THE CONSTRUCTION OF ANTI-SYMMETRICAL WAVELET AND BUILDING EXTRACTION FROM REMOTE SENSING IMAGERY

Yi LIN, Shaoming ZHANG, Feng XIE, Ying CHEN

Department of Surveying and Geoinformatics, Tongji Univ., Shanghai 200092, China - linyi@mail.tongji.edu.cn

Commission III, WG III/4, ThS-7

KEY WORDS: Anti-symmetrical wavelet, Multi-Scale Edge Detection, Lifting wavelet, Parameter Feature Matching, Corner Points Recognition, 3D Building Object Extraction.

ABSTRACT:

The principal technical problem of 3D building semi-automatic acquisition from remote-sensing images was discussed by using wavelet analysis, combining digital photogrammetry and computer vision. A set of anti-symmetrical wavelet (ASWlet) functions and corresponding filters were deduced, e.g., multi-scales, symmetry, approximation compact support, good local regularity and smoothness. And it is a powerful tool to realize optimal edge detection. On the basis of the edge detection result, the improved chain code expression of image edge was used to describe the line feature. By using the linear template based on edge feature extraction and the binary image morphology we recognize the corners automatically. And then the anti-symmetric lifting wavelet algorithm to proceed the feature matching for getting the corresponding image points was proposed. Finally, via stereo intersection, we got the outline of 3D building from the stereo images.

1. INTRODUCTION

Extracting 3D information from objects from 2D remote-sensing images remains an important and essential task in photogrammetry vision. So, the significance of 3D reconstruction and expression in many projects is not only in theory, but also in practice. Large numbers of research on these aspects have been done, but the technique for fast acquiring the earth's surface information and reconstructing the 3D landscape is still in its initial stage. The difficulty arises, of course, from the fact that an image is a 2D projection of the scene affected by noise and different defect exists in various reconstruction algorithms. Consequently, the knowledge of how to optimize and improve the automation and intelligence level of building reconstruction has increased the demand for photogrammetry vision, and has been the aim that one has been working at hard in the field of photogrammetry and remote sensing.

The research on human vision mechanism and the rapid development of computer techniques will provide new ways for image feature extraction, and the research on human vision system shows that the spatial/frequency multi-resolution analysis based on wavelet transformation methods coincides with human vision characters. It reveals the multi-resolution, multi-channel characters of human vision perception processes. Therefore, the wavelet application in digital image processing has drawn intensive attention of the researchers, and today it has become the hotspot of the research on image feature extraction.

In this paper, we attempt to make use of wavelet analysis, combining digital photogrammetry and computer vision to develop a critical technique of building semi-automatic acquisition from remote-sensing images. Therefore how to realize and improve the automation and intelligence level is our studious aim. Aimed at extracting the 3D building automatically or semi-automatically, we try to search for a new effective thought of edge feature extraction, which is according to human vision perception process. Here a set of Anti-symmetrical wavelet (ASWlet) functions and corresponding filters were deduced, e.g., symmetry, approximation compact support, good local regularity and smoothness. And it is a powerful tool to realize optimal edge detection. On the basis of the edge detection result, the improved chain code expression of image edge was used to describe the line feature, using the linear template based on wavelet edge detection to recognize the corners automatically. And then the anti-symmetric lifting wavelet was adopted to process the feature matching for acquiring the corresponding image points. Finally, via the stereo intersection we got the outline of 3D building from the stereo images.

In the following sections, we will discuss the method in detail.

2. THE CONSTRUCTION OF THE ASWLET WAVELET AND THE EDGE DETECTION

2.1 Marr Hypothesis and Construction of Anti-symmetric Wavelet

Marr (1982) has pointed out that describing images in human vision has multiresolution characteristics, whose basic meaning is that the description of targets provided by a retina system is an ordered sequence, and the scales magnitude is according to geometric series. Extending the hypothesis to the intensity detection of images, he proposed two instructive principles: 1) the changes of an image's intensity exist in each scale, so the optimized detection operator for them must be multi-scale, with large scales detecting the obvious outlines and small scales detecting the fine details of sudden changes in images; 2) sudden changes of intensities will result in the appearance of extremum in first derivative, and second derivative of a smooth function traverses zero point.

