AUTOMATIC SATELLITE IMAGE REGISTRATION BY COMBINATION OF STEREO MATCHING AND RANDOM SAMPLE CONSENSUS

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KEY WORDS: Automatic registration, precision correction, RANSAC, stereo matching.

ABSTRACT: In this paper, we propose a new algorithm for automated image registration or precise correction of satellite images. We assume that ground control points used previously are stored within the system. The algorithm first applies matching between the GCP chips stored and a new image to be registered and creates new control points. An automated stereo matching based on normalized cross correlation will be used for matching. Then the algorithm applies Random Sample Consensus to discriminate false matches from being considered for modeling. We believe that robust estimation scheme is important for automated image registration. We carried out experiments with SPOT images over three test sites. Through stereo matching, a number of control points were generated. The RANSAC was applied to the control points. All outliers were correctly identified for all three test sites and mapping functions estimated without outliers. The accuracy of estimation was comparable to that of estimation with control points generated all by manual measurements. The results support that our algorithm can be used for robust automated registration.

1. INTRODUCTION

In order to utilize remotely sensed images in geographic applications, it is necessary to relate image coordinates to a reference coordinate system (datum), to a map, or to a reference image. This process is referred to as image registration. After registration, we may rearrange the pixel values of the raw image so that the grids of new image align with reference coordinate system. This process is called as geometric correction. In processing satellite images, there are two kinds of geometric correction. One is systematic correction and the other is precision correction. Systematic correction is to rearrange (or resample) the image with ancillary information given from the satellite on-board sensors and without ground control points whereas precision correction uses ground control points. Precision correction offers higher accuracy than systematic one but does require significant human operation. In this paper, we propose a new methodology for automated image registration with ground control points or precision correction of satellite images.

As mentioned, image registration or precision correction requires ground control points (GCPs), a point whose image coordinates and whose reference coordinates are known. Traditionally they have been generated by human operators. Substantial human involvements are required for the task and reduction of human involvements became an important issue.

This paper will address a new algorithm for reducing such human involvement in image registration by automatically generating ground control points. We assume that ground control points used previously are stored within the system and create a new ground control points for a new image to be registered by stereo matching. There are many previous publications dealt with the automation in this step, in particular for the preparation of error-free ground control points [1-3]. It is however important to notice that while devising error-free stereo matching scheme is very difficult, a simple robust estimation can help the robustness of automated image registration to a great deal. We accordingly will use the Random Sample Consensus (RANSAC) scheme[4] in order to filter out any mismatches from stereo matching and achieve reliable automation in image registration. The detailed explanation is given in the next section.

2. AUTOMATIC IMAGE REGISTRATION METHOD

Our algorithm works in two steps: The first one is the automated generation of control points using stereo matching. The second one is the robust estimation of mapping functions using control points filtered out through the RANSAC. Although the algorithm in this paper can be extended to other type of images, we limit our discussion here to satellite images. We assume that satellite images will possess ancillary data, i.e., the information on approximate coordinates of four corners, tilt (or incidence) angle and scene orientation angle. We further assume that we have a-priory knowledge on the approximate error boundaries of the ancillary data.

For the generation of control points, we first define the region of interest (ROI) for a new image to be registered (hereby "target" image). A ROI is defined by extending scene boundaries defined in ancillary data of a target image to allow for errors in them. Then GCP chips within the ROI is searched for. Then matching proceeds between the target image and GCP chips. Results of matching constitute new GCPs of the target image.

For stereo matching, we use the normalized cross correlation as a measure to determine the correspondence. In this step, the ancillary data of the target image and GCP chips are utilized. The size of target window is set adaptively according to the scale difference between the GCP chips (reference) and the target image. The scale difference is mainly due to differences in ground sampling distances and different incidence angles. A proper scale factor must be introduced to take this into account. Different scene orientation angles between the reference and target image (or window) imply that the ground foot-prints of the reference and target windows do not coincide even though the center points of reference and target windows are perfectly aligned. This effect can be eased by rotating the target window to the amount of orientation difference. Through this procedure, we can generate GCPs automatically.

The second step is the robust estimation of a camera model for the target image. This can be done by removing mismatches by RANSAC and estimating camera models with control points remained. The Random Sample Consensus (RANSAC) proposed by [4] is a powerful and robust estimator in the presence of outliers (or mismatches). We can apply the RANSAC without the prior knowledge of error distributions. As long as we can tell the boundaries between "inliers" (or true matches) and outliers the RANSAC works. In our case of automatic registration, we can distinguish the inliers and outliers by the amount of camera modeling error. When we establish a camera model and a control point deviates from the model by more than, say, three pixels, we can tell the point is not supporting the model. The RANSAC works by estimating a model with minimum required number of control points selected randomly and checking whether other control points support the model. It repeats these procedures for a certain number of times and chooses the best model that has the largest supports. After that, it re-estimates the model using those control points used for the best model and other supporting control points. In fact, robust estimation is one of the key elements in many computer vision problems. It is somewhat strange that for automated registration this scheme has not been popular. Here, we will show that robust estimation can work for our purpose.

