A Site Model Based Change Detection method for SAR Images

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Abstract

In this paper, a new method of site model based change detection is presented for multitemporal synthetic aperture radar (SAR) images. It first constructs a site model offline making use of a high resolution image of the fixed site, and then accurate registration is carried out between the model and the images. With the location information contained in the site model, the region of interest (ROI) can be extracted easily and robustly. Finally, the significant changes are obtained by comparing the invariant features extracted separately from the shapes of targets in ROI of two images. The experiment of change detection for two SAR images of airport demonstrated the validity of the proposed method.

1. Introduction

Change detection is an important process to analyze the difference between the two images of the same scene [1]. Due to the ability of SAR to form high-resolution images with relative invariance to weather and lighting conditions, recently, SAR image change detection has been widely used in earth monitoring, earth observation, damage assessment, land cover dynamics and so on.

SAR image change detection has been studied for many years, but it is still a difficult problem. Owing to the jitter of imaging platform, the change of flight attitude and the difference between the sensors, perspective distortions always exist between SAR images of the same scene. In order to correlate information obtained from the scenes in the two images, it is necessary to have the images registered. Once each point in one image can be correctly mapped to its corresponding point in the other image, we can easily find the regions of same scene in different images and analyze the differences between them. However, image registration is still an unsolved open problem, and many developed image change detection methods assumed that the two SAR images have been well mapped.

Recently, many methods for SAR image registration have been proposed, in which point based SAR image registration methods are most widely used due to their high accuracy and robustness to noise. However, there are still two key issues in point based methods: point extraction and transformation estimation. The accurate point extraction is the foundation of the high accurate image registration, but during the SAR imaging process, speckle noise will be inevitably generated in images by the interference of wave reflections. The speckle noise not only reduces radiometric resolution of images, but also hides important information to some extent [2], which brings difficulties to accurate point extraction. Depending on the points, the deformation between two images can be estimated. The well-known methods such as ICP [3], TPS-RPM [4] and SC[5] have high computation complexity and can't meet the requirement of real-time task.

On the basis of image registration, the change detection can be performed by making a direct comparison of same ROI from two images. Inglada and Mercier [6] use the ratio of the local means in the neighborhood of each pair of co-local pixels. Though this method is robust, it is limited to the comparison of the first order statistics. In [7], the maximum a posteriori (MAP) probability decision criterion and the simulated annealing (SA) energy minimization procedure are adopt to search for an optimal image of changes while the observed images are modelled as MRFs. This method suffers from the inference of speckle noise. In addition to the above methods based on pixel intensity, several methods detect the changes between the two images based on target features. In [8], change detection of SAR images is completed based on texture and the spatial information. Chang and Zhang [9] successfully segmented the changed and unchanged area before and after flood disaster while local geometric structure information is used to construct invariant features. Though the features are invariant to image distortion, these methods need to extract targets from the whole image. Owing to the improvement of spatial resolution in recent years, SAR images usually contain various geometric objects and more abundant spatial information. A large number of small metal and other dim targets appear in the form of pure pixels as well [2]. Therefore, target detection on the whole image always lead to a large number of false alarms and the performance of the algorithms is greatly reduced. In this case, if the location of ROI are known and we only need to detect the targets in the ROI, not only is the performance highly improved, but also the computation complexity is effectively reduced.

To overcome the shortages and strength the advantages of feature based change detection, we intend to develop a site model based system for SAR image change detection. In this paper, we firstly generate a site model from images with high resolution, and the position of ROI and relative position between some special regions are stored. On the one hand, the relative positon between the special regions are used to make a fine co-registration with images, and on the other hand, ROI can be easily extracted with high accuracy from the registered images using its location information contained in the site model. Then, we only need to detect the targets in ROIs and analyze the changes between targets based on their features. Since some prior information is stored in the site model, the proposed method can be seen as a knowledge-aided automatic change detection method, which has the great potential to improve the change detection performance.

2. Site model based change detection

The proposed method includes three stages: site model construction, image registration and change detection.

