A NEW IMAGE MATCHING ALGORITHM WITH MODIFIED GREEDY ALGORITHM FOR REMOTE SENSING IMAGERY

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ABSTRACT:

This paper proposes a new approach to image matching by epipolar constraint and local reliability constraint for Remote Sensing Image. We define a new measure of matching support according to the local reliability constraint. A new search strategy—modified greedy algorithm is developed for robust image matching. This strategy only selects those matches having both high matching support and low matching ambiguity. The proposed algorithm has been tested and works remarkably well in remote sensing imagery stereo pairs.

1. INTRODUCTION

Many applications in digital photogrammetry and remote sensing rely on image matching. These applications include image fusion and registration, automatic change detection for land use, environment monitoring and disaster assessment, three-dimensional reconstruction of the terrain, measuring and analyzing natural and agricultural vegetation, matching stereo images to recover shape for autonomous navigation, and aligning images from different medical modalities for diagnosis. With the dramatic increase in data volumes and types of sensors, image matching became also crucial for content-based retrieval of remote sensing data and image data from large data repositories.

But image matching belongs to the class of so-called inverse problems, which are known to be ill posed (www.photogrammetry.ethz.ch). Image matching is ill posed, because for a given point in one image, a corresponding point may not exist due to occlusion, there may be more than one possible match due to repetitive patterns or a semi-transparent object surface, and the solution may be unstable with respect to noise due to poor texture. Ill-posed problems can be converted to well-posed problems by introducing advance knowledge about the problem. A whole range of assumptions usually holds true when dealing with image matching: The scene depicted in the images is rigid; the object surface is piecewise smooth; the object surface is opaque. Those are called the local reliability constraint.

As described in (www.cfar.umd.edu), numerous techniques for image matching were classified based on the used feature space, search strategies, similarity measures, and achievement subpixel accuracy. These are listed as follows (see Table 1).

From the Table, there are many algorithms such as genetic algorithm, relaxation algorithm and Hopfield networks, Linear Programming, etc, which are usually used to be search Strategy in image matching. Relaxation algorithm and Hopfield networks generate local minima and do not usually guarantee that correspondences are one-to-one, and genetic algorithm, simulated annealing, linear programming and least squares matching are time consuming. Tree and graph match need extract good feature in left and right image, which is impossible for remote sensing images with 2.5-10m resolutions. Winner-takes-all as a steepest-descent approach may get stunk easily at a bad local minimum. To overcome these problems, An modified greedy algorithm has been put forward. This algorithm makes use of point location information and local grey information; it can supply an access to one-to-one correspondence and ensures the reliability of the matching results.

2. DESCRIPTIONS OF SUGGESTED MATCHING METHOD

2.1 Point Feature Selection

The choice of a point feature detector certainly has an impact on the results produced by a given matching scheme. We detects the feature points with SUSAN interest operator (www.fmrib.ox.ac.uk), because the SUSAN has the desired qualities of feature detectors: Good Detection: There should be a minimum number of false negatives and false positives; Good Localization: The edge location must be reported as close as possible to the correct position; Response: There should be only one response to a single edge; Speed: the algorithm should be fast enough to be usable in the final image processing system. The steps required for finding SUSAN corners are as follows: Place a circular mask around the pixel in question; Calculate the number of pixels within the circular mask which have similar brightness to the nucleus, These define the USAN; Subtract USAN size from geometric threshold to produce a corner strength image; test for false positives by finding the USAN's centroid and its contiguity; Use non-maximal suppression to

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find the corners. Figure 2 and Figure 3 show the performance of the SUSAN.

