Building Extraction from High Resolution SAR Imagery in Urban Areas

DONG Yansheng¹,³, CHEN Hongping², YU Deyong³, PAN Yanzhong³, ZHANG Jingshu³
1. Beijing Research Center for Information Technology in Agriculture, No. 11 Middle Shuguanghuayuan Road, Haidian District, Beijing 100097, China
2. Key Laboratory of Regional Climate-Environment Research for Temperate East Asia, Institute of Atmosphere Physics, Chinese Academy of Sciences, Beijing 100029, China
3. State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University, No. 19 Xinjiekouwai St., Haidian District, Beijing 100875, China

© Wuhan University and Springer-Verlag Berlin Heidelberg 2011

Abstract In this paper, the textural characteristics of the buildings were quantified by using two texture descriptors, namely, Square Root Pair Difference (SRPD) and \( G_i \). Then, a novel method, based on SRPD and \( G_i \), to extract building areas in urban areas from very high resolution SAR images is presented. The results showed that this method has the ability to differentiate buildings from the complicated features in urban areas, which can be employed for land mapping and provides support for relief operations.

Keywords building detection; high-resolution SAR; texture; urban remote sensing

CLC number P237

Introduction

The recently launched TerraSAR-X, Radarsat-2 and COSMO/SkyMed satellites provide high-resolution SAR data with a spatial resolution of up to one meter, which can reveal a number of important urban landscape elements inside urban areas.¹ The Very High Resolution (VHR) SAR satellite data allows identification of individual buildings, fostering research on the use of weather-independent radar data for rapid post-earthquake building damage assessment and risk monitoring.²,³ However, SAR images are in general more complex than optical images and need to be understood and correctly interpreted by highly skilled experts. For this reason, we see in recent literature, that a semi-automated approach, based on the computation of local autocorrelation and gray-level co-occurrence matrix to assist extraction of human settlement extent in High Resolution (HR) SAR images at a medium-scale has been developed.⁴,⁵ These studies showed this approach is highly accurate and confirmed it as an effective model to extract built-up areas at a local or regional scale. However, there are few studies that have addressed urban building fine feature detection. Thus, efforts to improve

► Received on February 26, 2011.
► Supported by the National Key Technology R & D Program of China (No.2008BAK49B04); the Project of State Key Laboratory of Earth Surface Processes and Resource Ecology, Beijing Normal University.
► DONG Yansheng, Ph.D. His interests are around remote sensing and GIS application in earthquakes and agricultural disasters.
► E-mail: dyansheng@gmail.com
automatic extraction of buildings in urban areas using high resolution SAR images are still worthwhile.

This paper documents a novel method that uses two geostatistical texture descriptors, namely, the Square Root Pair Difference (SRPD) and $G_i^*$ to rapidly extract built-up areas both at the area (city block) level and at the individual building level. This methodology proved to be effective and that building block detection can be extracted from sub-meter VHR SAR images. The approach described here allows “rapid identification” of a building block from HR SAR Imagery in urban areas rather than “more precise”. This “rapid and definite” approach is especially suitable for non-experts requiring building damage assessment in emergency scenarios.

The remainder of the paper is organized as follows. Firstly we introduce the theoretical basis of semivariance and Getis-Ord statistics and then present the processes of this novel method by integrating the two geostatistical texture descriptors. Secondly, we describe building detection by using two VHR SAR satellite images (COSMO/SkyMed and TerraSAR-X) under two different urban conditions. Finally, we describe conclusions and a summary of future work.

1 Methodologies

The semivariance methodology has been frequently used to describe the local textures of remotely sensed images and then applied to improve classification accuracy.\cite{6-8} Semivariance will be used here to quantify the building texture of two VHR SAR satellite images: TerraSAR-X and COSMO/SkyMed.

The aim of this work is to generate, in a rapid way, building maps inside an urban area based on VHR SAR satellite data. Direct exponential semivariance values will be used. Three types of semivariogram models have been categorized: Gaussian, exponential and spherical. Lark demonstrated that the SRPD texture descriptor is preferred over the standard estimator of semivariance, because the SRPD values are less likely to be affected by outliers. It is defined as: \cite{9}

$$SRPD_{(h)} = \frac{1}{N_h} \sum (ABS(DN_i - DN_{i+h})) \quad (1)$$

where $N$ is the number of pixel pairs at distance $h$ used to calculate the SRPD, and the SRPD is based on the square root of the difference between two pixels $DN_i$ and $DN_{i+h}$ at distance $h$ apart.

Getis-Ord statistics can identify the clustering of high and low values that are used to distinguish the targets of bright or dim from SAR images. $G_i^*$ is calculated as follows: \cite{10}

$$G_i^*(d) = \frac{\sum W_i(d)x_j - W_i^*x}{s(W_i^*(n-W_i^*)/(n-1))^{\frac{3}{2}}} \quad (2)$$

Where $n$ is the number of the considered neighboring pixels, and $W_{ij}$ is the weight matrix specifying the connection schemes between localities $i$ and $j$.