2.1. Site model construction

For important monitoring regions, they have been monitored for a long time and have many images. So it is feasible for us to choose an image with good quality and high resolution. Then, CAD can be used to construct a binary site model, in which, the points of ROIs and the centroids of some special regions have the gray value of 0, and other points are 1. Fig. 1 illustrates the construction of a site model for an airport based on a SAR image. Fig. 1 (a) is a SAR image of the airport with high resolution, and the runway and the waters are extracted from the SAR image manually. Here, the waters are taken as special regions as their gray values in the SAR image are smooth and they can be extracted easily. The site model is given in Fig. 1(b), in which the points of runway are represented by black. Besides, the centroids and contours of waters are also represented by black. Note that, the contours are not included in the site model, we show it in Fig. 1(b) only for the convenience of understanding.

2.2. Image registration based on the geometric topological reference

Due to the difference between the sensors or the difference between the flight attitude of the sensor, there may be distortions between SAR images of the same area. The purpose of image registration is to find the correspondence between points in two images. In this paper, before change detection, two SAR images need to be accurately registered to the site model. If the attitude of SAR imaging platform changes slightly during repeated flight, the distortion between SAR images can be approximated to similarity transformation. Therefore, this paper focus on the similar transformation between SAR images. SAR image registration can be divided into two sub-steps: feature extraction and feature matching. Owing to the robustness to noise and simple for extraction, the image registration is accomplished relying on geometric topological reference as the centroids of special regions are used.

Assuming a general 2-D similar transformation transforms point p in the original image into its corresponding point q in the deformed image by

$$[x_q, y_q] = [x_p, y_p]\begin{bmatrix} s & 0 \\ 0 & s \end{bmatrix}\begin{bmatrix} \cos\theta & \sin\theta \\ -\sin\theta & \cos\theta \end{bmatrix} + [t_x, t_y] \quad (1)$$

where, (x_p, y_p) and (x_q, y_q) are the coordinates of p and q in their own images, s, θ and $[t_x, t_y]$ represent the scaling, rotation and translation respectively. Let $P = \{p_1, p_2, ... p_m\}$ and $Q = \{q_1, q_2, ... q_n\}$ are the centroids of special regions from the two images. Because of the length invariance of the similar transformation, for two pairs of corresponding points, we have

$$\frac{d(q_{i'}, q_{j'})}{d(p_i, p_j)} = s \quad (2)$$

where $(q_{i'}, q_{j'})$ and (p_i, p_j) are correspondences, and $d(\cdot,\cdot)$ is the distance between the two points. Due to Eq. (2) , given a complete matching set (CMS), we have

$$\begin{aligned} & C_{CMS} = \{(p_i, q_{i'}), (p_j, q_{j'}), ..., (p_k, q_{k'})\} \\ & \Leftrightarrow \forall (p_t, q_{t'}) \in C_{MS}^c \\ & \& \ \forall (p_h, q_{h'}) \notin C_{CMS}, \exists (p_t, q_{t'}) \in C_{MS}^c \\ & s.t \frac{d(p_h, p_t)}{d(q_{h'}, q_{t'})} \neq \frac{d(p_i, p_j)}{d(q_{i'}, q_{j'})} = c \end{aligned} \quad (3)$$

In Eq. (3), the ratio factor $c \in R$, C_{MS}^c is a matching set, in which any two point pairs have the constant ratio factor c , that is

$$C_{MS}^c = \{(p_i, q_{i'}), (p_j, q_{j'}), ..., (p_k, q_{k'})\} \Leftrightarrow \frac{d(p_h, p_t)}{d(q_{h'}, q_{t'})} = c \quad (4)$$

$$\forall (p_h, q_{h'}), (p_t, q_{t'}) \in C_{MS}^c$$

The geometric topological relationship between two corresponding point sets are given in [10], that is

1) For collinear points, if two point pairs are included in the supporting index set (SIS) of each other, the intersection of the two SISs is a CMS, that is

$$\{(p_i,q_{i'}),(p_j,q_{j'})\}\subseteq(C_{SIS_{ii'}}\cap C_{SIS_{jj'}})\Rightarrow C_{SIS_{ii'}}\cap C_{SIS_{jj'}}\ is\ a\ C_{CMS} \quad (5)$$

In Eq. (5), $C_{SIS_{ii'}}$ is the SIS of the point pair $(p_i,q_{i'})$, and point pairs belong to one of its SIS all satisfy Eq. (1). In other words,

$$\frac{d(p_i,p_j)}{d(q_{i'},q_{j'})}=c, \qquad \forall(p_j,q_{j'})\in C_{SIS_{ii'}} \quad (6)$$