Yi Lin, Ph.D, Associate professor, Department of Surveying and Geoinformatics, Tongji University.

Considering the characteristics of symmetry and multi-scale of edge features in images and the characteristics of wavelet functions' extremum detections, we deduced an anti-symmetric wavelet according to Marr hypothesis, with the Gaussian function as the scale function.

A 2-D *Gaussian* normal distribution can be represented as

$$\varphi(x,y)=\frac{1}{2\pi\sigma^2}e^{-\frac{1}{2\sigma^2}(x^2+y^2)} \quad (1)$$

which meets the condition

$$\iint_{R^2}\varphi(x,y)dxdy=\iint_{R^2}\frac{1}{2\pi\sigma^2}e^{-\frac{1}{2\sigma^2}(x^2+y^2)}dxdy=1. \quad (2)$$

Formula (2) shows that the Gaussian normal distribution function is a smooth function, and images' mean peculiarity stays unchanged after processing. To facilitate the discussion, we first deduce the wavelet function and the wavelet filter from the Gaussian function's one-dimensional representation and then extend it to two-dimensions (Lin, 2004).

According to the peculiarity that the scale exhibits progressional variety, we deduced a group of multiscale wavelet filters from the two dimensional Gaussian smooth functions and called them anti-symmetrical wavelet as follows:

$$\left.\begin{aligned} h(s,x)_k &= \frac{1}{2\pi}\int_{-\pi}^{\pi} e^{(-\frac{3s^2\sigma^2\omega^2}{2})} e^{jk\omega} d\omega \\ g(s,x)_k &= \sqrt{\frac{2}{\pi}}\int_{-\pi}^{\pi} j\omega e^{(-\frac{3s^2\sigma^2\omega^2}{2})} e^{jk\omega} d\omega \end{aligned}\right\} \quad (3)$$

The lowpass impulse response of the filter is symmetric at the origin, the highpass response of the filter is anti-symmetric at the origin and the truncation error is very small. They have the characteristics of approximation compact support and smoothness. Meanwhile nine groups of filter response coefficients are given to realize the feature extraction from coarse to fine and to provide a useful tool for multiscale edge detection.

2.2 Two-dimensional Wavelet Transformation and Edge Detections in Images

The two-dimensional Gaussian normal function (1) can be expressed separately as

$$\varphi_s(x,y)=\varphi_s(x)\varphi_s(y) \quad (4)$$

Therefore the two branches of a wavelet function can be described accordingly:

$$\left.\begin{aligned} \varphi_s(y) &= \frac{1}{\sqrt{2\pi}s\sigma}e^{-\frac{y^2}{2s^2\sigma^2}} \\ \psi_s(y) &= \frac{-y}{\sqrt{2\pi}s^3\sigma}e^{-\frac{y^2}{2s^2\sigma^2}} \end{aligned}\right\} \quad (5)$$

From the deduction in the previous section, we can obtain a group of filter coefficients in the *y* direction:

$$\left.\begin{aligned} h(s,y)_k &= h(s,x)_k \\ g(s,y)_k &= g(s,x)_k \end{aligned}\right\} \quad (6)$$

At last, a wavelet transformation can be implemented with the convolution of the image and the corresponding filters:

$$\begin{bmatrix} W_s^I f(x,y) \\ W_s^{II} f(x,y) \end{bmatrix} = \begin{bmatrix} f*(G_s,H_s) \\ f*(H_s,G_s) \end{bmatrix} \quad (7)$$

The filters in formula (7) consist of filter response coefficients:

$$H_s=\{h(s,x)_k\}, \quad G_s=\{g(s,x)_k\}.$$

From (7), the grads' module on the pixel (*x*, *y*) is:

