STEREO MATCHING BETWEEN IMAGES OF LARGE SLOPE BASED ON MULTI-SCALE DIRECTIONAL WAVELET TRANSFORM

Zhao Xi-an, Chen Zhi-xue, Zhu Guang
College of Geomatics, Beijing University of Civil Engineering and Architecture, Beijing,100044, China.
zhaoxian@bucea.edu.cn, *zhixue-uxdd* @163.com, *zhuguang*@bucea.edu.cn,

1. INTRODUCTION

The stereo matching is a fundamental aspect of some problems in digital photogrammetry. The stereo matching will not be robust, while the image changes in illumination, rotation or scaling. This paper presents a method based on the multi-scale directional wavelet transform for feature extracting and stereo matching, which is invariant to image changes in illumination, rotation or scaling. The experiments show that the method is accurate and robust for extracting features and stereo matching for the slope images by unpiloted –aircraft, close-range and airplane. The major stages for extracting features and stereo matching in bigger slope images are also presented

2. THE FEATURE POINTS AT MULTI-SCALE

2.1 The Two-dimensional Directional Wavelet

A two-dimensional Gaussian function is defined as follows:

$$\theta(x,y)=\frac{1}{\sqrt{2\pi\sigma}}e^{-\frac{(x^2+y^2)}{2\sigma^2}} \tag{1}$$

its first -order partial derivatives with respect to a directional vector $\vec{n}=(\cos\alpha,\sin\alpha)$ is defined as:

$$\psi^{\alpha}(x,y)=\frac{\partial\theta(x,y)}{\partial\vec{n}}=\cos\alpha\frac{\partial\theta(x,y)}{\partial x}+\sin\alpha\frac{\partial\theta(x,y)}{\partial y} \tag{2}$$

We have the directional wavelet transform as follows

$$Wf^{\alpha}(x,y)=\psi^{\alpha}(x,y)*f(x,y) \tag{3}$$

2.2 The Feature Points based on the Wavelet Transform at Three Scales

(1) The wavelet images built at three scales

A digital image G_o（m, n） is processed by the directional wavelet transform at three scales, shown in figure 1.

(2) Extracting feature points at three scales

If one point satisfies

at scale two , the high frequency images, $\left(\sqrt{(D_2^0)^2+(D_2^{90})^2},\ \sqrt{(D_2^{45})^2+(D_2^{135})^2}\right)=\max$, at scale one , the high frequent images, $\left(\sqrt{(D_1^0)^2+(D_1^{90})^2},\ \sqrt{(D_1^{45})^2+(D_1^{135})^2}\right)=\max$, and at scale zero, the low frequency images , $(dg_1,dg_1,dg_1,dg_1)\geq T$, where,

$$dg_1 = \left|G_o(i,j) - G_o(i,j+1)\right|, \quad dg_2 = \left|G_o(i,j) - G_o(i+1,j)\right|,$$

$$dg_3 = \left|G_o(i,j) - G_o(i+1,j+1)\right|, \; dg_4 = \left|G_o(i,j) - G_o(i+1,j-1)\right|,$$

then the point will be defined as a keypoint or feature point , and its coordinate (i,j) each scale will be recorded.

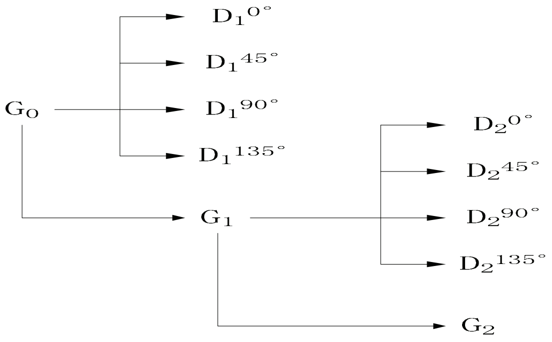

Figure 1: the directional wavelet transform at three scales

3. FAST STEREO MATCHING BASED ON DIRECTIONAL DESCRIPTORS

The stage is implemented on the low frequency image G_1, which belongs to scale one. Firstly the dominant orientation at each keypoint is defined based on local image gradient. Then a directional descriptor for one 64 dimensional vector at each point is built. After the stereo matching based on the dominant direction and directional descriptor is done, the parallax between images is achieved, which will be used at next stage.

