A study of change detection from satellite images using joint intensity histogram

Yasuyo Kita
National Institute of Advanced Industrial Science and Technology (AIST)
Information Technology Research Institute
AIST Tsukuba Central 2, 1-1-1 Umezono, Tsukuba, Japan
y.kita@aist.go.jp

Abstract

Detection of appearance/disappearance of objects from satellite images is generally very difficult since background pixels also change their intensity values owing to various factors. In this paper, we propose a method to estimate such background intensity changes by analyzing the joint intensity histogram of compared images. Considering the fact that background intensity changes tend to make clusters with ridges on the joint histogram, dominant ridges are detected using Hough transformation. Then, the joint histogram is classified into clusters according to the dominant ridges. Clusters of background intensity changes are distinguished based on covariance of each cluster. Pixels showing intensity change other than the background intensity changes are extracted as candidates of "significant" change. The prospect of this method is examined through experiments using real satellite images.

1. Introduction

Change detection from satellite images is important in many applications such as environmental conservation, city planning and surveillance for security[1]. However, it is generally difficult to discriminate "significant" intensity changes, such as caused by the appearance/disappearance of building structures, from intensity changes of the background. Although, in many methods, Principle Component Analysis based linear transformation of intensity is used to decrease the influence of the change in environmental illumination[2][3], the effect is generally insufficient since factors which changes the intensity of background pixels are often more complex in actual scenes. On the other hands, in [4], usage of the joint intensity histogram has been proposed to deal with such complex background intensity changes. The joint intensity histogram is a two-dimensional (2D) histogram of combinatorial intensity pairs, $(I_1(\mathbf{x}), I_2(\mathbf{x}))$, where $I_{1(2)}$ and $\mathbf{x}$ represent the intensity level (0-255) of each image and the positions of pixels on images, respectively. The method estimates background intensity changes based on the analysis of ridges of clusters observed on the joint histogram. Pixels of "significant" change are detected with small false positive by removing the pixels showing these background intensity change. The method showed promising results using surveillance images which are taken with the intervals of ranging from a few minutes to an hour. However, in the case of satellite images, both ridges and clusters on the joint histogram are not so clear because of various noisy disturbances such as local misalignment of 3D structures owing to different camera direction, intensity change of fields due to seasonal difference and so on.

In this paper, we improve the change detection method [4] so as to be applicable to satellite images with such complex joint intensity histogram. In Section 2, we model intensity changes between images in terms of factors causing the changes to see the relation between the ridges on joint histogram and the factors. In Section 3, a method on the basis of the relation is proposed to estimate background intensity changes. Then, some preliminary experimental results and discussions are presented in Section 4 and 5 respectively.

2. Clusters on joint histogram

In Fig. 1(a), we pick up a pair of images of a parking lot taken with one hour interval at the fall of evening to see the relation between clusters on joint histogram and factors which cause intensity changes. In this case, background pixels change their intensities in some different ways: some area changes its brightness directly proportional to illumination strength ("Direct-proportion"), while another area becomes brighter drastically by coming out from shadow to being in the sun ("Out-of-shadow"). There is also area which gets darker by coming into shadow from being in the sun ("In-to-shadow"). For detecting appearance/disappearance of objects from the scene, it is vital to grasp such background intensity changes as accurately as possible.