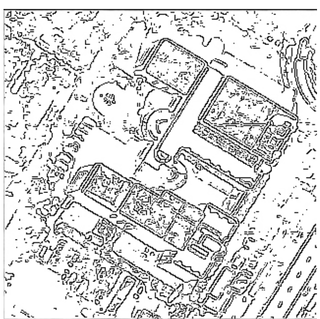
$$M_s f=\sqrt{|W_s^I f(x,y)|^2+|W_s^{II} f(x,y)|^2} \quad (8)$$

The grads' direction is

$$A_s f=\arctan\frac{W_s^{II} f(x,y)}{W_s^I f(x,y)} \quad (9)$$

We can use direction profile detection (Chen, 2003) to perform extremum detections and acquire the edges in images with the grads' modules and the directions obtained from formula (7), (8) and (9). In fact the convolution according to formula (7) can be done in a dyadic space, i.e., $s=2^j$. If we don't need to generate multi-channel images, then there is also no need for "extractions", and even no need for lowpass filters. We can reach the destination of multi-channel detection with different filter scales($s=1.75^j$) (Cheng, 1998).


(a) original image


(b) $s=(1.75)^0$

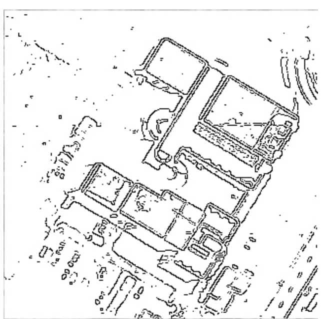

(c) $s=(1.75)^2$

Figure 1. Multi-scale feature extractioin (σ=0.5)

Figure 1 shows the results of edge extractions through wavelet transformations in one channel but with different scales. From this we can see that by using large scales some details in the image are neglected and the main edge features are intensified; on the other hand, with smaller scales more details are kept.

Generally, in buildings' reconstructions we are focusing more on their outlines of images, and their details can be enriched with textures. We can efficiently extract edges of images with appropriate scales according to actual needs. We can also construct multi-scale edge images in the same channel with the use of the anti-symmetric multi-scale wavelet filters, thus facilitating the restriction of noise (Cheng, 1998).
The wavelet filter proposed in this paper is based on edge extremum. Under the induction of maximum and direct map, it can locate the edges at sub-pixel accuracy, and doesn't generate fake edges. So it is superior to the method of zero cross method (Peng, 1999).

2.3 Edge thinning, tracking and parameters representation

The result of edge detection is to get edge lines and Y-tracks of image structure, which have cryptic information of knowledge of the image. We can get the knowledge of edge feature via edge detection, thinning, tracking and parameters' representation. So we can obtain full understanding about the information of knowledge of image from a lower-grade to a higher-grade level. With this knowledge we can get the shape of the object in 3-D space.

We describe edge features by the use of orientation chain coding because of the obviously structured feature of building in large scale remote sensing images. The orientation chain code has a simple structure and powerful ability to describe the direction and is available to further representation of the line moments for the purpose of feature parameter matching.

Here we improved the representation of an 8-neighborhood chain code. The improved chain code can indicate the dimensional direction of the feature vector and provide the important constraint condition for feature matching (Chen, 2003).

The line moment can represent edge feature very well because of its invariability for translation, scale and rotation. In addition, it has good computational efficiency. Moreover, we can easily get the moment characteristic quantity of any section of the edge, which is useful for comparing the local similarity. The equation (10) gives the low-level center moments of line features.

$$\left.\begin{aligned}
\mu_{1,0} &= \sum_{i=1}^{n} \Delta l_i x_i = \sum_{i=1}^{n} \Delta l_i \left(x_{i-1} + \frac{1}{2}\Delta x_i \right) \\
\mu_{0,1} &= \sum_{i=1}^{n} \Delta l_i y_i = \sum_{i=1}^{n} \Delta l_i \left(y_{i-1} + \frac{1}{2}\Delta y_i \right) \\
\mu_{1,1} &= \sum_{i=1}^{n} \Delta l_i x_i y_i = \sum_{i=1}^{n} \Delta l_i \left(x_{i-1} + \frac{1}{2}\Delta x_i \right)\left(y_{i-1} + \frac{1}{2}\Delta y_i \right) \\
\mu_{2,0} &= \sum_{i=1}^{n} \Delta l_i x_i^2 = \sum_{i=1}^{n} \Delta l_i \left(x_{i-1} + \frac{1}{2}\Delta x_i \right)^2 \\
\mu_{0,2} &= \sum_{i=1}^{n} \Delta l_i y_i^2 = \sum_{i=1}^{n} \Delta l_i \left(y_{i-1} + \frac{1}{2}\Delta y_i \right)^2
\end{aligned}\right\} \quad (10)$$