For all equations mentioned above, SRPD descriptors were used to define the textural characteristics of building pixels and $G_i^*$ descriptors were used to identify “building hotspots”. The SRPD can work as an edge detector, while $G_i^*$ has a similar averaging effect.\cite{11} SRPD and $G_i^*$ texture images basically display the rough texture of the building. Building pixels are concentrated in the high-region for both of the variables of the SRPD and $G_i^*$ texture spectrum, therefore a building can be detected. The followings are the building detection processes.

1 Deriving the SRPD and $G_i^*$ values. After the denoising process of SAR images with the Lee filter, the Eqs. (1) and (2) mentioned above are used to calculate the SRPD and $G_i^*$ texture values. Window size, the lag distance and direction are the three key factors to calculate SRPD. Generally the range of image semivariogram is taken as the optimal window size.\cite{12} Meanwhile, only lag distances which up to 1/3 of the window size dimension can produce meaningful results.\cite{6} Lag distance is a vector. Generally, the omni-direction texture value is the average of four directions value obtained by 0°, 45°, 90°, and 135°. Meanwhile, $G_i^*$ texture values are calculated by a window size and a spatial weight matrix corresponding to this window.

2 Clustering the SRPD and the $G_i^*$ texture images. An ISODATA clustering process is carried out using an unsupervised classification and three classes (smooth, middle and rough textures) are generated. For rough textures of buildings, the inference rule is defined as: when both of SRPD and $G_i^*$ textures are high, the possibility of texture images is also high. Based on this rule, the high values of SRPD and $G_i^*$ are stacked to classify buildings.
(3) Post-processing. In urban SAR images, many objects are confused due to the presence of “false alarms” including buildings, tall trees, and metal railings in the rough textures. To reduce misclassification, the rough texture area is reevaluated by simply considering the area of the building hotspots. In general, buildings occupy a larger area, so the smaller objects are removed from the results of the cluster image.

2 Experimental results and analysis

The above algorithm was verified using two different urban conditions and two different sensor data: COSMO/SkyMed and TerraSAR-X. The final algorithm accuracy assessment was carried out based on visual interpretation from VHR optical images.

2.1 The COSMO/SkyMed scenario

The test image covers a 446 by 593 pixel area and its spatial resolution is 2.5 m. According to Eq. (1), the SRPD texture is related to the window size, the lag distance and direction. According to Woodcock[13], the value of the range of semivariograms is sensitive to the most predominant feature class in the image. To determine the optimal extraction window size of SRPD values for buildings, five sample areas where a building is the predominant feature were manually extracted to calculate omni-directional SRPD values. The semivariogram is shown in Fig. 1.

Fig. 1 shows that the range for all samples is approximately 5 pixels, suggesting that a window size of $5 \times 5$ pixels would be adequate for a texture transformation for the building pixels. In this study, an omni-directional texture transform using SRPD was carried out with a window size of $5 \times 5$ pixels and a lag distance of 2 pixels. At the same time, a $Gi^*$ texture layer was derived by using a window size of $5 \times 5$ pixels. When a SRPD texture layer was derived, an ISODATA clustering process was implemented. The entire SRPD image was classified into three classes: smooth, mid-range and rough texture. The building in the SRPD texture is mostly classified as rough texture. Meanwhile, a $Gi^*$ layer was performed in the same way.

The SRPD and $Gi^*$ have different effects when processing building texture. As shown in Fig. 2, the SRPD can work as an edge detector, while $Gi^*$ has a similar averaging effect. In Fig. 2 (a), SRPD texture was able to detect the edge of the building, but a hole occurs in the central part of the building. Fig. 2 (b) showed that $Gi^*$ texture is good at identifying building hotspots, but not at edge detection. The built-up areas shown in Fig. 2 (c) were extracted by merging SRPD and $Gi^*$ layers. The VHR optical image of IKONOS-2 showed in Fig. 2(d) acted as a ground truth to verify the extracted results.

Fig. 1 Semivariogram of the sample building pixels

Fig. 2 The results comparison of building detection

The original image of COSMO/SkyMed is showed in Fig. 3 (a). The extracted buildings from the composite texture layer of SRPD and $Gi^*$ are shown in Fig. 3 (b). By visual interpretation of VHR optical IKONOS-2 image, 101005.91 m² of built-up areas are discerned, while 124181.25 m² of built-up areas were detected from the COSMO/SkyMed image, so
The overall accuracy of building detection was 81.34%.

