Automatic Satellite Image Registration by Combination of Matching and Random Sample Consensus

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***Abstract*—In this letter, we propose a new algorithm for automated registration of satellite images. Here, registration means finding the relation between image coordinates and a reference coordinate system. The algorithm consists of two steps. The first one is the automated generation of control points. An automated matching based on normalized cross correlation will be used. We have improved the accuracy of matching by determining the size and shape of match windows according to incidence and scene orientation angles. The second one is the robust estimation of mapping functions from control points. We used the random sample consensus (RANSAC) algorithm for this step. We argue that it is the second step which gives the robustness of any automated registration algorithms. We carried out experiments with SPOT images over three test sites. Through matching, a number of control points were generated. 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.**

***Index Terms*—Automatic registration, matching, precision correction, random sample consensus (RANSAC).**

I. 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. In this letter, we define this process as image registration. Registration here is a global registration and ignores local deformations, since we can assume a rigid body transformation between the three-dimensional (3-D) world and satellite images.

In general image registration requires control points (CPs). A CP is a point whose image coordinates and whose reference coordinates are known. Traditional approach to acquire CPs is by human operators. In order to accurately register images to a reference datum, for example, global positioning system (GPS) surveying is often involved. For image-to-map registration human operators have to identify image points that correspond to a point on a map. Such substantial human involvements make image registration a laborious, tedious and costly process. Reduction of human involvements in the process of image registration has been a hot research theme.

The process of image registration can be composed of three steps [1]: 1) sufficient number of CPs are prepared; 2) CPs are used to estimate a mapping function between the image to be registered to the reference datum, to a map, or to a reference image; 3) using the mapping function images are resampled to align with the reference system. It is the first step that requires human operations most. Much of previous literature has dealt with automation in the first step. For the preparation of error-free CPs, the automatic selection of various image features as candidate control points [1]–[3], the use of multiresolution or wavelet-based approach for matching [4]–[6], the use of invariant properties of image features [7]–[11], generic algorithm-based matching [12], and the use of additional information such as digital terrain models (DTMs) [13] have been studied among others.

It is, however, impossible to guarantee error-free match results at every occasion. Matching may fail for satellite images taken with different viewing conditions or for very repetitive patterns, etc. For automated image registration, studies on the second step above, i.e., robust estimation of mapping functions at the presence of outliers, are demanding.

This letter deals with the first and second steps of image registration. We will show that automated image registration is feasible with the combination of automated matching and a robust estimation technique. In doing so, we emphasize the role of robust estimation in automated registration. The work described in this letter has been carried out as a part of development work of a ground receiving and preprocessing system for remote sensing satellites. Our intension is to use the automated image registration algorithm for processing satellite images within the system so that precision geometric correction of satellite images can be done automatically. Hence we concentrate our research on registering satellite images with respect to ground reference coordinate systems.

We will use an automated matching algorithm for the generation of CPs from satellite images. In this algorithm, we design match constraints using ancillary data attached to each satellite image. The search range and the shape of match windows are set automatically. We do not hire any sophisticated processing further. In this way, we believe our algorithm can be applicable to wider range of images. Results of automated matching will contain unavoidable errors. For robust estimation of mapping functions in presence of outliers, we will use the random sample consensus (RANSAC) algorithm [14]. This algorithm has been

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reported to handle outliers successfully in many applications [15]–[18]. We will show that it works too for automated image registration.

We tested our approach with SPOT images over three test sites. For all sites, all outliers (or false matches) have been successfully identified. Correct mapping functions have been obtained, whose accuracy was close to the mapping function estimated with CPs obtained by human operations.