Where, x_i, y_i = the node coordinates of feature vector and

$$\Delta l_i = \sqrt{(x_i - x_{i-1})^2 + (y_i - y_{i-1})^2}$$

$$\Delta x_i = \begin{cases} \cos(c_i \times 45^o) & c_i \text{ is even number} \\ \sqrt{2}\cos(c_i \times 45^o) & c_i \text{ is odd number} \end{cases}$$

$$\Delta y_i = \begin{cases} \sin(c_i \times 45^o) & c_i \text{ is even number} \\ \sqrt{2}\sin(c_i) & c_i \text{ is odd number} \end{cases}$$

there are five center moments can constitute the directional invariant moments for later feature matching.

3. AUTOMATIC CORNER POINT RECOGNITION

It is easy to get the homologous points via image matching using the corner points or inflection points of the building. Then we can obtain the contour feature. After analyzing the SUSAN algorithm (Smith, 1997), a new method of corner point recognition based on wavelet edge detection and linear template was proposed. The method could be summarized as follows:

1) To determine the approximate position of the corner point on the image and intercept the window's image centering on the point, feature the extraction to get the edge feature image of the window, which is called image aggregation ***A*** according to the view of morphology (Chen, 2003).

2) To set a round template whose radius is ***R*,** the radius could be determined by the rough offset from the centre of windows to the exact position of the corner point. In figure 2, ***R*** is 3 pixels, the values of 8 direction elements of the template are non-zero, and the remained elements are zero. The template is called structural element ***B***, which is also an image aggregation and suitable to the structural feature of building.

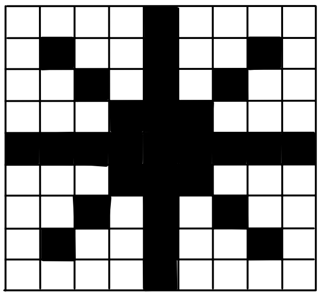


Figure2.Linear templet

3) To move the template in the window image, and cap image set A by using the structuring element ***B***. Then get a new set ***C***,

$$\mathbf{C} = \mathbf{A} \cap \mathbf{B} \quad (11)$$

In fact this step is to probe the image set by using a structural element. The elements $c_i(x,y)$ are non-zero in the set **C** only when the edges are exist in the probing windows,

$$c_i(x, y) = c_i(\vec{r}) \neq 0 \quad (12)$$

and then count the non-zero element in a new image set to get the number of feature points in every probed windows,

Yi Lin, Ph.D, Associate professor, Department of Surveying and Geoinformatics, Tongji University.

$$N_j = \sum_{R^2} c_i(\vec{r}) \tag{13}$$

4) To compare all values of ***N*** and get the maximum of them,

$$N_k = \max\{N_1\ N_2 \cdots N_j\} \tag{14}$$

Thus k corresponding to the coordinate of $(\vec{r}_k)$ in the image is the corner point.

Figure 3 shows one example of corner point recognition. The method depends on binary image morphology after feature extraction, instead of recognizing the corner points on gray-scale images. Thus it can locate the corners accurately without gray and geometry threshold.