2) For non-collinear points, if three point pairs are included in the supporting index set (SIS) of each other, the intersection of the three SISs is a CMS, that is

$$\begin{aligned}&\{(p_i,q_{i'}),(p_j,q_{j'}),(p_k,q_{k'})\}\subseteq(C_{SIS_{ii'}}\cap C_{SIS_{jj'}}\cap C_{SIS_{kk'}})\\&\Rightarrow C_{SIS_{ii'}}\cap C_{SIS_{jj'}}\cap C_{SIS_{kk'}}\ is\ a\ C_{CMS}\end{aligned} \quad (7)$$

Eq. (6) and Eq. (7) provide a way to find CMSs from two point sets. For collinear point pairs, given two point pairs, if the intersection of their SISs with same ratio factor include themselves, then the intersection of the two SISs is a CMS. If three point pairs are non-collinear, and the intersection of their SISs with same ratio factor includes themselves, then the three intersection is a CMS.

Though all point pairs in a CMS can be treated as corresponding point pairs since they have a same similar transformation, only the point pairs in the CMS with the ratio factor s are the ones have the same transformation with images. In [10], the transformation of each CMS is computed and the best transformation is verified by the mean distance between the original points (points in the site model) and their correspondences in the transformed images. Apparently, it is time consuming. To address this problem, the area ratio of regions is adopt in this paper. As the centroids of some regions are treated as points for registration, the area ratio of regions which correspond to a corresponding point pair should be the square of the ratio factor, that is

$$\frac{S_{i'}}{S_i}=c^2 \quad (8)$$

S_i and $S_{i'}$ are the area of regions whose centroid are p_i and $q_{i'}$ respectively. Eq. (8) can be used to screen the candidate corresponding point pairs to improve the efficiency of the algorithm.

2.3. Target detection

The ROI can be easily extracted from the registered images since the position of ROI are stored in the site model. The difficulty is how to detect targets in ROIs. There are several target detection methods [11]~[13]. Generally, the constant false alarm rate (CFAR) [14] can be chosen according to its wide adaptability.

Note that, false alarm will inevitably exist in CFAR detection and the area of targets can be used to remove the false targets. In addition, a target may be distributed to several sub-regions, it is necessary to cluster the target points after detection. Only the extracted targets whose areas are in a particular range are recognized as aircrafts.

2.4. Change detection based on target features

Change detection not only detects the changes between two images, but also analyzes and describes the changes. For movable targets such as aircrafts, we need to detect whether the targets appear, disappear, move or have no change. The criteria of judgment are given as follows .

a) Target has no change: two targets which located in the same position in the reference image and the new image are completely same.

b) Target appears: a target is detected at a certain position in the new image, but in the same position and its neighborhood in the reference image, the same target is not detected..

c) Target disappears: a target is detected at a certain position in the reference image, but in the same position and its neighborhood in the new image, the same target is not detected.

d) Target moves: at a certain position, a target is detected in the reference image, and a same target is detected at the neighborhood in the new image.

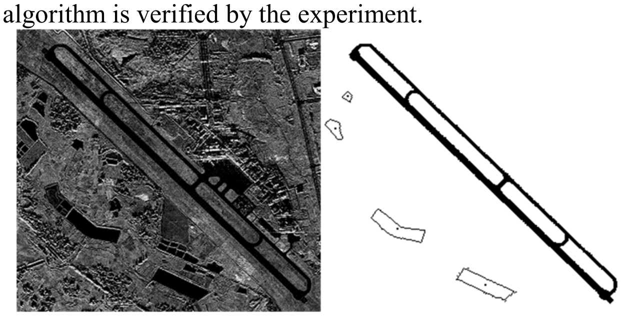
Between the two compared images, not only the position, but also the attitude of the same aircraft may change. If change analyses only depends on the traditional gray correlation, the change category (d) will be misjudged to category (b) and (c). Therefore, in order to have correct change detection, it is necessary to further extract the features that are not sensitive to the attitude of the targets. For a movable target, attitude change is mainly angle rotation. There are many rotation invariant features [15]~[17]. Considering the robustness and efficiency of the algorithm, shape matrix moment [18] is adopted in this paper. A similar invariant feature is extracted based on the relative areas of the shape contained in concentric rings which are located in the shape centroid.

