

## HIGH-PRECISION DEM PRODUCTION FOR SPACEBORNE STEREO SAR IMAGES BASED ON SIFT MATCHING AND REGION-BASED LEAST SQUARES MATCHING

Shi Xiaotian<sup>a</sup>, Zhang Guo<sup>a,b</sup>, Wang Xia<sup>b</sup>

a. State key laboratory of information engineering in surveying, mapping and remote sensing of Wuhan University, Hubei 430079, China;

b. Satellite of Surveying and Mapping Application center, State Bureau of Surveying and Mapping, Beijing 100830, China

### Commission I, WG: I/2

**KEYWORDS:** Matching, Stereo, DEM, Radargrammetric, Application strategy.

#### ABSTRACT:

Generally, there are two ways to generate Digital Elevation Model (DEM) using synthetic aperture radar (SAR) data, which are Interferometer Synthetic Aperture Radar (InSAR) and radargrammetry. Considering the disadvantages of InSAR data, such as the limit of terrain and the influence of water content, the application field of InSAR is relatively limited, while radargrammetry is more widely applied since it does not have such limits. However, for high-precision stereo SAR imagery, since the terrain distortion caused by shooting angle cannot be eliminated and the speckle noises are obvious, the classical matching algorithms for optical stereo images do not have the same effect on SAR data.

Based on the experience of optical stereo image matching, this paper proposes a new algorithm which combines the feature of SIFT image matching, region-based least squares matching and TIN. First, SIFT matching is used as the initial matching to obtain the sparse DEM, then by using TIN the matching points are forecast, finally the region-based least squares matching is adopted to get accurate matching points. In this paper, COSMO-SkyMed and TSX stereo images of Lanzhou area are used to validate the proposed method. Experiment results show that the algorithm can be effectively used in stereo SAR matching and high-precision DEM production.

#### 1. INTRODUCTION

Generally speaking, in remote sensing, there are 3 ways to get the terrain information of the earth. They are Navigation Satellite Timing And Ranging Global Position System (GPS), Synthetic Aperture Radar (SAR) and Light Detection and Ranging (LiDAR).

Among them, Synthetic Aperture Radar (SAR) is special for its feature as can be used in all weather, all time and is strong permeability. With those advantages, SAR is used as an important data for extracting the height. While InSAR has its special needs in data in order to avoid the decorrelation between the two images, radargrammetry does not require so much as InSAR does. So radargrammetry can be used more

flexibly. But radargrammetry has its own problem that needed to be solved. In geometries, mainly owing to the big change in nadir angle and different height of terrain, stereo images have different geometric deformation. And owing to the influence of speckle noise, some feature of terrain may be covered. So it is hard to match two SAR stereo images.

In optical image matching, SIFT matching and Region-Based least squares matching have been proved to be feasible and effective, But SAR image is different. Because the influence carried by speckle noise, if we simply using SIFT matching, then we can not get the result which is good enough. As we texted in the past, the points in SAR stereo images get by SIFT matching is accurate. But the points are not dense enough and are not distributed. So when we using those corresponding image points to get the height of earth by forward intersection

and using TIN to product DEM, it has some problems, such as large area without data and the low accuracy. Region-Based least squares matching is reliable, accuracy and flexibly in theory, But compare with SIFT matching Region-Based least squares matching needs initial height to iterative calculus. Here based on the advantage of SIFT matching and Region-Based least squares matching and the success of the application of those two algorithm in optical image we figure a new way to matching stereo SAR images which can avoid the shortage of those two algorithm. That is using SIFT matching for initial matching, then add points and using TIN to forecast the match point. Using the initial corresponding image points to calculate the initial height, and then using the initial height in Region-Based least squares matching to calculate the right corresponding image point.

## 2. ALGORITHM INTRODUCTION

### ■ 2.1 SIFT MATCHING

SIFT(scale invariant feature transform) is a algorithm that can transform an image into a large collection of local feature vectors which are invariant to image translation ,scaling and rotation(Lowe, 1999). So in the same area, the same SIFT keypoints exacted from images stand for the same terrain stably. In SIFT matching there are 2 steps which are extract the keypoints and describe, match the keypoints.