(a) Edge feature image (b) Corner recognition result

Figure 3. Corner points' extraction

4. IMAGE MATCHING BASED ON LIFTING ASWLET

4.1 Anti-symmetric lifting wavelet and the decomposition and reconstruction of image

In this section, a novel "split-merge-split" lifting algorithm for anti-symmetrical wavelet is proposed and can be realized through the following steps:

1) Supposing $f(x, y)$ is the image function, first let the image split at the horizontal direction. The result is to deposit the low frequency information of image s_c at even number positions, and deposit the high frequency information dc at odd number positions, as follows (Lin, 2007),

$$Split(f_j)_c = (s_c, d_c) \tag{15}$$

$$\begin{aligned} s_c &= H_c f_j \\ d_c &= G_c f_j \end{aligned} \tag{16}$$

2) After finishing splitting and decomposing in every row, do the merge once more. Then get the horizontal direction decomposed image.

$$(f_j)_r = merge(s_r, d_r) \tag{17}$$

3) To split the image at the vertical direction (the serial number of image row is r). The result is to deposit the low frequency information of image ss at even number position at horizontal and vertical directions, and deposit the high frequency information sd,ds,dd at the crossed position of even and odd numbers , as follows,

$$Split((f^j)_r) = \begin{pmatrix} ss, sd \\ ds, dd \end{pmatrix} \tag{18}$$

$$Split((f^j)_r) = \begin{pmatrix} ss, sd \\ ds, dd \end{pmatrix} \tag{18}$$

$$\left.\begin{array}{ll} ss = H_r(f_j)_c & c, r \text{ are even number} \\ sd = H_r(f_j)_c & c \text{ is odd number}, r \text{ is even number} \\ ds = G_r(f_j)_c & c \text{ is even number}, r \text{ is odd number} \\ dd = G_r(f_j)_c & c, r \text{ are even number} \end{array}\right\} \tag{19}$$

4) Taking the low frequency image *ss* as a new input, proceeding the next level decomposition, and if it meets the demand we can stop the decomposition.

Figure 4 represents the four steps described above.

According to the decomposition method, the formed image presented parity permutation. Figure 4 shows the decomposition algorithm of ASWlet lifting wavelet, when *ss* is the low frequency information; *sd* is the vertical direction feature; *ds* is the horizontal direction feature; *dd* is the diagonal direction feature. During the operation we did the *(2j-1)* of interval extraction.

The method could maintain the on-site computation property of lift wavelet. In the meantime, it has a strong expressive ability as for the high frequency feature of the three constituent (vertical, horizontal and diagonal direction) on the decomposed image. The result of wavelet transform could be used in image match.

Imaged reconstruction can be realized according to the inverse process of the above-mentioned steps. Figure 5 shows the results of image decomposition by using ASWlet lifting wavelet and the linear lifting wavelet.

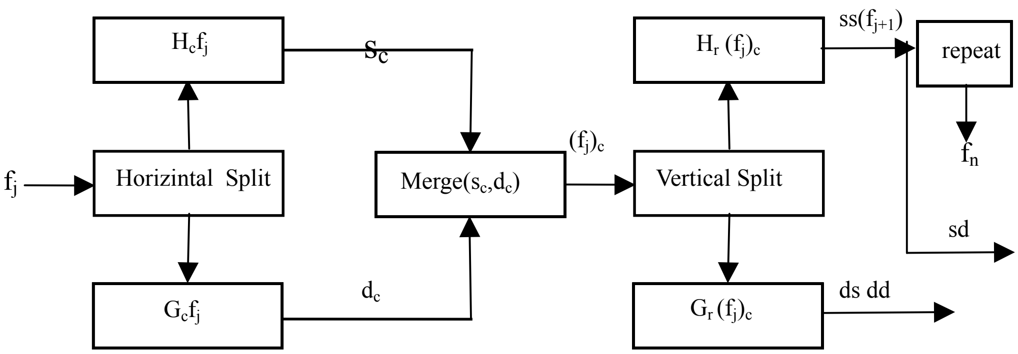
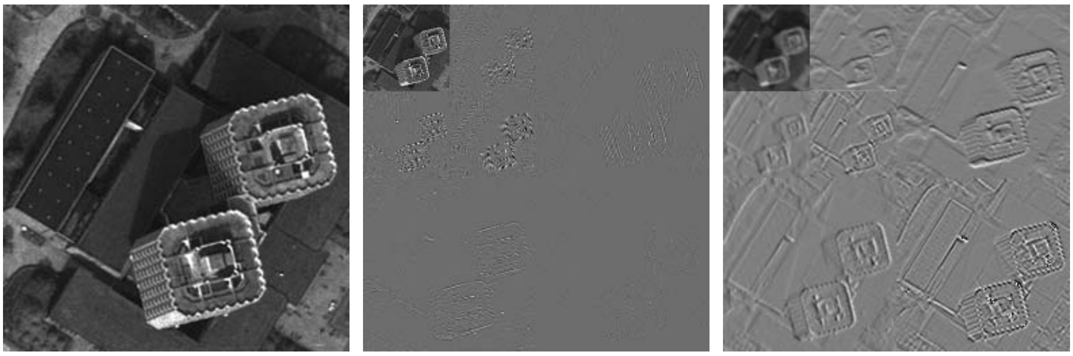