II. First Step: Automated Generation of CPs

We will explain the first step of our approach, automated generation of control points. We assume that there are a number of previously and probably manually registered images (reference images) and CPs used for previous registration. For automated generation of CPs, we can match new images (target images) against and register with respect to reference images.[1] On the other hands, we can reuse CPs used for previous registration by storing CP chips, small image patches centered on the CPs with their reference coordinates. We can match target images against these CP chips. If CP chips contain ground reference coordinates, we can register target images with respect to a ground reference system.[2] In either case, we also assume that target images have ancillary data, which describe information on imaging geometry (tilt angle, platform position, image orientation angle, etc.), image boundary coordinates (usually in a geodetic coordinate system) and acquisition time. Such information contains errors but can be used as initial approximations.[3]

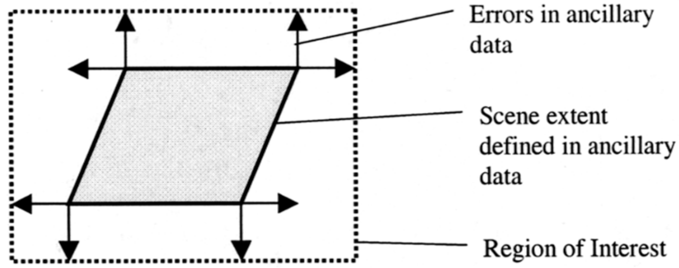
The procedures of automated generation of CPs are as follow. First, we define a region of interest (ROI) by extending scene boundaries defined in ancillary data of a target image to allow for errors in them [see Fig. 1(a)]. Next, we search for CP chips that are within the ROI or reference images that overlap with the new image. Then matching proceeds between the target image and CP chips or between the target image and reference images. Results of matching constitute new CPs of the target image.

For matching, we use the normalized cross correlation as a measure to determine the correspondence. We can utilize ancillary data of the target image to estimate initial image location of a reference point (i.e., a point in the reference image or the center point of a CP chip), since we know the approximate scene boundaries and the coordinates of the reference point. We can limit the search range as the amount of (maximum) errors in scene boundary information. We can also use ancillary data to define match windows adaptively [see Fig. 1(b)]. The size of match window is set adaptively to compensate the scale difference between a CP chip and target image. The scale difference is mainly due to the different ground sampling distances and incidence angles. Different scene orientation angles between a CP chip and target image imply that the ground foot-prints of the chip and target windows do not coincide even though their center points are perfectly aligned. This effect can be eased by rotating the target window to the amount of the orientation difference.

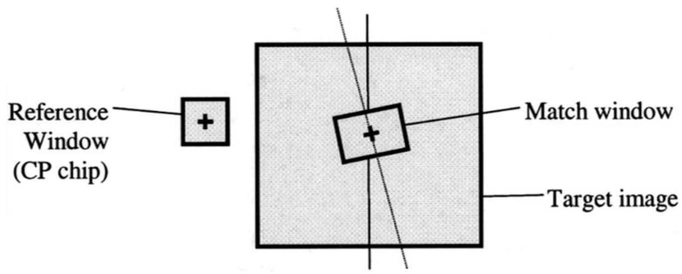
[1]Image-to-image registration

[2]Image-to-map or image-to-datum registration

[3]For SPOT images, errors of boundary coordinates specified in their ancillary data are well less than ± 2 km [19].



(a)



(b)

Fig. 1. Determination of region of interest and match windows. (a) Determination of ROI. (b) Determination of match window adaptively.

Through the procedures described above, we can generate CPs automatically. If we use reference images to match against a target image, a resulting CP will be composed of reference image coordinates $(C_{\rm ref}, R_{\rm ref})$ and target image coordinates $(C_{\rm target}, R_{\rm target})$. If we use CP chips for matching, a resulting CP will be composed of reference ground coordinates $(X_{\rm ref}, Y_{\rm ref}, Z_{\rm ref})$ and target image coordinates. In either case, CPs will contain false matches and these must be removed from modeling. This can be done during our second step of automated registration: robust estimation of mapping functions.

III. Second Step: Robust Estimation of Mapping Functions

The second step of automatic image registration is the estimation of mapping functions using CPs generated from the first step. Although a lot of previous publications have focused on the first step, we believe the second step is very crucial for accuracy and robustness of automated image registration. CPs from the first step will always contain false matches. These will act as outliers and hinder accurate estimation of mapping functions if naïve estimation methods are used. We need robust estimation to overcome the effects of false matches and achieve correct mapping functions.

RANSAC [14] is a powerful and robust estimator in the presence of outliers. It does not require prior assumption of the distribution of outliers. As long as we can postulate boundaries between inliers and outliers [20], we can use RANSAC to cope with outliers. It works by estimating a model with the 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 reestimates the model using all supporting control points.

