Automatic Generation of GCP Chips from High Resolution Images using SUSAN Algorithms

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Abstract: Automatic image registration is an essential element of remote sensing because remote sensing system generates enormous amount of data, which are multiple observations of the same features at different times and by different sensor. The general process of automatic image registration includes three steps: 1) The extraction of features to be used in the matching process, 2) the feature matching strategy and accurate matching process, 3) the resampling of the data based on the correspondence computed from matched feature. For step 2) and 3), we have developed an algorithms for automated registration of satellite images with RANSAC(Random Sample Consensus) in success. However, for step 1), There still remains human operation to generate GCP Chips, which is time consuming, laborious and expensive process. The main idea of this research is that we are able to automatically generate GCP chips with corner detection algorithms without GPS survey and human interventions if we have systematic corrected satellite image within adaptable positional accuracy.

In this research, we use SUSAN(Smallest Univalue Segment Assimilating Nucleus) algorithm in order to detect the corner. SUSAN algorithm is known as the best robust algorithms for corner detection in the field of compute vision. However, there are so many corners in high-resolution images so that we need to reduce the corner points from SUSAN algorithms to overcome redundancy. In experiment, we automatically generate GCP chips from IKONOS images with geo level using SUSAN algorithms. Then we extract reference coordinate from IKONOS images and DEM data and filter the corner points using texture analysis. At last, we apply automatically collected GCP chips by proposed method and the GCP by operator to in-house automatic precision correction algorithms. The compared result will be presented to show the GCP quality.

Keywords: GCP Chip, SUSAN, Automatic Precision Correction.

1. Introduction

Geometric correction is the transformation of a remotely sensed image so that it has the scale and projection properties of a map. In general, in order to correct the image, we use ground control points(GCPs) to achieve higher geometric accuracy. However, it's very time consuming and laborious process. Therefore there have been many research in the world to correct the image automatically[1][2][3][4][5].

The general process of automatic image registration include three steps: 1) The extracting of feature to be used in the matching process, 2) the feature matching strategy and accurate matching process, 3) the resampling of the image based on the correspondence computed from matched feature. For step 2) and 3), we have developed an algorithms for automated registration of satellite images with RANSAC(Random Sample Consensus) in success[6][7].

However, for step 1), There still remains human operation to generate GCP Chips that is time consuming, laborious and expensive process.

The main idea of this research is that if there are previously corrected satellite image within adaptable positional accuracy, we are able to automatically generate GCP chips using the corner detecting algorithms and texture analysis. Then, these GCP chips can be used as an input to automatic precision correction.

The precision of IKONOS GEO image, known as 15m CE 90%, is high enough to successfully apply to correct Landsat-7 panchromatic image.

In this research, we automatically generate GCP chips from standard geometrically corrected IKONOS images(GEO Level) with using SUSAN(Smallest Univalue Segment Assimilating Nucleus) algorithms. Then, we extract reference coordinate from IKONOS images and select GCP candidate using diverse texture analysis(homogeneity, entropy, variance and dissimilarity). We will show the results that these GCP chips can be applied to in-house automatic correction algorithms in success.

2. Methodology

The experiment was carried out as illustrated in Fig. 1 briefly.

At the first, because there are a lot of difference between the resolution of IKONOS and Landsat-7 panchromatic, we will do downsample IKONOS GEO image to Landsat-7 resolutions. And then we will extract the corner points in IKONOS images using SUSAN algorithm. Since there are a lot of corner points in the image, we will need to reduce the number of corner points and select GCP candidate using texture analysis

At last, we make the GCP chips and apply to automatic precision correction of Landsat-7 panchromatic image with in-house automatic precision correction algorithm.

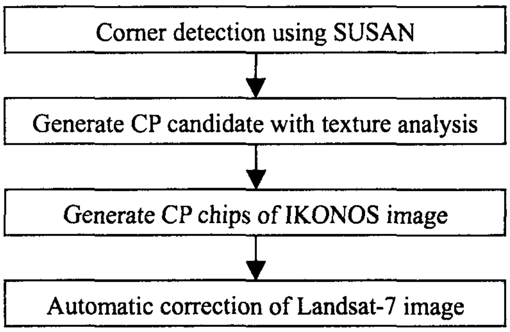

Fig. 1. Procedure of automatic precision correction using SUSAN and texture analysis

1) Corner detection using SUSAN algorithms

Ground control points(GCPs) are well-defined and easily recognizable features which geolocational coordinate are known. In general, human operator selects a feature of an image, the intersection of road, corner of breakwater, corner of playground and etc, use them for image correction. In this research, we use SUSAN algorithms to automatically detect corner in satellite image.

The SUSAN(Smallest Univalue Segment Assimilating Nucleus) is known as robust algorithm to detect corner and edge in the image in the field of computer vision.

The SUSAN principle is implemented using digital approximation of circular masks (sometimes known as windows or kernels). If the brightness of each pixel within a mask is compared with the brightness of that mask's nucleus, then an area of the mask can be defined to have the same (or similar) brightness as the nucleus.