2.2 Image Pyramids Generation

Hierarchical methods (Zhang,) are used in many matching algorithms in order to reduce the ambiguity problem and to extend the pull-in range. They are employed from coarse to fine, and results achieved on one resolution are considered as approximations for the next finer level. For this task images are represented in a variety of resolutions, leading to so call image pyramids. A typical image pyramid, in which the resolution from one level to the next is reduced by a factor of 3, is depicted in figure 4. A coarser resolution is equivalent to a smaller image scale and a larger pixel size. Thus, the ratio between the (fictitious) flying height and the terrain height increases as the resolution decreases, and local disturbances such as occlusions become less of a problem. When image pyramids is used, feature extraction should be carried out on each resolution level separately, since features can vanish or be displaced from one level to the next due to the low pass filtering which is inherently present when decreasing the resolution.

2.3 Measure of the Reliability for a Candidate Match

In traditional image matching algorithms, some criterion, such as the bridge model (Zhang, 1996), SM (www.inria.fr), is used to decide that a sample is or is not to belong to a certain classification. But the bridge model only takes local gray information into account; the SM (www.inria.fr) only takes spatial relationships into account. The results from traditional image matching algorithms are therefore inharmonious and unreliable. So we define a new support for a candidate match that takes all local reliability constraint into account.

Consider a candidate match $(\mathrm{m_{Li}},\mathrm{m_{Rj}})$, where $\mathrm{m_{Li}}$ is a point in the left image and $\mathrm{m_{Rj}}$ is a point in the right image. Let $\mathrm{N(m_{Li})}$ and $\mathrm{N(m_{Rj})}$ be respectively the neighbors of $\mathrm{m_{Li}}$ and $\mathrm{m_{Rj}}$ with in a distance of radius R. We define a measure of support for a match, which we call the strength of the match(SM for abbreviation), as

$$\mathrm{SM}(\mathrm{m_{Li}},\mathrm{m_{Rj}}) = \rho(i,\mathrm{j}) \sum_{n_{Lk}\in N(\mathrm{m_{Li}})} [\max_{n_{Rl}\in N(\mathrm{m_{Rj}})} \frac{\rho(ij,kl)\cos(ik,jl)\,\delta(\mathrm{m_{Li}},\mathrm{m_{Rj}};n_{Lk},n_{Rl})}{1+dist(\mathrm{m_{Li}},\mathrm{m_{Rj}};n_{Lk},n_{Rl})}] \tag{1}$$

Where $\rho(ij,kl)$ is the normalized cross correlation of the image segment (i, k) in left image and the image segment (j,l) in right image , if the size of image segment (j, l) is different to the size of the image segment (i, k), a re-sampling for (j, l) relative to (i, k) should be completed to ensure their same size before comparing their normalized cross- correlation.

Where $\rho(i,\mathrm{j})$ is the normalized cross correlation of the image block in left image which center is the i point and the image block in right image which center is the j point, $\rho(i,\mathrm{j})$ is the self support.

And $\cos(ik,jl)$ is direction cosine between the vector (i, k) in left image and the vector (j, l) in right image, if the vector (i, k) has the same direction with the vector (j, l), the candidate match will largely contribute to the match.

$$\cos(ik,jl) = \frac{ik \bullet jl}{|ik||jl|} \tag{2}$$

Where $dist(\mathrm{m_{Li}},\mathrm{m_{Rj}};n_{Lk},n_{Rl})$ is the average distance of the two pairings, ie

$$dist(\mathrm{m_{Li}},\mathrm{m_{Rj}};n_{Lk},n_{Rl}) = [d(\mathrm{m_{Li}},n_{Lk})+d(\mathrm{m_{Rj}},n_{Rl})]/2 \tag{3}$$

With $d(\mathrm{m},n)=\|m-n\|$, the Euclidean distance between m and n, and

$$\delta(\mathrm{m_{Li}},\mathrm{m_{Rj}};n_{Lk},n_{Rl}) = \begin{cases} \exp(-r/\varepsilon_r) & \text{if } \mathrm{r}<\varepsilon_r \\ 0 & \end{cases} \tag{4}$$

