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A New Landsat Image Co-Registration and Outlier Removal Techniques

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Abstract : Image co-registration is the process of overlaying two images of the same scene. One of which is a reference image, while the other (sensed image) is geometrically transformed to the one. Numerous methods were developed for the automated image co-registration and it is known as a time-consuming and/or computation-intensive procedure. In order to improve efficiency and effectiveness of the co-registration of satellite imagery, this paper proposes a pre-qualified area matching, which is composed of feature extraction with Laplacian filter and area matching algorithm using correlation coefficient. Moreover, to improve the accuracy of co-registration, the outliers in the initial matching point should be removed. For this, two outlier detection techniques of studentized residual and modified RANSAC algorithm are used in this study. Three pairs of Landsat images were used for performance test, and the results were compared and evaluated in terms of robustness and efficiency.

Key Words : Image co-registration, Area Based Matching, Studentized Residual, Modified RANSAC.

1. Introduction

Recently, the usage of satellite imagery has greatly increased due to the development of various sensors (optic, multi-spectral, hyperspectral etc.) in remote sensing and photogrammetry society. Image co-registration or finding conjugate points must be done just in case of handling several satellite imagery acquired from different time periods. Image matching technique is the typical procedure to do this. There are two kinds of image matching techniques, which are area based matching and feature based matching. Even though each of them has pros and cons, none of them can prevent outliers and mis-matching points. For this reason, numerous studies have attempted to find the solution about outlier removal. Fisher (1981) proposed RANSAC as an alternative opposite to conventional approach. Chen (1998) suggested RANSAC based Darced techniques to overlap 3D images. Moreover Chum. (2004) estimated epipolar geometry using RANSAC. Kim and Im (2003) proposed image co-registration with area-based matching and outlier removal techniques. Moreover Okabe (2003) studied object-recognition using RANSAC approach. In this study, the author processes image co-registration using pre-qualified

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area based matching and remove outliers among matching points with studentized residual and modified RANSAC Algorithm. After that, the efficiency and accuracy are evaluated of each outlier removal technique.

2. Iamge Co-Registration and Outlier Removal

1) Pre-qualified Area based Matching

Fig. 1 shows the flow chart of pre-qualification area based matching which is used in this study.

Throughout pre-qualification and initial approximation, binary edge-map is created from reference image and use them as interested points. That means that the processing time of whole matching procedure is significantly reduced compared with general area based matching. The cross-correlation for matching threshold is set to 0.85 and the size of matching window is 11 by 11 pixels.

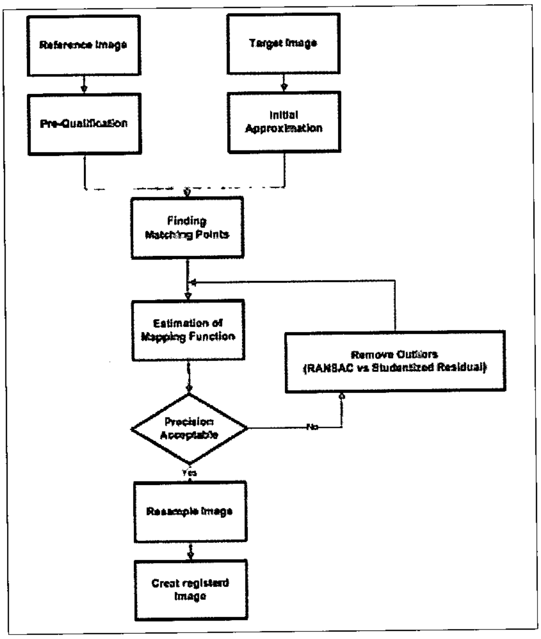

Fig. 1. The Flow Chart of Pre-Qualified Area Based Matching

2) Outlier Removal

The initial set of matching points always includes outliers and decreases co-registration accuracy. Landsat TM/ETM+ images for the study, the RMSE of the first estimation is often more than one pixel, which is good evidence of outlier inclusion in the list of matching points. For the reason, it is natural that outlier detection and removal is very important procedure for high accuracy.