#### 2.1.1 The EXTRACTION OF SIFT KEYPOINTS x

In SIFT matching we need to extract the keypoints which are invariant to image translation, scaling and rotation. In order to computer and extract the keypoint efficiently, we use the difference of Gaussian function(Lowe, 2004). E.g.

$$\begin{aligned} D(x, y, \sigma) &= L(x, y, k\sigma) - L(x, y, \sigma) \\ L(x, y, \sigma) &= G(x, y, \sigma) * I(x, y) \\ G(x, y, \sigma) &= \frac{1}{2\pi\sigma^2} e^{-\frac{x^2+y^2}{2\sigma^2}} \end{aligned} \quad (1)$$

where

$x, y$  = image coordinates

$\sigma$  = scale

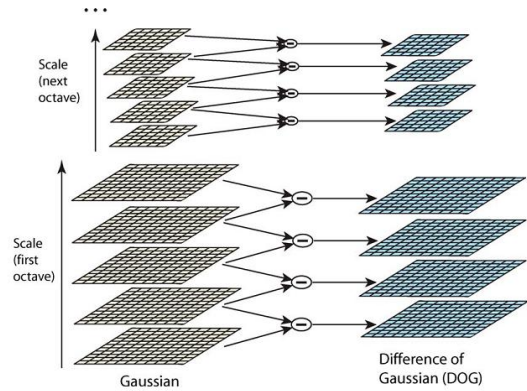


Figure 1. calculate DOG

and select the maxima and minima locations. Then, to make the position more accurate, we interpolate the data by using the quadratic Taylor expansion of the Difference-of-Gaussian scale-space function.

$$D(x) = D + \frac{\partial D^T}{\partial x} x + \frac{1}{2} x^T \frac{\partial^2 D}{\partial x^2} x \quad (2)$$

If the offset of the keypoint is larger than 0.5 then we change the keypoint and calculate again or if the offset is small than 0.5 then we add the offset to the keypoint to get subpixel estimate of the keypoint.

Finally the keypoint is select among the candidate location based on their stability.

#### 2.1.2 DESCRIBE AND MATCH THE KEYPOINTS

After those keypoint have been extracted, based on the local image gradient directions, assign one or more orientations .E.g.

$$\begin{aligned} m(x, y) &= \sqrt{(L(x+1, y) - L(x-1, y))^2 + (L(x, y+1) - L(x, y-1))^2} \\ \theta(x, y) &= \tan^{-1} \left( \frac{L(x, y+1) - L(x, y-1)}{L(x+1, y) - L(x-1, y)} \right) \end{aligned} \quad (3)$$

After calculate the orientation, set orientation histograms on 4x4 pixel neighborhoods with 8 bins each. Then compute the magnitude and orientation values of the samples in a 16 x 16 region around the keypoint .so each histogram contains samples from a 4 x 4 subregion of the original neighborhood region.

Furthermore, weighted the magnitudes by a Gaussian function with  $\sigma$  equal to one half the width of the descriptor window. Finally the descriptor is extracted.

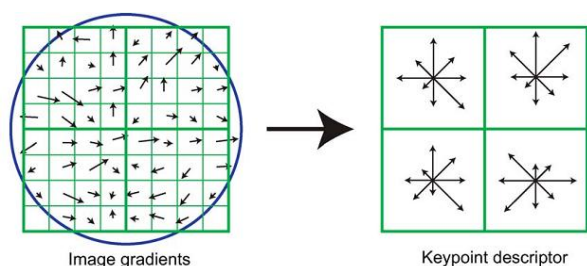


Figure 2. calculate the descriptor

In order to matching the corresponding image point, compare the two most similar keypoints of the stereo image. If the different is bigger than the threshold value then we believe is the right corresponding image point.

Here, to make matching it more efficient, we use k-d tree accelerate the process.

### 2.2 TIN PREDICT THE POTENTIAL CORRESPONDING IMAGE POINT

After get the corresponding image points from SIFT matching, we use TIN (Triangulated Irregular Network) to predict to potential corresponding image point of the added point.

To predict the potential point, we use the points that in the left to build the TIN and set the x and y as the height of the corresponding points respectively. So we can predict the added point's corresponding image point's x, y respectively. and use the initial corresponding image point to calculate the initial height.

### 2.3 REGION-BASED LEAST SQUARES MATCHING

With the initial height, we can use the Region-Based least squares matching to calculate the accurate corresponding image point.

#### 2.3.1 THE RADIANT RELATIONSHIP

As showed in the figure 3. the left image is the matching image and the right image is the matched image,  $p_0(x_0, y_0)$  is the added point and  $p_1(x_1, y_1)$  is the corresponding image point.