3.1 the Dominant Direction

Image G_1 is a Gaussian smoothing function. The gradient magnitude m(i,j) and orientation θ(i,j) of the local region around each keypoint are computed as follows.

$$\begin{cases} m(i,j) = \sqrt{\left(G_1(i,j+1) - G_1(i,j-1)\right)^2 - \left(G_1(i+1,j) - G_1(i-1,j)\right)^2} \\ \theta(i,j) = \tan^{-1}\left(\dfrac{G_1(i,j+1) - G_1(i,j-1)}{G_1(i+1,j) - G_1(i-1,j)}\right) \end{cases} \tag{4}$$

The gradient orientation of the local region around the keypoint

$$0^\circ \le \theta(i,j) \le 360^\circ$$

is partitioned into 36 zones each 10^o . An gradient orientation histogram is formed from the gradient orientation of the local region. The histogram has 36 bins covering 360 degrees. Peaks in the histogram correspond to dominant directions of local gradients.

3.2 Direction Descriptors in 64 Dimension

Around each keypoint, a local region is defined by concentric circles, to a maximum extent 8 pixels. There are 8 concentric circles in the local region. The gradient orientation histogram is computed in each concentric cirques in 8 orientations（0^o、45^o、90^o、135^o、180^o、225^o、270^o、315^o）,in which the gradient magnitude in each orientation is summed. The direction descriptors in 64 dimension are formed. The coordinates of the descriptor and the gradient orientation about the region around are rotated relative to the dominant directions .

3.3 Stereo Matching based on Vector Distance

As the direction descriptor of one keypoint in main image is defined as X, the direction descriptor of keypoint i in assistant image is defined as Y_i. Here has

$$\min = | X - Y_i | \qquad (i = 1,2,\ldots,n) \tag{5}$$

It is known from Eq. (5) that keypoint i will be the stereo point matched. At last the image parallax is given.

4. ROBUST MATCHING BASED ON EQIPOLAR LINE CONSTRAIN

The stage is implemented in the low frequency image G_o.

4.1 Stereo Matching based on Keypoint

1) Harris operator

Select a local window in image, and compute follows.

$$M = G(\bar{s}) \otimes \begin{pmatrix} g_x^2 & g_x g_y \\ g_x g_y & g_y^2 \end{pmatrix}$$

$$I = \det(M) - k * tr^2(M) \tag{6}$$

Where, g_x is the gradient in x direction, g_y the gradients in y direction. $G(\bar{s})$ is a Gaussian function . $\det(M)$ and $tr(M)$ represent the determinant and trace of matrix M repectively. k is a constant. When one parameter in I is bigger than the threshold, the keypoint can be decided.

2) Stereo Matching on Keypoints

The searching window in assistant image is built using the parallax value. If the relative coefficient between two windows reaches maximum, the corresponding keypoint in assistant image is matched.

4.2 The Optimization Coplanar Model and Epipolar Line Constrain

1) The Optimization Coplanar Model

The two points in the stereopair satisfy the coplanar equation as follows.

$$L_1 + L_2 x + L_3 y + L_4 x' + L_5 xx' + L_6 xy' + L_7 yx' + L_8 yy' - q = 0 \tag{7}$$

The Random Sample Consensus (RANSAC) is used to compute iteratively the optimization coplanar parameters L.

2) Epipolar Line Constrain

Corresponding to each keypoint in main image $p(x_p, y_p)$, another keypoint $p'(x'_p, y'_p)$ exist in assistant image.If x'_p in $p'(x'_p, y'_p)$ is known, y'_p can be solved from Eq.(7) as follows.

$$y'^{*}_p = \frac{(1 - L_3^0) y_p - L_1^0 - L_2^0 x_p - L_4^0 x'_p - L_5^0 x_p x'_p - L_7^0 y_p x'_p}{(1 + L_6^0 x_p + L_8^0 y_p)}$$

If y'_p of keypoint $p'(x'_p, y'_p)$ is not equal to y'^{*}_p, the pairs of $p(x_p, y_p)$ and $p'(x'_p, y'_p)$ are discarded.

