Automated Mismatch Detection based on Matching and Robust Estimation for Automated Image Navigation

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ABSTRACT:

Ground processing for geostationary weather satellite such as GOES, MTSAT includes the process called image navigation. Image navigation means the retrieval of satellite navigational parameters from images and requires landmark detection by matching satellite images against landmark chips. For an automated preprocessing, a matching must be performed automatically. However, if match results contain errors, the accuracy of image navigation deteriorates. To overcome this problem, we propose the use of a robust estimation technique, called Random Sample Consensus (RANSAC), to automatically detect mismatches. We tested GOES-9 satellite images with 30 landmark chips. Landmark chips were extracted from the world shoreline database. To them, matching was applied and mismatch results were detected automatically by RANSAC. Results showed that all mismatches were detected correctly by RANSAC with a threshold value of 2.5 pixels.

KEY WORDS: Mismatch Detection, RANSAC, Matching, Landmark Detection

1. Introduction

Ground processing for weather satellites such as GOES, NOAA, MTSAT-1R includes the process called image navigation. It is also included in the ground processing for Communication, Oceanography and Meteorology Satellite (COMS), which will be launched in 2008. Image navigation is the process of determining the location of any pixel within an satellite image (Kamel, 1996). The principal part of image navigation is landmark detection. This requires matching satellite images against landmarks (Bass and McCann, 2000; Kamel, 1996; Kelly and Hudson, 1996), which is geographic features of known latitude and longitude (Kelly and Hudson, 1996).

In order to effectively use meteorological observations, satellite image pre-processing must automatically be preformed in real-time. Therefore image navigation also has to be performed automatically in pre-processing. However, matching in landmark detection often includes mismatch results. For automatic matching and landmark detection, we need to overcome mismatches.

Automatic matching has been studied in various fields. (Alatan and Onural, 1998; Chen et al., 1999; Kim and Im, 2003; Zhang et al., 2000). Kim and Im (2003) proposed automatic matching by robust estimation in SPOT satellite image. However, there are considerable differences between earth observation satellite image and geostationary weather satellite image. The differences include spatial resolution, cloud region, detection region.

The purpose of this study is to develop a technique to detect mismatches from geostationary satellite images. In the following sections, we will try to show that mismatch can be automatically distinguished by robust estimation, called Random Sample Consensus (RANSAC).

2. RANSAC

Fischler and Bolles (1981) suggested robust estimation technique, called Random Sample Consensus (RANSAC). Well-known estimation techniques such as Least Square Estimation (LSE) will make an estimate of wrong model(or function) if the data used for estimation includes great error. We can discriminate the data included great error (outlier) among data used for estimation by RANSAC.

To use RANSAC algorithm, we must determine parameters such as maximum iteration number and threshold to distinguish. The RANSAC estimate a model with a randomly selected data. The number of random samples are set to be the minimum number required for modeling. The algorithm calculates then using the data that are not used for estimation errors of estimation models. It counts the number of data whose error is smaller than the threshold value. This process is iterated up to the maximum iteration number. It selects the model whose number of supporting data is the largest. The supporting data and the randomly sampled data for this model are defined as inliers & all others outliers.

3. Experiments

3.1 Data used

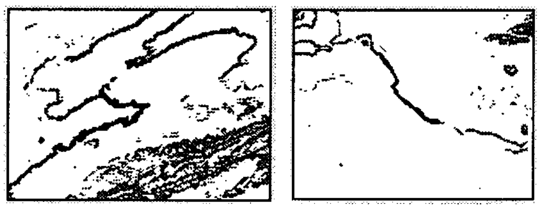
The images were formed from GOES-9 raw data, which received on October 21, 2004. We used only images of channel 2, which was detected at shortwave band because it could cover night side of the globe. This has 4 km spatial resolution.

Landmark chips were extracted from Global Self-consistent Hierarchical High-resolution Shoreline (GSHHS) database (Wessel and Smith, 1996). We formed image chips in 5° x 5° size and used 30 landmark chips in matching. Each landmark chip was projected to GOES-9 image coordinate for matching.