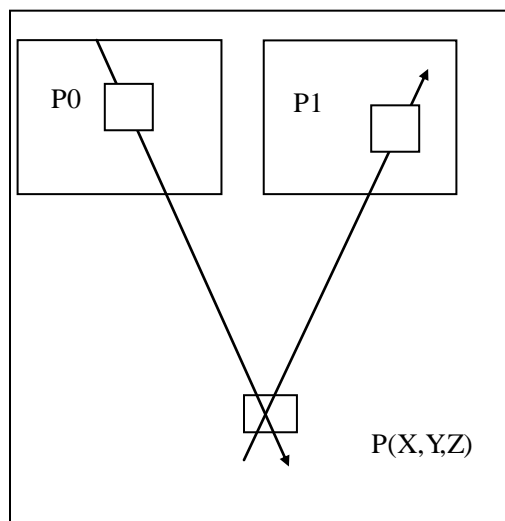


Figure 3. radiant relationship

In Region-Based least squares matching, firstly, we calculate three-dimensional coordinates position of the added point  $P(X, Y, Z)$  (ZHANG Guo, 2011). Then we calculate it back to the matched image. Without the consideration of random noise, the change of the radiation can be described as below.

$$g_0(x_0, y_0) = h_{01} + h_{11} \cdot g_1(x_1, y_1) \quad (4)$$

where

$g_0(x_0, y_0)$  = the gray in left image

$g_1(x_1, y_1)$  = the gray in right image

$h_{01}, h_{11}$  = the variates in radiation

### 2.3.2 THE GEOMETRICAL CONSTRAINT OF PROJECTION MODEL

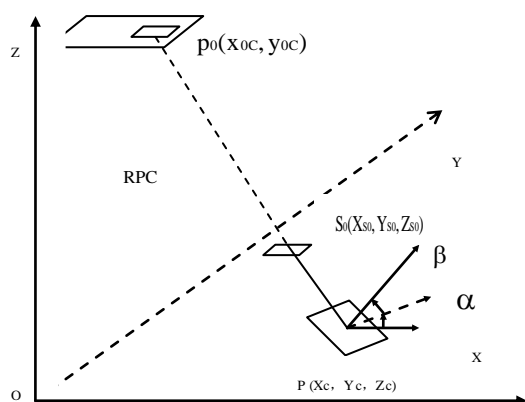


Figure 4. geometrical constraint of projection model  
figure 4 shows the projection relationship of the Region-Based least squares matching. In figure 2,  $p_0$  is the added point we use rational polynomial coefficients (RPC)(ZHANG Guo,2010) to calculate the Coordinate P in the slope . Through P the normal line is decided by  $(\alpha, \beta)$  . And the slope can be described as follow.

$$a(X - X_c) + b(Y - Y_c) + c(Z - Z_c) = 0 \quad (5)$$

$$\left. \begin{aligned} a &= \cos \alpha \cos \beta \\ b &= \sin \alpha \cos \beta \\ c &= \sin \beta \end{aligned} \right\}$$

Here, in order to simulate the projection of single-center projection, we make a fake projection centre at the height of  $Z_{s0}$  e.g  $S_0(X_{s0}, Y_{s0}, Z_{s0})$ . As the distant is short, we regard the projection between the fake projection centre and point in the slope as parallel projection. So we can get the projection equation as follow.

$$\left. \begin{aligned} X &= X_{s0} + \lambda(X_0 - X_{s0}) \\ Y &= Y_{s0} + \lambda(Y_0 - Y_{s0}) \\ Z &= Z_{s0} + \lambda(Z_0 - Z_{s0}) \end{aligned} \right\} \quad (6)$$

where

$(X_{s0}, Y_{s0}, Z_{s0})$  =the coordinate of the fake projection

centre

$(X_0, Y_0, Z_0)$  =one coordinate in the slope

$\lambda$  = projection coefficient

With the consideration of radiant relationship and geometrical constraint of projection model the error equation is showed as fellow:

$$v_{g0(s_0, l_0)} = dh_{01} + g_1(s_1, l_1) \cdot dh_{11} + h_{11} \left( \frac{\partial g_1}{\partial s_1} ds_1 + \frac{\partial g_1}{\partial l_1} dl_1 \right) - (g_0(s_0, l_0) - h_{01} - h_{11} \cdot g_1(s_1, l_1))$$

in the error equation the variates are the height of the centre of the slope  $Z_c$ , direction angle  $\alpha, \beta$ , the variates in radiation  $h_{01}, h_{11}$ .