Where r is the relative distance difference given by

$$r = \frac{|d(\mathrm{m_{Li}},n_{Lk})-d(\mathrm{m_{Rj}},n_{Rl})|}{dist(\mathrm{m_{Li}},\mathrm{m_{Rj}};n_{Lk},n_{Rl})} \tag{5}$$

With this strength of the match, the distortion caused by ground slope will be rectified, and the quality of the image match will be improved, and a match pair to the strength of a match is the exponential of the negative relative error r, which is strictly monotonically decreasing function of r. When r is very big, then $\exp(-r/\varepsilon_r)\to 0$, and the candidate match can be ignored, other wise when the difference is very small, then $\exp(-r/\varepsilon_r)\to 1$, and the candidate match will largely contribute to the match.

2.4 Search Strategy with Modified Greedy Algorithm for Global Image Matching

For a matches pairs (www.inria.fr), we define a q, witch indicates how unambiguous each a matches pairs. This is defined as

$$q = 1 - SM^{(2)} / SM^{(1)} \tag{6}$$

Where $SM^{(1)}$ is the SM of the matches, while $SM^{(2)}$ is the SM of the second best candidate match. Then q is ranging from 1(unambiguous) to 0 (ambiguous). If q of a march is less than a certain value, the match is considered as null match.

Modified Greedy Algorithm works as follows, those matches whose SM are large than a certain value and whose q are large than a certain value are selected as correct matches. Thus, ambiguous potential matches will not be selected even they have high SM, and those having weak SM will not selected even they are unambiguous.

2.5 Check the False Match

When updating the matches by modified greedy algorithm, we gain correspondence points, but they are not real correspondence points, we use the local reliability constraint to check the bad match (Zhang). So the matched points from modified greedy algorithm are used to calculate the coefficients for the polynomial transformation. This is simply a matter of solving an over-determined system of linear equations in a least-squares method using SM as the weight of the matched points.Once the coefficients of the polynomial have been calculated, it is possible to identify and remove non-isolated inconsistent matches. This is accomplished by computing the following Euclidean distance for each set of matched points *((u,v),(x,y))*,

$$d = \sqrt{(u - f_x(x,y))^2 + (v - f_y(x,y))^2} \tag{7}$$

Where f_x and f_y are the computed polynomials. A bad match is identified by a distance d higher than a chosen threshold (we used 2 pixels). The most inconsistent match is removed and a new polynomial is computed in an iterative process, until no matched point set breaks the chosen threshold.

2.6 Interpolate the Null Match Point

To get null match point parallax, finite element method (www.uni-karlsruhe.de) can be used to interpolate the parallax of the null match point, for every neighbor point of null match point，

$$\begin{aligned} Zp &= (1-dx)(1-dy)Z_{ij} + dx(1-dy)Z_{i+1,j} \\ &+ (1-dx)dyZ_{i,j+1} + (1-dx)(1-dy)Z_{i+1,j+1} \end{aligned} \tag{8}$$

The smoothing condition can be expressed by that the second derivative should be zero. In discrete case, they are the second differences of parallax in the X and Y directions should be zero. The error equations:

$$\begin{cases} v_x = (Z_{i+1,j} - Z_{ij}) - (Z_{i,j} - Z_{i-1,j}) \\ i = 2,\cdots,m-1; j = 1,\cdots,n \\ v_y = (Z_{i,j+1} - Z_{ij}) - (Z_{i,j} - Z_{i,j-1}) \\ i = 1,\cdots,m; j = 2,\cdots,n-1 \end{cases} \tag{9}$$

Where m,n are the row and column number of grids. The principle for adjustment is least square as following:

$$\sum_{k=1}^{n_p} v_k^2 w_k + \sum_{i=2}^{m-1}\sum_{j=1}^{n} v_{xij}^2 w_{xoj} + \sum_{i=1}^{m}\sum_{j=2}^{n-1} v_{yij}^2 w_{yoj} = \min \tag{10}$$

Where n_p is the number of correspondence points, w_k , w_{xoj} and w_{yoj} are weights, they can be set according to the SM of correspondence points.