Fig. 1(b) shows the joint intensity histogram of the

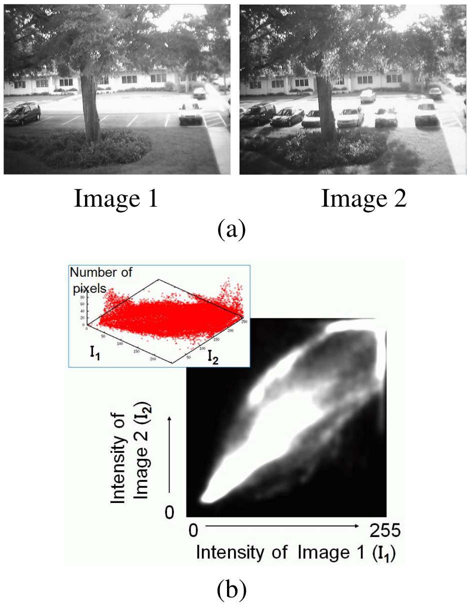

Figure 1. Example of Joint histogram

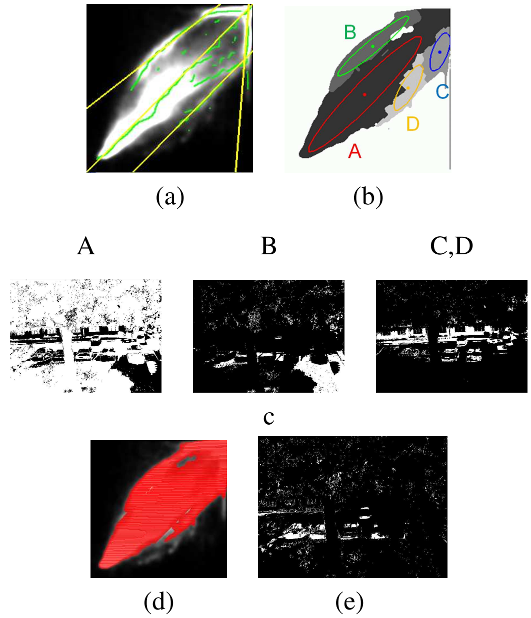

Figure 2. Relation between pixels and clusters on joint histogram

images, $H(I_1, I_2)$, which is smoothed by the 2D Gaussian filter of $\sigma_G = 3.0$. In the 2D diagram at the lower right of the 3D diagram, the frequency of combinatorial intensity pairs of (I_1, I_2), h_{I_1,I_2}, is represented by brightness.

Here, we make an assumption that the intensity change at every $\mathbf{x}$ can be represented by a linear formula, $I_2(\mathbf{x}) = aI_1(\mathbf{x}) + b$, where the parameters (a, b) are fixed by the factor making the change. For example, if the factor is change in illuminating radiation from E_1 to E_2, $(a, b) = (E_2/E_1, 0)$. As another example, if a new object with intensity of I_c appears, $(a, b) = (0, I_c)$. When intensity changes caused by the same factor, (a_c, b_c), occur at many pixels, h_{I_1,I_2} becomes large along the line of $I_2 = a_cI_1 + b_c$. Actually, there are some fluctuation of (a, b) so that a ridge appears along the line on the joint histogram. Therefore, line formula of the projections of the ridges on the (I_1, I_2) plane should give hints on factors changing intensities of many pixels. From now, we simply call the projections of the ridges on the (I_1, I_2) plane as "ridge projections". Intensity changes (I_1, I_2) included in the cluster making a ridge can be estimated as changes caused by the factor corresponding to the ridge.

3. Method for estimating background intensity changes

Based on the idea described in Section 2, we propose the following strategy for detecting appearance/disappearance of objects between images:

I) Classification of ridge projections into groups of the same line formula
II) Clustering of joint histogram based on the detected line formulas
III) Detection of background intensity change (I_1, I_2) according to distribution of each cluster
IV) Extraction of pixels with intensity change other than background intensity changes

Hough transformation seem to be one of the best strategy to detect lines for Process I). Process II) can be implemented by using a watershed-like segmentation of $H(I_1, I_2)$. For Process III), singular value decomposition of covariance matrix of $H(I_1, I_2)$ in each cluster is used. Process IV) is done by the same way as proposed in [4]. Concrete algorithm is as follows:

1. Detecting (I_1, I_2) on ridge projections
   Local minima of h_{I_1,I_2} in the diagonal direction are detected using the following condition:
   (I_1, I_2) is detected when
   $$h_{I_1-1,I_2+1} < h_{I_1,I_2} \quad \& \quad h_{I_1+1,I_2-1} < h_{I_1,I_2}$$
   The green points in Fig. 2(a) show detected possible ridge points in the case of the joint histogram of Fig. 1(b).

2. Detecting lines representing ridge projections by Hough transformation
   By letting the detected ridge points (I_1, I_2) vote with the weight of h_{I_1,I_2}, the best line which represents ridge projections is detected. After removing

ridge points around the line, the same procedure is repeated to detect the next best line. While repeating this process, removed ridge points are labeled by the identifier of each detected line. The four yellow lines in Fig. 2(a) show the result in the case of the joint histogram of Fig. 1(b).

3. Classifying (I_1, I_2) pairs by a watershed-like procedure
   (I_1, I_2) pairs are segmented in a watershed-like manner by using labeled ridge points as core points. In more detail, this process is carried out by labeling (I_1, I_2) based on adjoining already labeled (I_1, I_2) in the order of descending h_{I_1,I_2}. The four gray regions in Fig. 2(b) show the result obtained from the lines in Fig. 2(a).