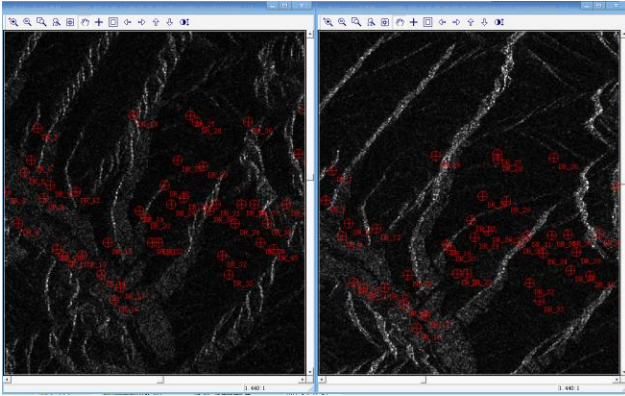
### 3. EXPERIMENT AND RESULT

To test the effect of this, here we use the stereo pairs in Lanzhou to product DEM.the detail of data is show in below

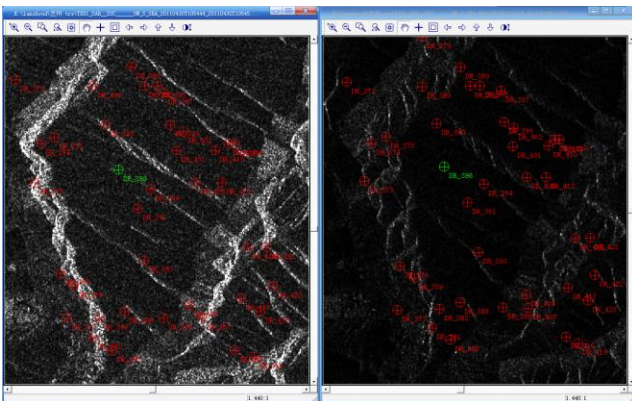
satellite	Image mode	date	Incidence angle	Lat and lon of centre
COSMO-SkyMed	HI	2011-4-22	24.7 °	N36.17 ° E103.93 °
	HI	2011-5-17	41.0 °	N36.18 ° E103.84 °
TerraSAR-X	SM	2011-4-30	28.7 °	N36.20 ° E103.81 °
	SM	2011-5-16	44.4 °	N36.15 ° E103.81 °

Table 1 detail of data

After matching, we can get the image pair of corresponding image point



corresponding image point of COSMO-SkyMed



corresponding image point of TerraSAR-X

We compare the DEM produced by those corresponding image points with a 1:10000DEM

COSMO-SkyMed	1:10000 DEM	Residuals of height	TerraSAR-X	1:10000 DEM	Residuals of height
1778.9	1777.2	1.7	1504.5	1497.4	7.1
1794.2	1794.1	0.1	1788.7	1784.8	3.9
1789.6	1782.1	7.5	1801.8	1806.6	4.8
1783.9	1773.3	10.6	1809.2	1784.8	14.4
1780.5	1773.3	7.2	1573.2	1577.6	4.4

Table 2. accurate of DEM

#### 4. CONCLUSION

This method is effect to match stereo SAR image , but in some area the result is not good enough .after analysis the data and algorithm, we realize that those situation happen because SIFT matching cannot get enough corresponding image points,

so the initial height is not accurate enough to calculate the right point.

To avoid this kind of fault, in the future we need to try different filter to improve result of SIFT matching and try some different ways to forecast the initial height.

#### 5. REFERENCES

Lowe,D.G. 1999. Object Recognition from Local Scale-Invariant Features.In International Conference on Computer Vision, Corfu, Greece, pp.1150-1157.

Lowe,D.G. 2004. Distinctive Image Features from Scale-Invariant Keypoints. International Journal of Computer Vision,60(2),pp.91-110.

ZHANG Guo,CHEN Tan,PAN Hongbo,JIANG Wanshou. 2011. Patch-based Least Squares Image Matching Based on Rational Polynomial Coefficients Model.Acta Geodaetica et Cartographica Sinica,40(5), pp. 592-597.

ZHANG Guo,FEI Wenbo,LI Zhen. 2010. Analysis and Test of the Substitutability of the RPC Model for the Rigorous Sensor Model of Spaceborne SAR Imagery [j]. Acta Geodaetica et Cartographica Sinica, 39(3),pp. 264-270.