This area is known as USAN (Univalue Segment Assimilating Nucleus) and contains much information about the structure of the image. From the size, centroid and second moment of the USAN, two dimensional features such as edges and corners can be detected. This approach has many differences than other well-known methods, the most obvious difference that no image derivatives are used and no noise reduction is needed[8].

As seen in the Fig. 2, the USAN area is at a maximum when the nucleus lies in a flat region of the image surface. It falls to half of this maximum very near a straight edge and falls even further when inside a corner. This property of USAN's area is used as the main determinant of the presence of the edges and corner of features[8].

2) Generate CP candidate using Texture analysis

When we use SUSAN algorithms to detect corner, there are a thousands of corner points in satellite image. In order to overcome the redundancy and select GCP candidates, we use texture analysis.

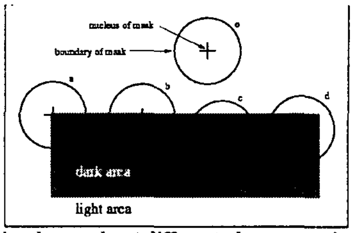

Fig. 2. Four circular masks at different places on a simple image

One commonly applied statistical procedure for interpreting texture uses image spatial co-occurrence matrix(SCM), which is also known as gray level co-occurrence matrix(GLCM). The use of SCM or GLCM in texture analysis is also referred to as the spatial gray level dependence method. Spatial co-occurrence matrix is a widely used texture and pattern recongnition technique in the analysis of remotely sensed data, and it has been successful to certain extent. There are a number of texture measures which could be applied to spatial co-occurrence matrices for texture analysis[9].

In this study, four texture measures based on the co-occurrence matrix were used: homogeneity, entropy, variance and dissimilarity. The formulae used to compute each measure from the spatial co-occurrence matix are as follow:

$$Entropy = \sum_{i,j=0}^{N_g-1} g^2(i,j)\ln g(i,j)$$

$$Homogeneity = \sum_{i,j=0}^{N_g-1} \frac{1}{1+(i-j)^2} g(i,j)$$

$$Variance = \sum_{i,j=0}^{N_g-1} (i-u)^2 g(i,j)$$

where N_g is the number of gray levels, *g(i,j)* is the *entry(i, j)* in the GLCM and $u = \sum_{i,j=0}^{N_g-1} i, g(i,j)$.

3. Experiment Datasets

For experiments in this paper, two types of satellite images were used. Table 1 summarizes the characteristics of each image. The first one was level GEO image of IKONOS panchromatic band. In order to match with Landsat-7 panchromatic image, the ground sampling distance of IKONOS image is downsampled in 15m. Also, we use Landsat-7 panchromatic images as a target image.

Table 1. The characteristics of satellite image used for experiments

Spec	Reference Image: IKONOS	Target Image: Landsat-7
Acquisition Date	April. 5, 2000	April. 2, 2002
Level	Standard Geometrically Corrected; GEO	1G
Resolution	1m	15m
Swath Width	11km	185km

Fig 3 shows the IKONOS panchromatic image that is downsampled in 15m. Note that white cross marks are the ground control point that is surveyed by GPS. Fig 4 shows the Landsat-7 panchromatic image used in target image. On the image, the extent of IKONOS image is shown as the red rectangle.

The test site we selected was "Bundang" city of the Republic of Korea.

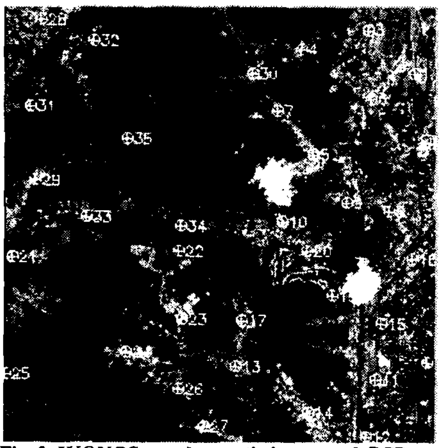

Fig. 3. IKONOS panchromatic image and GCP

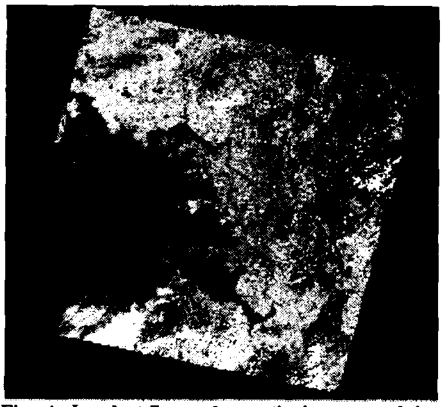

Fig. 4. Landsat-7 panchromatic image used in target image: Rectangle is a extent of IKONOS image

4. Results and Discussions

In this section, we comment on our experiences in applying the automatic generation GCP chips from IKONOS GEO Image to automatic precision correction algorithms.