In computer vision applications, RANSAC has been used in feature extractions [15], [21], [22], motions [18], estimation of epipoles [16], and estimation of two-dimensional (2-D)–3-D mapping functions of an uncalibrated camera [17]. Notably, RANSAC was used in automated registration of 3-D rigid objects [23]. In this example, RANSAC was combined with a search algorithm to generate control points. Here, we will use RANSAC for automated registration of satellite images, where search range is large, disparity values are diverse and hence frequent false matches unavoidable. We will show that RANSAC can work for our purpose.

We can divide the estimation of mapping functions for automated registration into three cases. The first case is the registration of a target image with respect to the reference image. This is a 2-D–2-D transformation and a mapping function can be estimated using correspondences between the reference and target images. However, our intension is automated precision correction of satellite images (or 2-D–3-D transformation) and this case will not be dealt here. Besides, this case has been studied by many colleagues [1], [3], [5]–[10], [24]. The second case is the registration of a target image with respect to the ground reference coordinate system. This is a 2-D–3-D transformation and the mapping function $\mathbf{M}_{\text{target}}$ will be estimated using correspondences between CP chips and the target image. Our letter will examine this case in detail and conclude whether automated registration in this case can be achieved. The third case is also the 2-D–3-D registration of a target image with respect to the ground reference coordinate system but uses the 2-D–2-D correspondence between the target and reference image coordinates. We will discuss the feasibility of this case in relation to the limitations of the second case.

A. Image-to-Map/Datum Registration With CP Chips

In this case, CPs are generated by matching a new image against CP chips. Each CP will consist of target image coordinates and ground reference coordinates. The mapping function $\mathbf{M}_{\text{target}}$ is the transformation from 3-D reference coordinates to 2-D target image coordinates. Its representation depends on the type of cameras, i.e., perspective, linear pushbroom, etc., used for image acquisition. In this letter, we focus on satellite images taken by linear pushbroom (LP) cameras. Among others, we will use the direct linear transformation (DLT) for LP images proposed by [25] as the relationship between 2-D image coordinates $(C_{\text{target}}, R_{\text{target}})$ and 3-D ground coordinates $(X_{\text{ref}}, Y_{\text{ref}}, Z_{\text{ref}})$. The DLT can be expressed as

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

where R_{target} is the direction of scanning, w a weight, and m_{ij} coefficients of the mapping function $\mathbf{M}_{\text{target}}$. RANSAC will be used to identify outliers, i.e., false matches between CP chips and the target image and to estimate $\mathbf{M}_{\text{target}}$ correctly.

B. Image-to-Map/Datum Registration With a Reference Image

In this case, we have 2-D–2-D correspondences between a target and reference image and wish to establish a 2-D–3-D relationship between the target image coordinates and ground coordinates. For this, we can use the epipolar relationship between the target and reference images. Epipolar relationship is not a transformation from the reference to target images per se but a property of correspondences between the two images uniquely defined by viewing geometry of the two. Epipoalr relationship can be explained by the fundamental matrix. The representation of the fundamental matrix $\mathbf{F}$ also depends on the type of cameras. For LP cameras, we can use the representation proposed by [25]

$$\begin{pmatrix} R_{\text{target}} & C_{\text{target}}R_{\text{target}} & C_{\text{target}} & 1 \end{pmatrix} \begin{pmatrix} 0 & 0 & f_{13} & f_{14} \\ 0 & 0 & f_{23} & f_{24} \\ f_{31} & f_{32} & f_{33} & f_{34} \\ f_{41} & f_{42} & f_{43} & f_{44} \end{pmatrix} \begin{pmatrix} R_{\text{ref}} \\ C_{\text{ref}}R_{\text{ref}} \\ C_{\text{ref}} \\ 1 \end{pmatrix} = 0.$$

The fundamental matrix $\mathbf{F}$ is a composition of the mapping function $\mathbf{M}_{\text{reference}}$ between the 3-D ground coordinates and 2-D reference image coordinates and the mapping function $\mathbf{M}_{\text{target}}$ between the 3-D ground coordinates and 2-D target image coordinate [25]. If the fundamental matrix $\mathbf{F}$ can be recovered from the correspondences between a reference and target images we know already the mapping function $\mathbf{M}_{\text{reference}}$, then it is possible to estimate the 2-D–3-D mapping function $\mathbf{M}_{\text{target}}$ from the fundamental matrix $\mathbf{F}$. However, robust estimation of the LP fundamental matrix $\mathbf{F}$ is not a trivial job, and comprehensive studies are required to automate such a job.