Among several mapping functions (or camera models) available for satellite images, we will use the direct linear transformation model (DLT) by Gupta and Hartley[5]. This algorithm is expressed in a matrix form and easier to handle. However, the algorithm described in this paper can work with other camera models. Estimating the mapping function of the DLT model is finding coefficients of m_{ij} using control points $\{C_{target}, R_{target}; X_{ref}, Y_{ref}, Z_{ref}\}$.

$$\begin{bmatrix} wC_{target} \\ R_{target} \\ w \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & m_{34} \end{bmatrix} \begin{bmatrix} X_{ref} \\ Y_{ref} \\ Z_{ref} \\ 1 \end{bmatrix}$$

3. RESULTS AND DISCUSSIONS

Three test sites were chosen for demonstration of our approach. For each test site, a stereo pair of SPOT images and GPS surveyed GCPs were prepared. Table 1 summarizes the characteristics of stereo pairs and GCPs.

Table 1. Summary of test scenes and test control points

Test Site	Taejon	Boryung	Junju
Scene Acquisition Date	L: Oct. 14, 1997 R: Nov. 15, 1997	L: March 1, 1997 R: Nov. 15, 1997	L: Oct. 14, 1997 R: Nov. 15, 1997
Incidence Angle	L: 29.7? R: 4.9?	L: -29.7? R: 0.5?	L: 29.7? R: 4.9?
Scene Orientation angle	L: 13.7? R: 11.3?	L: 8.1? R: 10.9?	L: 13.7? R: 11.3?
No. of GCPs	21	20	16

For each test site, the left image was used to create GCP chips and the right image as a target image to be registered. Small image windows were defined on GCPs over the left image and were stored in the system as GCP chips. The ancillary data of the right images were used to define a ROI and to search for GCP chips within the ROI. Since the GPS surveyed GCPs were all lying within the stereo coverage, all GCP chips created were searched for.

Automated matching was carried out. For each GCP chip, a point with highest normalized cross correlation (NCC) value was chosen as a correspondence. The search range was set as ? 2kms (or ? 200 pixels). Table 2 summarizes the result of automated stereo matching for the three test sites.

Table 2. Results of automated stereo matching. Each result shows the number of true matches versus the number of false matches.

Test site	Taejon	Boryung	Junju
NCC > 0.8 0.6 < NCC < 0.8 NCC < 0.6	7 : 0 7 : 7 NA	5 : 0 9 : 3 2 : 1	7 : 0 2 : 2 0 : 5
Total	14 : 7	16 : 4	9 : 7

Match results were classified by their highest NCC values. Within each class the number of true matches versus the number of false matches are shown. If a match point did not deviate from the manually measured correspondence by more than three pixels, it was classified as a "true" match. For Taejon, automated matching created 14 true matches and 7 false matches in total. In this case, if the NCC value was higher than 0.8, there was no false matches. If the NCC value lied between 0.6 and 0.8, there were 7 false matches among 14 match points. For the other two sites, test results can be read similarly. Figure 1 shows a few examples of true and false matches for Taejon test site. It is notable that there are quite different brightness patterns between the GCP chips and the right image patch even for the true matches.

Among the match results, the RANSAC selected randomly eight points for estimation and others for checking supports. For experiments, iteration number was set to 2000 for all three, although there are means to automate such iteration number. The distance of three pixels was used again to decide whether a CP was supporting the estimation or not. The best model, which had the largest supports, was re-estimated with all supporting GCPs. Table 3 summarizes the estimation of $\mathbf{M}_{target}$ through the RANSAC. For comparison, $\mathbf{M}_{target}$ was also estimated using all manually measured control points.