SUSAN corner detector is applied to a IKONOS image and total of corners are found 2143 points.

When we only use SUSAN, there are a lot of corners in the image, as seen in Fig 5. We needs to reduce the corner points in order to improve the computing time effectively.

Also, as seen in Fig 5, there is a corner point of cloud and cloud shadow. These corner points are not suitable for ground control points.

To overcome this redundancy, we select 35 points from these results based on texture parameter (homogeneity, entropy, variance and dissimilarity) for each ascending order or descending order. Even though there are still corner points of cloud and cloud shadow in reference image after selection process. So automatic precision correction algorithms effectively remove these points from camera modelling.

Below Fig 6 shows that GCP candidates selected by higher variance. As seen in Fig 6, our approach is very much like that of human operator.

Fig 7 shows GCP candidates effectively selected using variance parameter with ascending order. The GCP distribution is suitable for image correction.

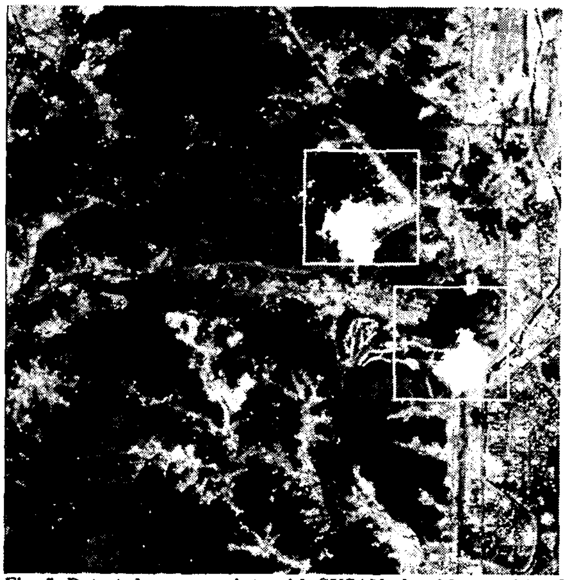

Fig. 5. Detected corner points with SUSAN algorithms: white dot are corner points: white rectangle is corner points of cloud and cloud shadow.

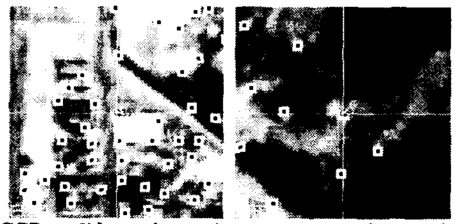

Fig. 6. GCP candidate using variance parameter. Center of image is the result of using variance parameter, black dots are corner point after using SUSAN algorithm

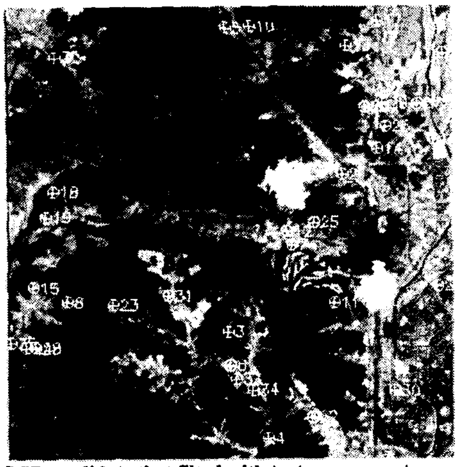

Fig. 7. GCP candidate that filted with texture parameter

Table 2 is the result of our approach. We select 35 GCP candidates using diverse texture parameters(Entropy, Homogeneity, Variance, Dissimilarity) with ascending or descending order.

These GCP candidates are used as input to the next stage of automatic precision correction. The result shows that homogeneity parameter with descending order result is much higher precision than other parameter. However, variance parameter with ascending produced more true matching points and more equivalent GCP distribution than homogeneity parameter.

Also, the inappropriate GCP candidate in the image such as corner of cloud and cloud shadow are perfectly removed by our in-house algorithms.

The result of comparison between human operator and proposed algorithms is given in Table 3. Table 3 shows that Model RMSE of human operator with GPS survey result is the best result. However, our method is virtually identical to human operator within 0.5 pixels.

Table 2. The result of automatic precision correction.

Texture Parameter	Descending		Ascending	
	True/False	Model RMSE	True/False	Model RMSE
Entropy	19/16	N/A	22/13	0.779
Homogeneity	20/15	0.705	20/15	0.748
Variance	20/15	1.408	25/10	0.908
Dissimilarity	20/15	1.110	21/14	1.244

Table 3. The result of human operator.

	True/False	Model RMSE
GPS Survey	21/14	0.432
IKONOS Geo	18/17	0.813

5. Conclusions

In this paper, we have introduced automatic GCP generation method from the IKONOS panchromatic images.

Proposed method can provide GCP chips from satellite image without human operation, hence make the whole precision correction process fully automated.

Our initial experiment indicate that variance parameter is likely to be more adaptive than using other texture parameter. And there is no difference between our method and human operator in this study.

Acknowledgement

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