In Section IV, we will describe the automated image registration using CP chips, point out limitations, and discuss the feasibility of the automated image registration using reference images.

TABLE I
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 CPs	21	20	16

IV. RESULTS AND DSISCUSSIONS

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

For all three sites, the acquisition dates of the left (“L”) and right (“R”) image were not very close, unfortunately. For Taejon and Junju, the difference of acquisition date was about one month, during which season changes from autumn to winter. For Boryung, the left was taken in the spring and the right in the winter. Seasonal changes as well as different illumination conditions made brightness patterns of stereo images appear very different. False matches were deemed unavoidable. We

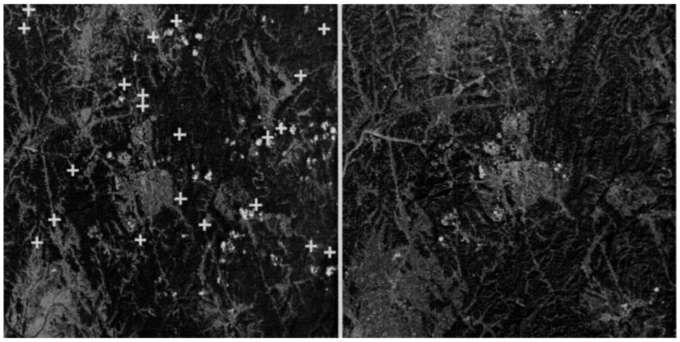


Fig. 2. Left and right SPOT image pair for the Taejon test site. The white crosses in the left image are the location of GPS-surveyed control points. CP chips centered on these points were generated and matched against the right image.

chose the left image (L) and the right image (R) of a stereo pair with difference incidence angles. Scene orientation angle depends on incidence angles and longitude of satellite position. They do not vary much between the left and right image, in general. Fig. 2 shows the left and right image pair of the Taejon test site and the location of CPs in the left image.

A. Image-to-Map/Datum Registration With CP Chips

First, automated registration was tested with CP chips. We created CP chips by defining small image windows from the left image for each test site. The right images were regarded as the image to be registered. The ancillary data of the right images were used to define a ROI and to search for CP chips within the ROI. In our experiments, the GPS-surveyed CPs prepared were within the stereo coverage of the left and right images. For each site, CP chips were all lying within the ROI of the right image.

Automated matching was carried out between CP chips and the target images. In order to check the effect of adaptive patch, matching was repeated twice: once with the conventional rectangular patch with a fixed size and once with the adaptive patch. For each CP chip, a point with highest normalized cross correlation (NCC) value was chosen as a correspondence. The search range was set as ± 2 km (or ± 200 pixels). Table II summarizes the result of automated matching for the three test sites.

For each test site, results from a conventional patch ("C") and adaptive patch ("A") were given. Match results were classified by their highest NCC values. Within each class, the number of true matches versus the number of false matches is 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 with the conventional patch created 11 true matches and ten 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 was between 0.6 and 0.8, there were ten false matches among 16 match points. When adaptive patch was applied, the number of true matches increased (from 11 to 14). As before, if the NCC value was over 0.8, all matches were correct. If the NCC value was between 0.6 and 0.8, there were seven true and seven false matches. For the other two sites, test results can be read similarly. For the three sites, adaptive patch improved the results: for Taejon and Boryung, the number of true matches was increased; and for all three, the NCC values

TABLE II
RESULTS OF AUTOMATED MATCHING WITH CONVENTIONAL RECTANGULAR PATCH ("C") AND WITH ADAPTIVE PATCH ("A"). EACH RESULT SHOWS THE NUMBER OF TRUE MATCHES VERSUS THE NUMBER OF FALSE MATCHES

Test site	Taejon		Boryung		Junju	
Patch shape	C	A	C	A	C	A
NCC > 0.8	5:0	7:0	4:0	5:0	4:0	7:0
0.6 < NCC < 0.8	6:10	7:7	6:3	9:3	5:5	2:2
NCC < 0.6			3:4	2:1	0:2	0:5
Total	11:10	14:7	13:7	16:4	9:7	9:7

of true match became higher. The adaptive patch worked better than the conventional patch. Fig. 3 shows a few examples of true and false matches using an adaptive patch for the Taejon test site. It is notable that there are quite different brightness patterns between the CP chips and the right image patch even for the true matches.