(1) Studentized Residual

The mapping function that is used in this study is affine transform. This affine transformation which is the well-known linear system is used as a mapping function. Equation 1 shows that the formulation of affine transform.

$$\begin{bmatrix} X_1 \\ Y_1 \\ \cdot \\ \cdot \\ X_p \\ Y_p \end{bmatrix} = \begin{bmatrix} x_1 & y_1 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_1 & y_1 & 1 \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot & \cdot & \cdot \\ x_p & y_p & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & x_p & y_p & 1 \end{bmatrix} \begin{bmatrix} m_1 \\ m_2 \\ m_3 \\ m_4 \\ m_5 \\ m_6 \end{bmatrix} + \begin{bmatrix} \varepsilon_{x1} \\ \varepsilon_{y2} \\ \cdot \\ \cdot \\ \varepsilon_{xx} \\ \varepsilon_{yx} \end{bmatrix}$$

$$R_{2p\times 1} = S_{2p\times 1} \cdot M_{6\times 1} + \varepsilon_{2p\times 1} \qquad (1)$$

where $\varepsilon \sim N(0, I\sigma^2)$, p is the number of matching points, N denotes a normal distribution, and I is an identity matrix of 2p×2p. X and Y is the coordinates after transformation and x and y is before transformation. Vector M is six affine transformation parameters. The equation 2 and 3 shows least square estimate of M and residual ε.

$$\hat{M} = (S^T S^{-1})\, S^T R \qquad (2)$$

$$\begin{aligned} \varepsilon &= R - \hat{R} = R - SM = (I - S(S^T S)^T S^T)R \\ &= (I - H)R \end{aligned} \qquad (3)$$

From equations (2) and (3), the distribution of the ith residual is:

$$\varepsilon_i \sim N(0,(1 - h_{ii})\delta^2) \qquad (4)$$

where hii is the (i, i) element of the matrix H, which is the "hat matrix.". The variance of the residual is not a constant but a function of matrix S. This means that simple comparison of the magnitudes of residual is not a good criteria to remove outliers. Instead of that, the standardized ith residual with respect to n observations and k parameters is:

$$r = \frac{e_i}{s\sqrt{1 - h_{ii}}} \tag{5}$$

where, $s = \sqrt{\frac{e^T e}{n - k}}$

This is a rather robust criterion for evaluation of an observation. The approximate distribution of the standardized residual was calculated by Lund (1975). Moreover, Weisberg (1980) proposed a simple equation that converts from standardized residual to studentized residual which follows a t-distribution.

$$t = r(\frac{n - k - 1}{n - k - r_1^2})^{\frac{1}{2}} \sim t(n - k - 1) \tag{6}$$

Considering the number of matching points is more than thousands, normal distribution can be used instead of t-distribution. That is to say, it's easy to remove outliers among matching points using studentized residual which has statistical meaning.

(2) Modified RANSAC

RANSAC (Random Sample consensus) is the alternative method conventional fitting method. Instead of using as much of the data as possible to create an initial solution and attempt to eliminate outliers, RANSAC selects small number initial data set as small as possible and enlarges this set with consistent data applying threshold to raw dataset. If there is enough compatible data, RANSAC employs conventional fitting algorithms to create the model. The greatest advantages of RANSAC are that this algorithm guarantees to create solution or model from any given data set. Theoretically, 3 matching points should be used to create initial affine model. However, the distribution of sample points is a critical condition to acquire mapping function which satisfies acceptable accuracy. For this reason, the author applies modified RANSAC. First, The whole scene is divided into 16 section as fig. 2 shows, then select one point from each section. That means 16 points are used for generating initial model instead of just 3 points.

1	2	3	4
5	6	7	8
9	10	11	12
13	14	15	16

Fig. 2. 16 Sections of whole image.

The other issue that we have to consider is the number of iteration. Basically, the iteration is perfomed as many as possible which means we should take into account the total combination of whole data. Let w be the probability that any selected matching point is within threshold of the model and select n good data points, the expected number of trials k is

$$E(k) = \frac{1}{b} = w^{-n} \tag{7}$$

Generally, we would like to exceed E(k) trials by adding one or two standard deviations for stability and accuracy of model.

There's another approach to determine the number of iterations. If we are sure of the probability z, which is one of our random selections is an error-free set of n sample points, the number of iteration k is

$$k = [\log(1 - z)/\log(1 - b)] \tag{8}$$

where, $b = w^n$

3. Experiments

3 pairs of landsat images which cover Korea

Table 1. Specification of landsat imagery.