3. Experiments

The SAR images of an airport are taken to verify the validity of our proposed method. The changes of airplanes in the runway are detected and analyzed. Because of the different attitude of the sensor platform or the difference between the sensors during the two imaging processes, there is similar distortion between the reference image (Fig. 2 (a)) and the new image (Fig. 4 (a)). First of all, the two images need to be registered with the site model separately. The site model (Fig. 1 (b)) is constructed from a high-quality SAR image (Fig. 1 (a)) artificially. The site model contains the coordinates of all points of runway, the coordinate of centroids and area of four waters.

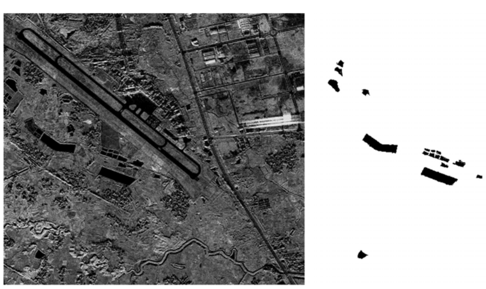
For the reference image (Fig. 2 (a), because the gray of waters is smooth, waters were extracted by region growing while all points in the image were treated as candidate seed points and regions are further selected by their area. The results of water extraction are shown in Fig. 2 (b). Then, the reference image is registered to the site model using GTI. Fig. 3(a) is the registered reference image. As the runway in the registered reference image has the same location with the one in the site model, the runway in the registered reference image is easily extracted (Fig. 3(b)). Then we had the same treatment on the new image (Fig. 4(a)), and Fig. 4(b), Fig. 5(a) and Fig. 5(b) are waters extracted from the new image, the registered new image and the runway extracted from the registered new image, respectively. Once the runway of two images were extracted, CFAR is applied to detect the airplanes on them, and the detected airplanes are marked in Fig. 6(a) and Fig. 6(b).

Depending on the comparison between the location and the shape matrix moment of airplanes, the results of change detection is described in Tab. 1. Apparently, our proposed algorithm has correct test result. Therefore, the validation of the algorithm is verified by the experiment.



(a) (b)

Figure 1: (a) The high resolution image used for the construction of the site model, and (b) the site model.

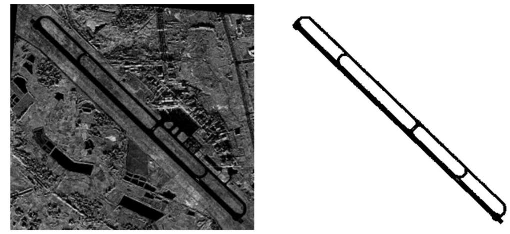


(a) (b)

Figure 2: (a) The reference image and (b) the result of water extraction.

Table 1: The results of change detection

Airplanes in the reference image	The changes of airplanes
1	Has no change
2	Moved to the location of No. 2 airplane in the new image
3	Disappeared from the new image

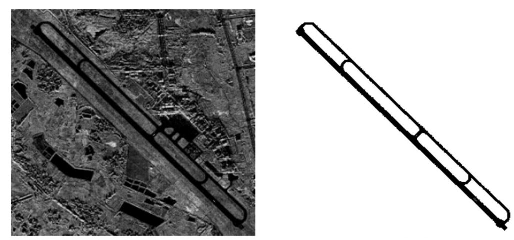


(a) (b)

Figure 3: (a) The registered reference image and (b) the result of runway extraction.

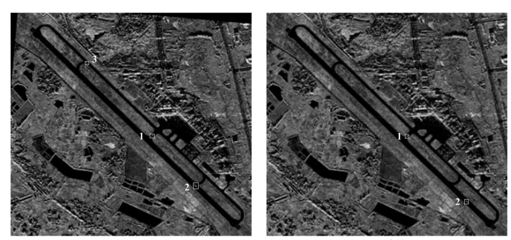
(a) (b)

Figure 4: (a) The new image and (b) the result of water extraction.



(a) (b)

Figure 5: (a) The registered new image and (b) the result of runway extraction.



(a) (b)

Figure 6: The results of airplane detection for (a) the registered reference image and the registered new image.

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