We could interpret the results in Table II to find a suitable threshold between true and false matches. For all three sites, the NCC value of 0.8, for example, seemed a good threshold. However, it is not possible to guarantee this threshold to other sites (see Section IV-B). More importantly, the number of true matches after thresholding was not sufficient enough to estimate $\mathbf{M}_{\text{target}}$. The DLT model $\mathbf{M}_{\text{target}}$ required the minimum number of control points of eight. Therefore, instead of selecting an optimum threshold to discern true and false matches or refining further the match results in Table II, we simply used all the match results for estimating $\mathbf{M}_{\text{target}}$.

Among the match results, RANSAC selected randomly eight points for estimation and others for checking supports. For experiments, the iteration number was set to 2000 for all three, although there are means to automate such iteration number [14], [26]. A 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 reestimated with all supporting CPs. Table III summarizes the estimation of $\mathbf{M}_{\text{target}}$ through RANSAC. For comparison, $\mathbf{M}_{\text{target}}$ was also estimated with all manually measured control points.

RANSAC has successfully detected outliers. For the 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 our approach. We need the number of inliers more than, say, nine for robust estimation of $\mathbf{M}_{\text{target}}$.

The modeling accuracy of $\mathbf{M}_{\text{target}}$ from RANSAC was compared to the modeling accuracy of $\mathbf{M}_{\text{target}}$ estimated by true CPs. 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 CPs used for the latter were error-free, whereas the CPs, inliers as well as outliers, used for the former contained errors.

Fig. 4 shows the result of precision correction of the target (right) image of the Taejon test site. It was obtained by resampling the original image so that the image coordinates align with the ground reference coordinates using $\mathbf{M}_{\text{target}}$ from RANSAC.