Fig. 3 Test site 1: COSMO/SkyMed image

The method we adopted in this paper is suitable to detect built-up areas in a rapid way. The contour of a larger size individual building located in sparsely built-up areas can easily be extracted. Comparing with ground truth observation, we noted that iron railings in test areas cause some image noise and affect extraction accuracy. Additionally, buildings enclosed by dense tall trees are very difficult to extract in optical remote sensed images, but are easily detected as hot-spot areas by the joint SRPD and Gi* method based on COSMO/SkyMed SAR Data.

2.2 TerraSAR-X scenario

The test image covers a 1735 by 1297 pixel area and its spatial resolution is 0.75 m×0.75 m. We selected a 9×9 pixel window with a lag distance of 1, 2 and 3 pixels to generate three SRPD texture images. The same procedure is applied by combining these three SRPD texture layers with a Gi* texture layer with a 9×9 pixel window to identify buildings. The TerraSAR-X image analyzed is shown in Fig.4 (a), while the final extracted buildings from the composite texture of SRPD and Gi* are showed in Fig.4 (b).

Fig. 4 Test site 2: TerraSAR-X image

Compared with manual interpretation of COSMO/SkyMed images, detection results based on TerraSAR-X image data are more precise for both the built-up area and for contours of individual buildings. Moreover, bridges over rivers can be nicely captured from the TerraSAR-X SAR image.

3 Conclusion

This study explores the joint use of the SRPD and Gi* texture descriptors based on the VHR SAR image to extract buildings both at the area (city block) level and at the individual building level. SRPD is good at detecting the outline of the building in VHR SAR image, while the Gi* is effective in solving the problem of hole phenomenon in the central part of the building. The joint SRPD and Gi* can extract an individual building from a 0.75 m×0.75 m spatial resolution VHR SAR image and the building outline from 2.5 m×2.5 m spatial resolution VHR SAR in a rapid way. From a disaster response perspective, the
method and results are helpful for rapid evaluation of disaster damage extent. The noise disturbance, caused especially by metal railings, is obvious and the mid-range texture of SRPD and Gi* may be confused with rough textures in urban areas. All these factors may affect detection accuracy. In future studies, we will filter the noise disturbances to improve the detection accuracy.

Acknowledgments

The authors would like to thank National Disaster Reduction Center of China (NDRCC) and Beijing Earth Observation Inc. (BEO) for providing the images.

References

[1] Gamba P, Tupin F, Weng Q (2008) Introduction to the issue on remote sensing of human settlements: status and challenges[J]. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 1(2): 82-86

[2] Chen K S, Crawford M M, Gamba P, et al. (2007) Introduction for the special issue on remote sensing for major disaster prevention, monitoring, and assessment [J]. IEEE Transactions on Geoscience and Remote Sensing, 45(6): 1515-1518

[3] Kuntz S, Scheuchl B, Duering R (2009) Rapid mapping of infrastructure in Maowen and Beichuan Counties after the May 2008 Earthquake[C]. Urban Remote Sensing Event, 2009 Joint, Shanghai

[4] Stasolla M, Gamba P (2008) Semi-automated extraction of human settlement extent in HR SAR images[C]. IGARSS 2008, Boston

[5] Gamba P, Aldrighi M, Stasolla M, et al. (2009) A detailed comparison between two fast approaches to urban extent extraction in VHR SAR[C]. Urban Remote Sensing Event, 2009 Joint, Shanghai

[6] Curran P J (1988) The semi-variogram in remote sensing: An introduction[J]. Remote Sensing of Environment, 24(3): 493-507

[7] Atkinson P M (1997) On estimating measurement error in remotely-sensed images with the variogram[J]. International Journal of Remote Sensing, 18(14): 3075-3084

[8] Song C, Woodcock C E (2002) The spatial manifestation of forest succession in optical imagery: The potential of multiresolution imagery[J]. Remote Sensing of Environment, 82(2): 271-284

[9] Lark R M (1996) Geostatistical description of texture on an aerial photograph for discriminating classes of land cover[J]. International Journal of Remote Sensing, 17: 2115-2133

[10] Wulder M, Boots B (1998) Local spatial autocorrelation characteristics of remotely sensed imagery assessed with the Getis statistic[J]. International Journal of Remote Sensing, 19(11): 2223-2231

[11] Ord J K, Getis A (2001) Testing for local spatial autocorrelation in the presence of global autocorrelation[J]. Journal of Regional Science, 41(3):411-432

[12] Franklin S E, Wulder M A, Lavigne M B (1996) Automated derivation of geographic window sizes for use in remote sensing digital image texture analysis [J]. Computers and Geosciences, 22(6): 665-673

[13] Woodcock C E, Strahler A H, Jupp D B (1988a) The use of semivariograms in remote sensing I: Scene, models, and simulated images[J]. Remote Sensing of Environment, 25(3): 323-348