Building detection from single high-resolution SAR image

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A new approach is proposed to extract the rectangular building footprints from single high-resolution synthetic aperture radar (SAR) image by combining region-based information with edge-based information. We build multiscale autoregressive (MAR) model and likelihood rate classifier for SAR image to extract region information. Edge information is extracted from SAR image by using constant false alarm rate edge detector. We propose a new optimization criterion which fuses the previous extracted region information and edge information to obtain the final building footprints. The experimental result shows that the proposed method can extract the building footprints effectively.

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Urban area building automatic detection from synthetic aperture radar (SAR) images plays an important role in a wide variety of application fields. Some methods have been proposed for building automatic detection from SAR images. Thiele *et al.*[1] devoloped a method for the detection of buildings from orthogonal multi-aspect interferometric SAR (InSAR) images based on the detection of edges and their combination to building footprints. Xu *et al.*[2] presented an algorithm for building reconstruction from multi-aspect polarimetric SAR (PolSAR) images. Simonetto *et al.*[3] proposed a building detection approach from stereoscopic high-resolution images. However, these techniques mainly rely on the availability of multi-dimensional data which implies that the area under investigation is imaged more than once with different viewing configurations (changed incidence and/or aspect angle)[4−6]. Few studies about building detection from single high-resolution SAR image can be found since it is more difficult than multi-dimensional data.

In this letter, based on the hypothesis that all buildings are rectangular, a novel method is proposed for building detection from single high-resolution SAR image, which combines region information with edge information of SAR image.

The main steps of the building region detection based on multiscale autoregressive (MAR) model and likelihood rate classifier[7] are summed up as follows.

1. Generate the multiscale sequence of different training sample images and original SAR image. The multiscale sequence $Y_L, Y_{L-1}, \cdots, Y_0$ of SAR image Y is built. Each pixel $Y_l(m,n)$ of Y_l is obtained by

$$Y_l(m,n)=\sum_{i=2m-1}^{2m}\sum_{j=2n-1}^{2n}Y_{l-1}(i,j). \tag{1}$$

2. Build the MAR models, as

$$X(s)=a_1X(s\overline{\gamma})+a_2X(s\overline{\gamma}^2)+\cdots+a_pX(s\overline{\gamma}^p)+w(s), \tag{2}$$

where $X(s), \cdots, X(s\overline{\gamma}^p)$ are the multiscale sequences of SAR image, $w(s)$ is prediction error residual, p is order of regression, and $a_1, a_2, \cdots, a_p$ are autoregressive coefficients.

3. Evaluate the prediction error residuals $w_0, w_1, \cdots, w_{L-1}$ for different clutter classes based on multiscale sequences of different training sample images.

4. The log-likelihood ratio test for classifying each pixel is given by

$$l=\sum_s \lg[p(w(s)|H_1)p(w(s\overline{\gamma})|H_1)\cdots p(w(s\overline{\gamma}^L)|H_1)]-\sum_s \lg[p(w(s)|H_0)p(w(s\overline{\gamma})|H_0)\cdots p(w(s\overline{\gamma}^L)|H_0)]. \tag{3}$$

For each pixel in the image, we choose between two hypotheses: the pixel is part of a building H_0 or background H_1 region. We compute the log-likelihood ratio l for each pixel $Y_0(s)$ and make it compare with a predetermined threshold η. If l is bigger than η, the pixel is building class, and vice versa.

The constant false alarm rate (CFAR) edge detector[8] is used to get edge information, and the edge is thinned by ridge filtering[2].

The local Hough transform is employed to detect straight segments from the thinned edges. To obtain the longer straight line segments that nearly parallels the long edge of the building, we choose a set of approximately parallel and neighboring line segments in black color in Fig. 1 and project them on their average straight line (whose ρ and θ values in the Hough space are computed as the average ρ and θ values of this group of line segments), i.e., the thickest straight line segment in Fig. 1.

The longer straight lines are used to define the initial rectangle buildings. For each straight line segment, the line segments adjacent to it and parallel or orthogonal to it are sought out first. Then each pair of parallel or orthogonal straight line segments may define an initial rectangle.