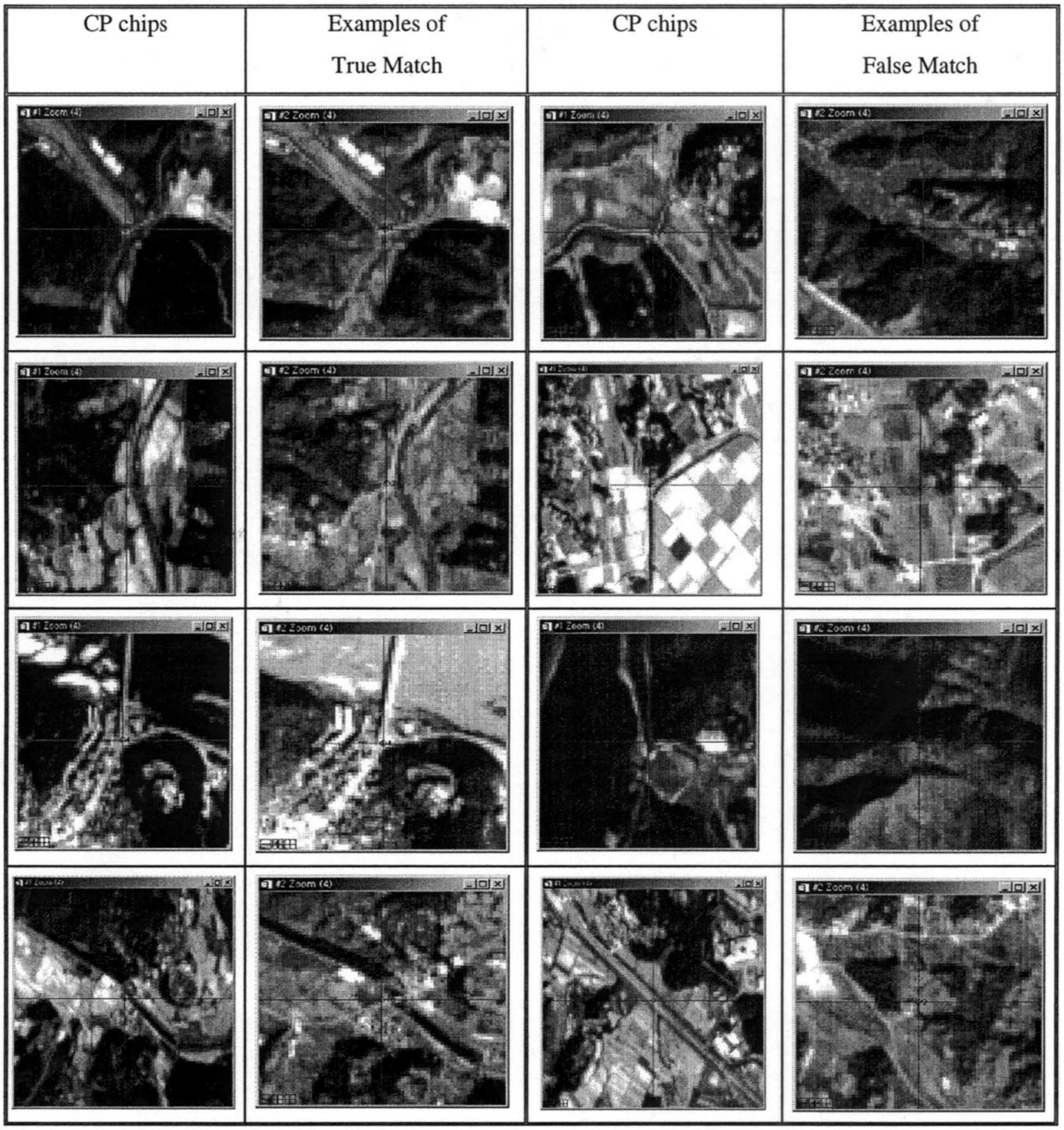


Fig. 3. Several examples of true and false matches for the Taejon test site.

TABLE III
ESTIMATION OF $\mathbf{M}_{\mathrm{target}}$ THROUGH 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, pixel)	0.70	0.79	0.90
Modeling with the true CPs			
- No. of points used for modeling	21	20	16
- Modeling error (RMS, pixel)	0.41	0.60	0.44

We could conclude that our approach of automated matching and robust estimation worked well for automated registration of new images using CP chips.

B. Image-To-Map/Datum Registration With a Reference Image

As we pointed out earlier, registration based on CP chips has one drawback. We need sufficient number of CPs and hence sufficient number of CP chips. We need more CPs for automatic registration then the manual case, since we have to allow for false matches. If we assume the maximum rate of false match as, say, 50%, the minimum number of CP chips will be 16. Or more precisely, if the maximum number of support is not more than one, it is likely that the estimated mapping function is false.

Matching target images against reference images can remove this drawback. It is possible to obtain as many CP chips as wanted from the reference images and use them for matching. As an example, we selected 200 points randomly from the left image of the Taejon test site. Among them, 121 points were found to be within the ROI of the right image. Automated