CP chips	Examples of True Match	CP chips	Examples of False Match

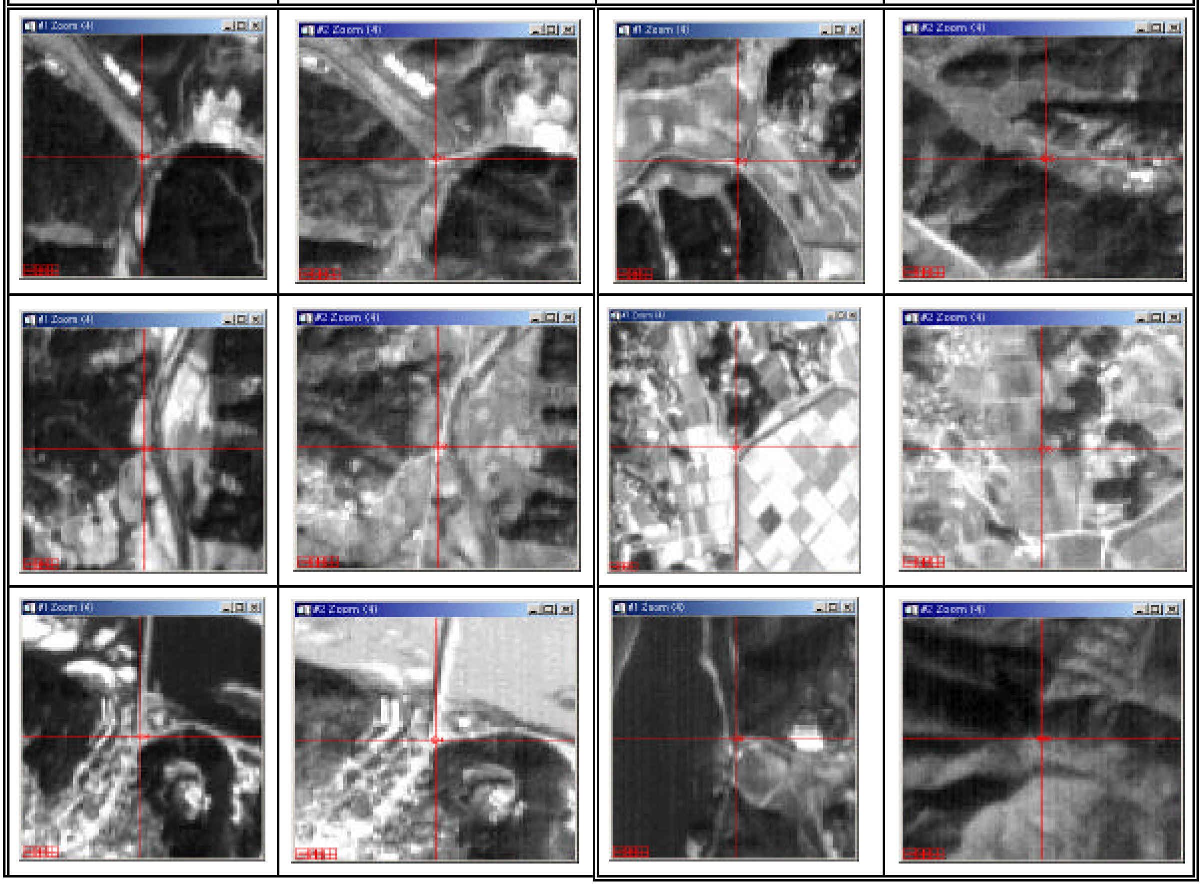

Figure 1. A few examples of true and false matches for Taejon test site.

Table 3. The estimation of $\mathbf{M}_{target}$ through the RANSAC

Test Area	Taejon	Boryung	Junju
Modeling with the RANSAC			
No. of points used for modeling	14	16	9
No. of outlier detected	7	4	7
Modeling error (RMS)	0.70 pixels	0.79 pixels	0.90 pixels
Modeling with the true CPs			
No. of points used for modeling	21	20	16
Modeling error (RMS)	0.41 pixels	0.60 pixels	0.44 pixels

The table 3 shows that RANSAC has successfully detected all outliers. For Junju site, there were several models that had the largest supporting number of one. This ambiguity was because the number of inliers was only one more than the minimum number of points required for modeling. Outliers were by accident lying closely to the estimation. This ambiguity was resolved correctly by taking the average supporting distance into account. This phenomenon indicates the limitation of the RANSAC or our approach. We need the number of inliers more than, say, nine for robust estimation of $\mathbf{M}_{target}$. The modeling accuracy of $\mathbf{M}_{target}$ from the RANSAC was compared to the modeling accuracy of $\mathbf{M}_{target}$ estimated by true GCPs. The accuracy of the former was lower than but comparable to that of the latter. For all three sites, it was better than one pixel. Note that the GCPs used for the latter were error-free whereas the GCPs, inliers as well as outliers, used for the former contained errors.

4. CONCLUSIONS

This paper proposed a method to solve the important problem of automated image registration. We emphasized the role of robust estimation in automated registration. We targeted satellite images, which normally possessed ancillary data. We devised a simple but efficient stereo matching algorithm to produce control points automatically. We then used the RANSAC to estimate mapping functions in the presence of outliers. The experiments supported that our algorithm worked well. As earlier results in other applications, this paper provides the successful application of the RANSAC in automated image registration and in automated precision correction of satellite images

REFERENCES

[1] J. Ton and A. K. Jain, “Registering Landsat images by point matching”, IEEE Trans. Geoscience and Remote Sensing, vol. 27, no. 5, pp. 642-651, Sept., 1989

[2] A. D. Ventura, A. Rampini, and R. Schettini, 1990, “Image registration by recognition of corresponding structures”, IEEE Trans. Geoscience and Remote Sensing, vol. 28, no. 3, pp. 305-314, May, 1990

[3] V. Govindu and C. Shekhar, “Alignment using distributions of local geometric properties”, IEEE Trans. Pattern Analysis and Machine Intelligence, 21(10):1031-1043, Oct. 1999

[4] M. A Fischler and R. C. Bolles, “Random Sample Consensus: A paradigm for model fitting with applications to image analysis and automated cartography”, Communications of the Assoc. Comp. Mach., vol. 24, no. 6, pp. 381-395, June 1981

[5] R. Gupta and R. Hartley, “Linear pushbroom cameras”, IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 19, no. 9, pp. 963-975, Sept. 1997