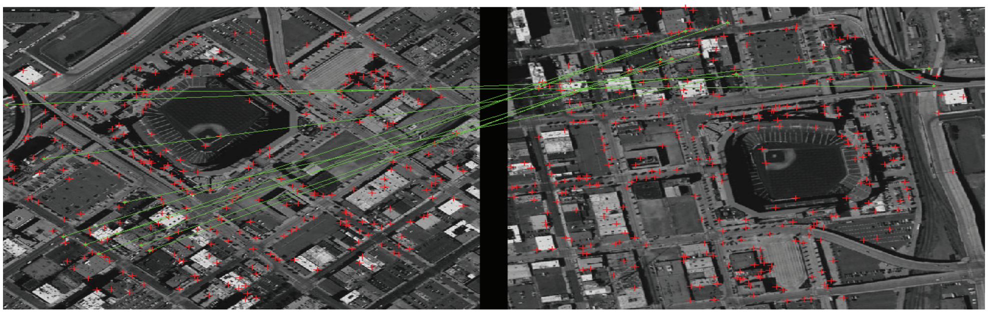

Figure 3: the stereo matching in aircraft images（assistant image rotated 125^o）

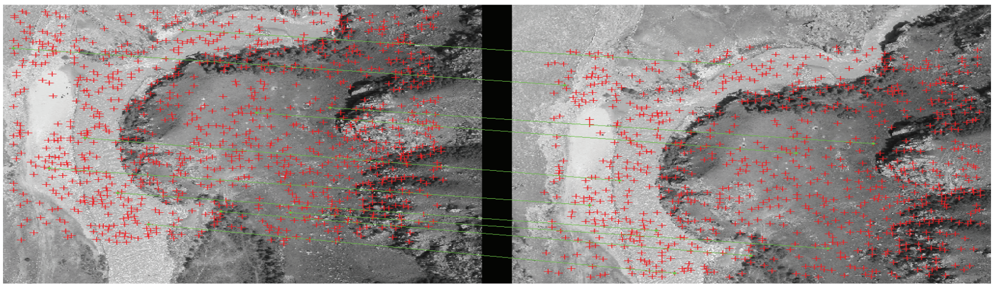

Figure 4: the stereo matching in unpiloted –aircraft images

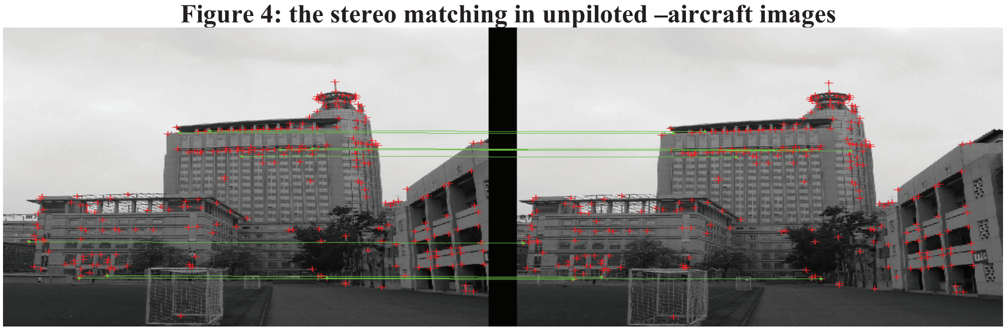

Figure 5: the stereo matching in close-range images

5. CONCLUSION

Our approach based on the multi-scale directional wavelet transform for feature extracting and stereo matching, is invariant to image changes in illumination, rotation or scaling. The experiments show that the approach is accurate and robust for extracting keypoints and stereo matching in stereopairs by airplane, unpiloted –aircraft and close-rang, in which images are large slope.Fig.3 shows the result by aircraft stereopair , Fig.4 by unpiloted –aircraft, Fig.5 by close-range.

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REFERENCES

[1] Zhao Xi-an. “Gaussian Symmetric and Antisymmetric Wavelets for Extracting the Geo-Objects in Remote Sensing and SAR Image” Wuhan: Wuhan university 2003.9.

[2] David G. Lowe, “Distinctive Image Features from Scale-Invariant Keypoints”. International Journal of Computer Vision,2004. vol. 2, no. 60: 91-110.

[3] Cheng Liang，Gong Jian-ya，Song Xiao-gang，Yang Xiao-xia，“A Method for Affine Invariant Feature Extraction with High Quality for Wide Baseline Stereo Image Matching”. ACTA GEODAETICA et CARTOGRAPHICA SINICA 2008.2, Vol.37 No.l : 77-82.