Path/Row	Sensor	Acquisition date	Resolution(m)	Band
P115 /R34	Landsat ETM+	1991-08-28	28.5×28.5	1
		2000-05-08	28.5×28.5	1
P115 /R35	Landsat ETM+	2000-05-08	28.5×28.5	1
		2004-04-17	28.5×28.5	1
P115 /R36	Landsat ETM+	2000-05-08	28.5×28.5	1
		2004-04-17	28.5×28.5	1

peninsula are used for experiments. These selected images have various land characteristics, Table 1 shows that the detailed information of images.

P115R35 covers western part of Korea, which is flat and little mountainous area. P115R34 contains eastern part of Korea, mountainous area. Last image, P115R36 is the southern part of Korea,.includes little land and sea. As mentioned above, the number of matching points is more than a thousand, even up to a few tens of thousands. If we use all matching points to create mapping function, it takes a long time to process regardless of outlier removal techniques. For efficiency, we divide the image into 16 sections and select 50 points in the order which has the highest correlation coefficient.

1) Studentized Residual

Throughout whole scene, 800 points are selected and remove ourliers using studentized residual. The confidence level of normal distribution is 95% and Table 2 shows the experimental result.

Because of SLC-off effect, P115R36 and P115R35 imagery have severe scratch throughout the

Table 2. Result using Studentized Residual.

Path/Row		Number of matching points	RMSE
P115R34	Before	790	1.464235
	After	532	0.444783
P115R35	Before	800	1.661428
	After	505	0.508992
P115R36	Before	641	1.639309
	After	391	0.489339

boundary. Due to these scratches, the number of matching point is smaller than that of P115R34. The results explains that 33 ~ 40% points of total matching points are removed as outliers (P115R34 : 33%, P115R35 : 37%, P115R36 : 40%). Expecially, P115R36 contains little land which is located in upper left part of image and most scene covers water area. So it has least number of matching points. However, the RMSE of each case is less than 0.5 pixels which means that this shows quite accurate results.

2) Modified RANSAC

Firstly, we create initial model using 16 points then remove point which has more than 1 pixel residual among total matching points. After that procedure, create adjusted model using remained matching points and compute RMSE. Basically, the remained points are highly dependent on initial model which means that it's dependent on 16 points that are chosen first step. According to equation 7, iteration is about 1000~14000 and 10600 according to equation 8. However, in terms of efficiency, we don't need to perform the whole iteration process. For this reason, the number of iteration is increased by 100 from 100 to 1000 and each step is done 3 times. Table 3 shows the results.

P115R34 and P115R36 images have well-distributed points even though P115R35 is SLC-off imagery. However, P115R36 has poor point distribution and RMSE value (0.303405) compared to P115R34 (0.226930) and P115R35 (0.280436).

3) Studentized Residual vs. Modified RANSAC

Compare the result of each algorithm. Modified RANSAC could have detected more outliers than the

Table 3. Results using modified RANSAC.

Path/Row	RMSE	Number of Matching Points
P115R34	0.226930	373
P115R35	0.303405	216
P115R36	0.280436	64.3

case of using studentized residual. Moreover, modified RANSAC algorithm has better RMSE value compared to the case of using studentized residual even though it has less matching point to estimate mapping function. In terms of preserving the number of data, using studentized residual is better performance. However, if we take into account that the affine transform is the basic linear transformation and it needs 3 points for exact solution, the large number of points doesn't guarantee better results. The other factor that we should consider is processing time as mentioned above. Fortunately, there's little difference between each case despite the intensive calculation process of modified RANSAC approach. It even has better RMSE which means more accuracy.

4. Conclusion

In this study, we performed the image co-registration by pre-qualified area based matching using 3 pairs of landsat imagery of Korea. To satisfy certain level of accuracy, the outliers in matching points are removed by applying studentized residual techniques and modified RANSAC approach. The RMSE in case of using modified RANSAC is better than the other and the value has changed from 0.2 to 0.3. For future work, affine transform could not be appropriate just in case of handling high resolution satellite image and could have serious errors depending on the ground condition. That means other mapping functions (collinearity equation, RPC etc) should be applied through same process of this study using various kinds of satellite imagery.

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