m)

Algorithm	$T_{PAN,\ SAR}$ [degree, m, m]	$T_{SAR,\ PAN}$ [degree, m, m]	Registration consistency (m)
NN Interpolation	[20.60, 69.14, 35.38]	[-20.50, -52.63, -56.45]	1.65
Linear Interpolation	[20.68, 67.68, 33.76]	[-20.62, -49.78, -53.26]	2.79
CC Interpolation	[20.63, 65.04, 33.63]	[-20.75, -49.47 -56.24]	2.28
PV Interpolation	[20.62, 66.85, 35.14]	[-20.60, -50.44, -56.49]	0.36

Table 3 Registration consistencies from registration of IRS PAN and Landsat TM images

Band	NN Interpolation	Linear Interpolation	Cubic Convolution Interpolation	PV Interpolation
1	0.5215 m	0.9171 m	2.0643 m	0.4685 m
2	0.7628 m	0.4983 m	0.8880 m	0.3541 m
3	0.9346 m	1.0296 m	1.4871 m	0.2961 m
4	4.8543 m	3.5667 m	4.9829 m	0.9926 m
5	2.2989 m	3.4768 m	1.6628 m	1.4562 m
7	3.2457 m	1.7474 m	5.1452 m	1.1825 m