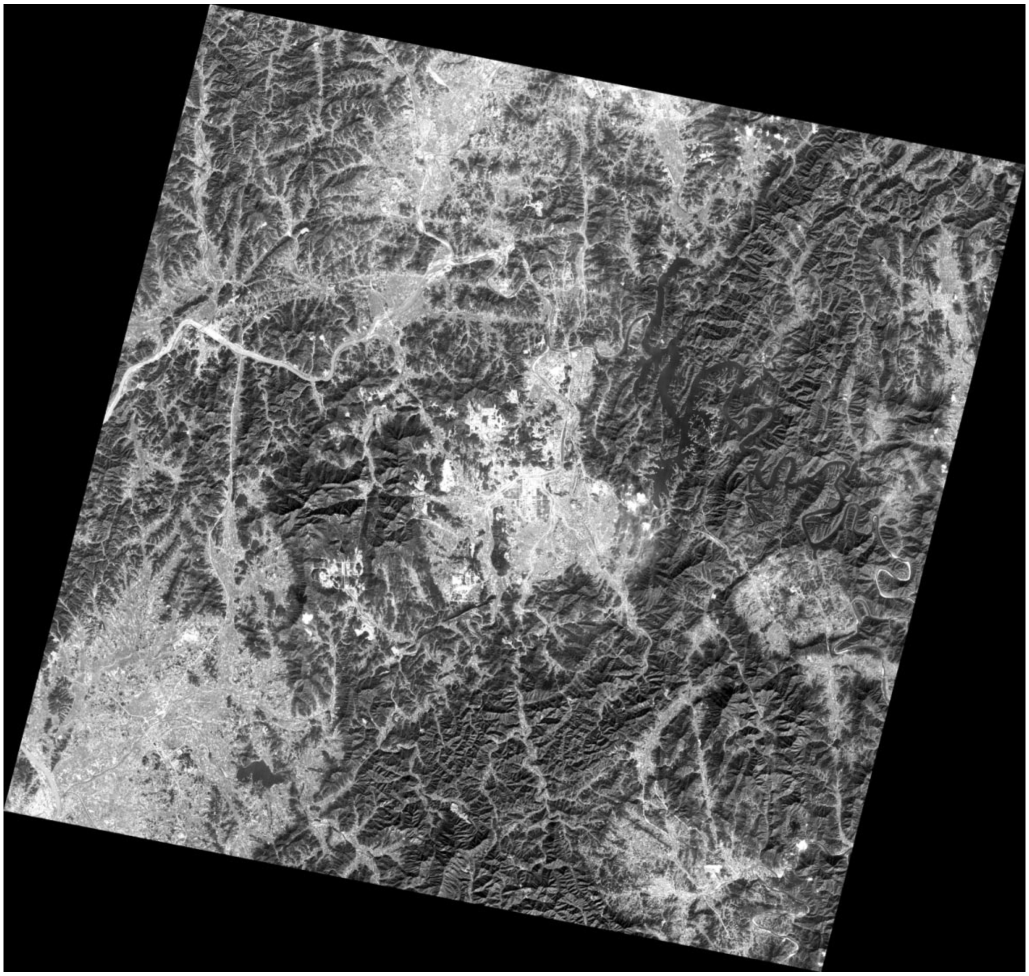


Fig. 4. Result of precision geometric correction of the target (right) image of the Taejon test site.

matching applied to these points. Among 121 point, 94 were matched correctly, while 27 points were falsely matched. Among the 27 false matches, there were four points whose NCC value was higher than 0.8.

This approach requires estimation of the LP fundamental matrix **F** from tie points. This is, however, not a trivial job. It is known that the **F** matrix is quite sensitive to noise, let alone outliers. Currently, research on robust estimation of the **F** matrix from tie points is being carried out. One other point to consider is memory requirement for the job. When we use CP chips, we need to store the chips of small size only. When we use reference images for registration, we need to store as many reference images as required. This will increase the requirement of online storage capacity. This can be one drawback of using reference images for registration.

In summary, it seems that the use of reference image instead of CP chips can ease the limitation of the minimum number of CP chips required. However, due to the fact that a reliable method to estimate **F** from tie points is yet to be developed and the additional memory requirement, we decided to use CP chips for our purpose of automated registration of satellite images. The reliable estimation of **F** from tie points is currently under investigation.

V. Conclusion

This letter proposed a method to solve the important problem of automated image registration. Registration here is a global registration and ignores local deformations. 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 matching algorithm to produce control points automatically. We then used 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 letter provides the successful application of RANSAC in automated image registration and in automated precision correction of satellite images

We compared the usage of CP chips and reference images for automated image registration. We chose the automated image registration using CP chips. We restate the limitation of this approach: this approach assumes that sufficient number of CP chips are available beforehand and works only when the number of inliers is larger than the minimum required number for estimation. If this condition does not meet, we recommend not to go further on automatic registration. To overcome this drawback we discussed the feasibility of using reference images instead of CP chips, which will remain for future work.

We intended to use the algorithm proposed here at satellite image receiving ground station, where a few hundreds of images are acquired each day. The algorithm will be implemented a part of precision correction software for KOMPSAT-2 (Korea Multi-Purpose Satellite) ground receiving system. We believe we can apply this algorithm to other types of images as far as information on approximate scene boundaries and imaging geometry is available.

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