Figure 4. Decomposition algorithm ASWlet



a Original image b Linear lifting wavelet c ASWlet lifting wavelet

Figure 5. Different results of image decomposition using two kinds of lifting wavelet

From figure 5b, we can see that there is very little non-zero information of high frequency portion in the decomposed image with linear lifting wavelet, which is useful to image compression. But it is difficult to show the features. However, figure 5c shows more clearly the image features in the horizontal, vertical and diagonal direction through image decomposition with the ASWlet lifting wavelet.

4.2 Image feature matching of ASWlet lifting wavelet

The strategy of feature matching could be summarized as:

1) Constructing the pyramid images using the above-mentioned ASWlet lifting wavelet for stereo image decomposition, and preparing for the layer matching.

2) Computing the gradient map and direction map, extracting the feature and analyzing the vector, and then using the multi-scale analysis to restrain noise and histogram filtering to get the feature map which is used for feature matching; On the top layer, matching the images via feature or feature parameters (Chen, 2000).

3) Representing the edge feature using line moment and matching the image via parameters to get the initial value.

4) Proceeding image reconstruction to prepare for the image matching on the next layer.

5) Matching the image in next layer, which is similar to 2).

6) Matching the image In the last layer using least square method and get the result in sub-pixel accuracy (Chen, 2006).

5. BUILDING MODEL AUTOMATIC EXTRACTION ON THE STEREO IMAGES

With the multi-scale edge detection based on the wavelet analysis, corner point recognition and feature matching, we studied the method of automatic extraction of the 3D building geometry model. Figure 6 shows one flow chart of semi-automatic building extraction on the stereo images