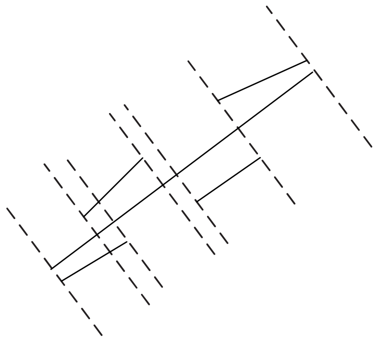

Fig. 1. Principle to generate longer straight line segment.

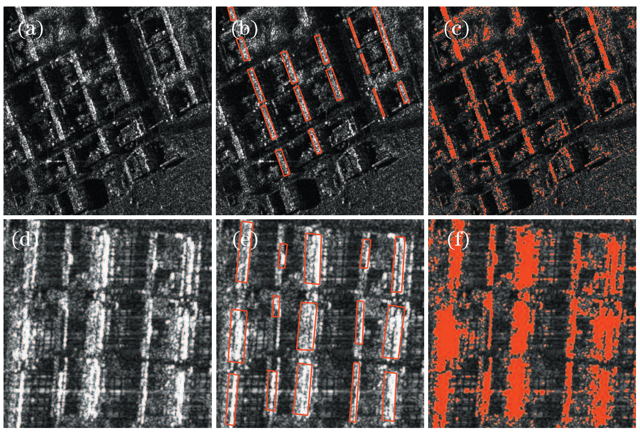

Fig. 2. Experimental results. (a) and (d): original SAR images; (b) and (e): the results of our method; (c) and (f): the results of MRF-based.

Let S_{R} be the set of the initial rectangles. R_i denotes each rectangle, $R_i \in S_{\mathrm{R}}$, $\{R_i^k\}_{k=1}^4$ denotes its four vertices. A mask M_i which is a box surrounding R_i is defined for the ith rectangle. The vertices of M_i is denoted as $\{M_i^k\}_{k=1}^4$, M_i^k is obtained by moving the corresponding vertices of R_i along their respective off-center directions by an offset (N_x, N_y). Here we set $N_x = N_y = 10$. Based on the region binary mask and the rectangle mask M_i, we compute the following four values: the number of building pixels (the value is 1 in the region binary mask) inside R_i , denoted by n_{1i}, that outside R_i but inside M_i by n_{2i}, the total number of pixels inside R_i denoted by N_{1i}, and the total number of pixels outside R_i but inside M_i denoted by N_{2i}. According to these parameters, we define the following optimization criterion:

$$\widehat{R}_i = \max_{R_i|M_i} \left\{ \frac{n_{1i}}{N_{1i}} \times \left(1 - \frac{n_{2i}}{N_{2i}} \right) \right\}. \qquad (4)$$

That is, to find the optimum $\widehat{R}_i$ that covers to the most the number of building pixels while leaving as few of them as possible within the domain between R_i and M_i. Several parameters are defined for each rectangle R_i, included the coordinate values (R_{ix}^1, R_{iy}^1) of the top right vertex, the length L, and the width W. By iteratively changing these parameters, we can get the maximum of $\widehat{R}_i$, which is the optimum rectangle. After some post-processing, we can get the final building footprints.

Two different SAR images are tested in the experiments. The first image has 512×512 pixels, and the size of the second image is 256×256. The same parameters are used. In the experiment regression order $p = 2$. For the CFAR edge detector, the parameters related are taken as a 7×3 window, 1 pixel gap, 4 directions and false alarm rate 0.01. To prove the effect of our method, we compare our method with the building detection method based on Markov random field in Ref. [9]. Experimental results are listed in Fig. 2. Obviously, the building detection results based on the proposed method in this letter have clearer shapes and edges and fewer miss detection situations. The extracted building footprints are more corresponding to the truth building footprints. However, the detection results based on MRF in Ref. [9] have more false detection situations and the obtained building footprints are more disordered. As expected, our method is more accurate to detect and recognize building footprints than the method based on MRF.

In conclusion, a new approach is proposed to detect buildings from the single high-resolution SAR data based on the hypothesis that all buildings are rectangular. Due to combining the region information with edge information, the proposed method can get the better building footprints and have fewer false detection situatons than other method. The building footprint detection with random shape is our further research area.

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