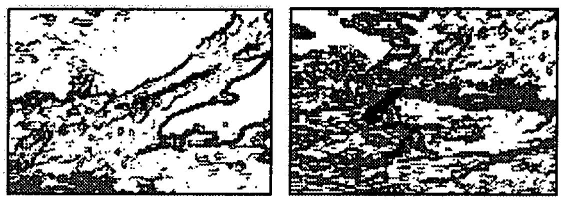
For effective matching, we extracted search images of small extents from the channel 2 GOES images. Size of the extracted search area is the double of landmark chips. Coordinate of each corner of the search area is determined by sensor model of GOES (NOAA/NESDIS, 1998).

3.2 Matching

The matching was performed by zero mean normalized cross-correlation algorithm. Figure 1 show the results of matches by overlapping landmark chips and search images. The results include examples of correct match (a), mismatch (b), ambiguous match (c). Ambiguous matches are those that could not be distinguished by naked eyes.



(a)



(b) (c)

Figure 1. The results of correct match (a), mismatch (b) and ambiguous match (c)

3.3 Mismatch detection

It needs a model that provide a relation between satellite image (2D) and landmark (3D) (Kim and Im, 2003) for RANSAC algorithm. We used a simple model of "Direct Linear Transformation (DLT)"(Kim and Im, 2003)

$$\begin{bmatrix} wc \\ wr \\ w \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

In above equation, (c, r) is column and row coordinates of GOES-9 image, (X, Y, Z) is Earth-fixed geocentric coordinates against (c, r), w is a scale factor. We estimated the coefficients of the DLT matrix by LSE in RANSAC. Estimation by DLT requires minimum 6 match results.

After RANSAC algorithm estimates the final model, it calculates outliers from the results of match. Those outliers are the results of mismatch.

4. Result and discussion

Table 1 shows the results of experiments using GOES images. Matching between these images and 30 landmark chips was performed.

Table 1. Number estimated an outlier to an inlier

Image ID	Visual inspection outlier number	Outlier number by RANSAC (Total; true)		
		Threshold 2.5 pix.	Threshold 5 pix.	Threshold 10 pix.
1	4	10 ; 4	7 ; 4	6 ; 4
2	5	10 ; 5	7 ; 5	6 ; 5
3	4	9 ; 4	7 ; 4	4 ; 4
4	5	11 ; 5	9 ; 5	8 ; 5
5	7	9 ; 7	9 ; 7	9 ; 7
11	1	9 ; 1	9 ; 1	9 ; 1
15	3	7 ; 3	5 ; 3	4 ; 3
16	3	6 ; 3	5 ; 3	4 ; 2
17	4	8 ; 4	7 ; 4	6 ; 4
18	4	7 ; 4	6 ; 4	5 ; 4
19	6	8 ; 6	6 ; 5	5 ; 5
20	2	4 ; 2	4 ; 2	3 ; 2
21	2	4 ; 2	3 ; 1	2 ; 1
22	2	8 ; 2	6 ; 2	3 ; 2
23	2	4 ; 2	4 ; 2	3 ; 2

We inspected visually the match results to count the true number of mismatches. The number is shown as "Visual inspection outlier number". Match results included very ambiguous matches mostly due to clouds. We assumed that it should be removed by cloud detection process, which would be applied in the future. We discarded ambiguous matches for further processing. Outlier detection by RANSAC was tried with several thresholds. The results in the table can be read as follows. '10; 4' means the RANSAC detected 10 outliers from the match results and among them 4 were actual mismatches. In this case, 6 correct matches were falsely detected as mismatches. As shown in the table, a number of outliers by RANSAC includes some inlier in most cases. Since our aim is to select only correct matches, we regard this over-detection little problem. However if true outliers are selected as inliers by RANSAC, they induce great errors. We tried to prevent this under-detection. The under-detection happened only at images 16, 19, 21 with thresholds 5, 10 pixels. When we applied the threshold value of 2.5 pixels, no outliers were mistaken as inliers.

5. Conclusions

This article has attempted to solve mismatching problem for the process of automatic landmark detection. Mismatches could be distinguished by the RANSAC estimation technique with 2.5 pixels threshold value. Consequently, it is possible to perform automatic landmark detection by RANSAC.

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