4. Calculating distribution of each cluster using covariance matrix
   In order to calculate variance of each cluster, singular value decomposition of covariance matrix of (I_1, I_2) with the weight of h_{I_1,I_2} is done for each cluster. The four ellipses in Fig. 2(b) illustrate the resultant covariance of each cluster. For each cluster, its line formula is recalculated using the mean of the cluster and the direction of the major axis. The standard deviation in the direction of the minor axis, σ, is used to estimate variance of the elements from the line.

5. Removing clusters corresponding to appearance/disappearance factors
   If a large object with constant intensity appears(disappears) on background consisting of variety of intensities, a cluster with a horizontal(vertical) ridge gives rise on the joint histogram. To obtain only clusters corresponding background intensity changes, clusters are removed when the tangent of the line formula, θ, satisfies the following condition:
   $\theta < (0 + \delta) \quad \text{or} \quad (90 - \delta) < \theta$
   Here, δ is error margin and set 10 degrees in the experiments of this paper.

6. Determining background intensity changes
   (I_1, I_2) pairs included in the detected clusters are determined as background intensity changes unless the distance of (I_1, I_2) from the line formula of the belonging cluster does not exceed 2σ. This condition is necessary to consider the case where a cluster smoothly connected with other small cluster caused by a different factor.

In the example of Fig. 2, intensity changes by “Direct-proportion” factor were detected as Cluster A, ones by “Out-of-shadow” factor are detected as Cluster B, and ones by “In-to-Shadow”factor as Cluster C and D as shown in 2(c).

By taking background intensity changes as “insignificant “ changes, a 2D table that classifies (I_1, I_2) into significant/insignificant changes can be built. In Fig. 2(d), insignificant (I_1, I_2) pairs are colored by red. Once we get the table, the same procedure proposed in [4] can be used to extract pixels showing “significant” change. In this example, pixels corresponding to five newly appearing cars are extracted, while most of background are removed as shown in 2(e).

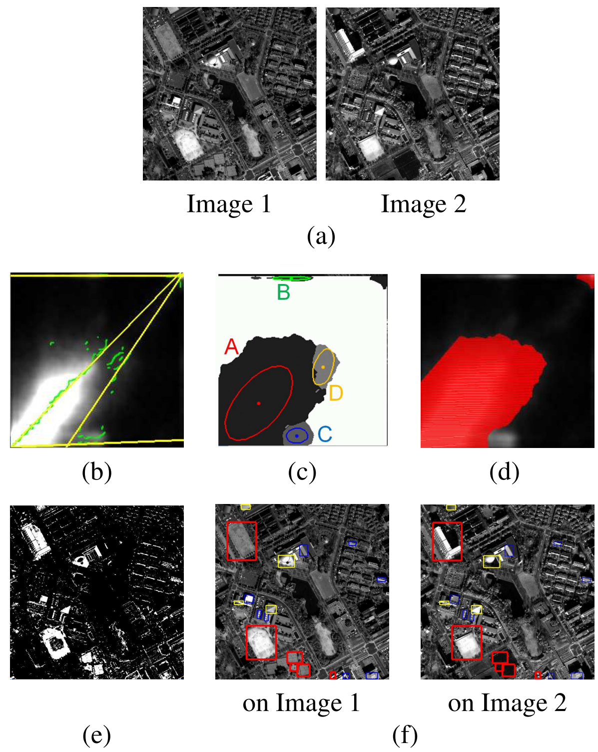

Figure 3. Experiment 1

4. Experiments

We have done preliminary experiments using Ikonos satellite images of Tsukuba city which taken in March of 2000 and in December of 2004 respectively. The images are divided into sub-images of 600x600 pixels before processing and are registered using maximization of mutual information[5]. Fig. 3 shows an example of the results. Fig. 3(b) shows detected ridge projection points and lines representing the ridge projections Fig. 3(c) shows detected four clusters with ellipses representing distribution of each cluster. The tangent of the major axis of each cluster are 49.6, 0.5, 3.2 and 72.5 degrees for A,B,C and D respectively. As a result, Cluster A and D were selected as clusters of background in-