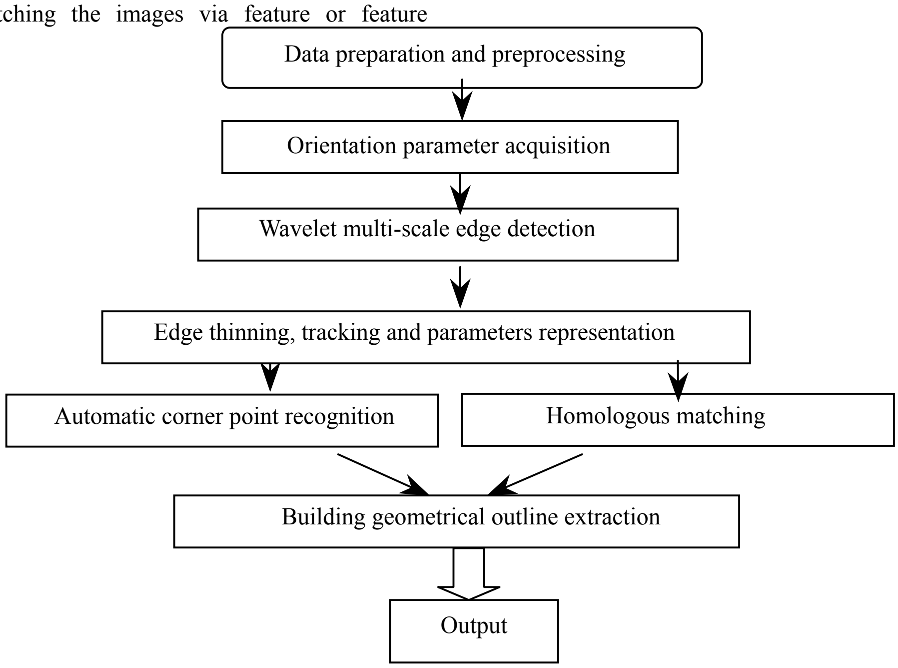


Figure 6. Flow chart of semi-automatic extracting building on the stereo images

From a stereo image, via above-mentioned handling, we can obtain a series of corresponding image points of key points on a building (such as corner points and inflection points). The 3D coordinates of these points could be obtained by stereo intersection. At last we perform the building geometrical outline extraction.

6. CONCLUSIONS

In this paper, the application of the wavelet analysis method on extracting the building from stereo images is described. Some new ideas and methods about how to solve several key questions are put forward. The results are summarized as follows:

1) The method of multi-scale feature extraction based on wavelet analysis was studied, and a new anti-symmetrical wavelet (ASWlet) function and corresponding filters have been proposed, which are symmetry, approximati on compact support, good local regularity and smoothness. Furthermore they are provided with very good multi-scales properties. When the scale is small, there are plentiful details in the detected result image. With large scales some details in the image are neglected and the main edge features are intensified. So we can realize optimal edge detection of buildings.

2) The algorithm of the lifting scheme ASWlet wavelet decomposition and reconstruction of image is studied, and the prediction function and update function were designed. The method could maintain the on-site computation property of lifted wavelets. In the meantime, it has strong expressive ability as for the high frequency feature of the three constituents on the decomposed image (vertical, horizontal and diagonal direction). The result of wavelet transform could be very useful to the next image match.

3) The basic principle and measure of semi-automatic building extraction is discussed and a new method of automatic corner point recognition is proposed. The method depends on binary image morphology after feature extraction, instead of recognizing the corner points on gray-scale image. So it can locate the corners accurately without gray and geometry threshold. Meanwhile, the description of invariant feature parameters and the feature matching based wavelet transform is adopted, which provides a fundamental basis for the semi-automatic extraction of the building from the remote sensing image.

4) On the basis of multi-scale edge detection based wavelet analysis we have studied corner point recognition and feature matching, the method of building model automatic extraction and 3D reconstruction on stereo images.

Based on remote-sensing image, we have investigated as well wavelet applications in different critical problems for the building automatic extraction. Experiments have proved the theories that we proposed were feasible and practical with high accuracy. The methods developed here are shown to be effective for improving efficiency on 3D building automatic acquisition and for speeding up the progress of digital city construction.

REFERENCE

Cheng, W. 2002. Wavelet Analysis and Application on Image Processing. Science Press, Beijing.

Chen, Y. 2000. Wavelet– Based Image Matching for Different Sensors. Inter. Archives of ISPRS，XXXIII B3/1, pp.177-182.

Chen Y. 2003. Digital Photogrammetry for Remote Sensing Images. Tongji University Press, Shanghai, pp.204 -206.

Chen, Y., Y. Lin 2006. Image matching and translation base on lifting scheme wavelet. Acta Geodaetica et Catographica Sinica, (1), pp:19-23.

Cheng, Z. 1998. Wavelet Analysis Algorithms and Application. Xi'An Jiaotong University Press, Xi'An.

Lin, Y., Y. Chen 2004. The construction of a Wavelet filter and multiscale edge detection. Computer Engineering and Applications, 40(35), pp.22-40.

Lin, Y., Y. Chen 2007. A direction profile detection for edge extraction with a Linear Lifting Scheme Wavelet. Journal of Tongji University(Natural Science), 35(12)

Marr, D. 1982. Vision. H. Freeman and Co.

Peng, Y. 1999. Wavelet transform and Engineering Application. Science Press, BeiJing.

Smith,S.M., Brady,J.M. 1997. New Approach to Low Level Image Processing. Int. Journal of Computer vision, 23(1).