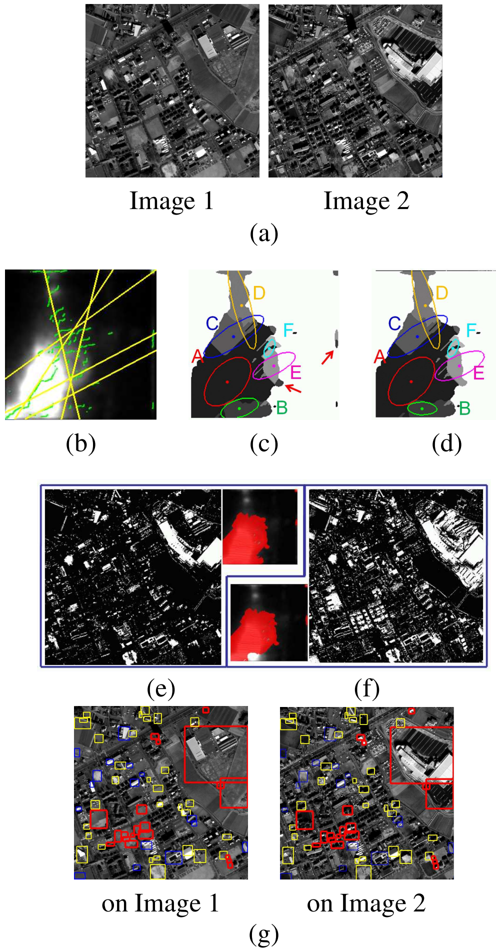

Figure 4. Experiment 2

tensity changes. According to this, "insignificant" intensity changes were determined as colored by red in Fig. 3(d). Pixels of "significant" change were extracted as shown in Fig. 3(e). By checking gradient correlation between the images for each region consisting of sizable connected groups of these pixels, areas with significant change can be detected as shown by red squares in Fig. 3(f)[4].

Fig. 4(a) is another example which shows more complicated joint intensity histogram. One of the reason for this is that the scene includes fields which change their intensities variously. Because of the complex ridges, some of detected lines look not so reliable (Fig. 4(b)). In Fig. 4(c), detected six clusters are shown with ellipses representing distribution of each cluster. From the tangent of the major axis of each cluster, Cluster A,B,C,E and F were selected as clusters of background intensity changes. According to this, "insignificant" intensity changes were determined and pixels with "significant" changes were extracted as shown in Fig. 4(e). Actually, pixels in the area where small houses newly appears in the lower left quarter of the scene were not detected in the result. This is because intensity changes in the area are actually included in Cluster B which was judged as a cluster of background intensity changes since the direction of the major axis of the cluster is 18.0 degrees. It comes from that Cluster B includes two outland clusters along the line detected by Hough transform, which are illustrated by the arrows on Fig. 4(c). If the outland clusters are removed manually, the major axis of Cluster B becomes almost horizontal (tangent of -1.5 degrees) as shown in Fig. 4(d). If Cluster B is judged as a cluster caused by an appearance of object according to this observation, table of "insignificant" (I_1, I_2) pairs and pixels of "significant" change become as shown in Fig. 4(f). Fig. 4g shows the results using the result of Fig. 4(f).

5. Conclusion

In this paper, we have proposed a method to estimate background intensity changes from joint intensity histogram to robustly detect appearance/disappearance changes from satellite images. The experimental results using satellite images shows that the proposed strategy has good potential, although implementation of robust clustering of joint intensity histogram has some problems to solve. We keep trying to improve this clustering processes.

Acknowledgments

We are thankful to Dr. I. Sato of Geologic Remote Sensing Research Group, Institute for Geoscience, AIST for data provision and discussions, and also to Dr. T. Nagami, Dr. T. Masuda, and Dr. N. Kita for their support to this research.

References

[1] Carlotto, M.J.: "Detection and Analysis of Change in Remotely-Sensed Imagery with Application to Wide Area Surveillance", *IEEE Trans. on Image Processing*, Vol. 6, No.1, 189–202, 1997.

[2] R. J. Radke, S. Andra, O. Al-Kofahi and B. Roysam: "Image change detection algorithms: a systematic survey", *IEEE Trans. on Image Processing*, Vol. 14, No.3, pp. 294–307, 2005.

[3] M. S. Moeller and T. Blaschke: "Urban change extraction from high resolution satellite image", In *Proc. of ISPRS Technical Commision II Symposium 2006*, pp. 151–156, 2006.

[4] Y. Kita: "Change detection using joint intensity histogram", In *Proc. of 18th International Conference on Pattern Recognition*, pp.351–356, 2006.

[5] R. Fransens, C Strecha, L V .Gool: "Multimodal and multiband image registration using mutual information", In *Proc. of ESA-EUSCC 2004*, 2004.