2.7 Subpixel Accuracy

In general, it is acceptable to achieve a matching result with an error of 1 pixel. But many applications like change detection, passive navigation, feature location measurements in remote sensing and digital photogrametry, image sequence analysis, and nondestructive evaluation require matching results with an error less than one pixel, also called super-resolution and subpixel accuracy. The previously mentioned applications have led to the development of many different algorithms for subpixel image matching.

Three algorithms for achieving subpixel accuracy (www.inrialpes.fr, Tian) are intensity interpolation, correlation interpolation, and single point LS matching.

Intensity Interpolation creates a much denser grid for the selected part of the reference image. Using the input image and the selected part performs a search. For the registration accuracy of 0.1 pixel, an N * N-pixel reference and an M x M-pixel input images, the search space is estimated at (10N – M + 1)* (10N – M + 1) positions. This is due to the fact that the new dimension of the reference image is equal to (10N x 10N). The matching accuracy depends on how accurately the new reference image approximates (by resampling methods) the original image. The intensity interpolation yields the best accuracy among others.

The correlation interpolation calculates the discrete correlation function between two images, fits an interpolation surface to samples of this function, and accurately searches for the maximum of the surface. The accuracy of this method depends on how well a correlation function around the peak approximates a parabola.

Single point least-squares matching is the most accurate image matching technique which is based on the similarity of gray levels. One image is chosen as the reference image, the reference image is transformed to the search image using approximate values for transformation. Due to radiometric errors and to the fact that the parameters of transformation are not known exactly, there will be gray level differences between the two images. It is the basic idea of LSM to estimate the parameters of transformation from these observed gray level differences by a least squares adjustment. The mathematical model can be expanded to other transformations and to handle also radiometric parameters. Due to the great number of observations, LSM is the most accurate image matching technique. However, it is very sensitive with respect to the quality of the approximations.

In this paper, we are not contemplating the development of any new subpixel accuracy techniques. However, as getting such additional resolution effects the execution time of time of image matching, we will use correlation interpolation in 1D matching and Least Squares matching in 2D matching to achieve subpixel accuracy.

2.8 2D matching

For reduce the search from 2D to 1D, we need computation of the unknown parameters of the epipolar geometry that needs a certain number of well-distributed conjugate points. These conjugate points are extracted by the following 2D matching: The SUSAN interest operator is used to select well-defined feature points that are suitable for image matching; Conjugate points are generated using modified hill climbing method (Zhang, 2005). The positioning of the search areas is determined by using the already known control points. For reliability, the threshold of acceptable normalized correlation coefficients is 0.9; Delete bad match point using epipolar geometry; Least squares matching is finally used to refine the image coordinates of these points in order to achieve subpixel accuracy. This procedure results in several hundreds of conjugate points.

The distribution of the conjugate points is the figure 5.

2.9 Quasi-Epipolar Image Generation

Unlike frame-based imagery, where all pixels in the image are exposed simultaneously, each scan line of the IKONOS image is collected in a pushbroom fashion at different instant of time. Thus, epipolar lines with linear CCDs become curves. A straight line for a small length but not for the entire image can approximate it. An epipolar curve for the entire image can be approximated only by piecewise linear segments. In our approach, the epipolar curve(Jiang,2002) for point (x_l, y_l) in the left IKONOS image is approximated by a quadratic polynomial and has the following form:

$$\begin{aligned} y_r &= a_0 + a_1 x_r + a_2 y_l + a_3 x_r x_r + \\ &a_4 x_r y_l + a_5 x_r x_r y_l + a_6 x_r x_r x_r \\ &+ a_7 x_r x_r x_r y_l \end{aligned} \tag{11}$$

Where the (x_r, y_r) are the pixel coordinates in the right IKONOS image and $a_0 - a_7$ are unknown parameters. Using the epipolar geometry, the quasi-epipolar image pair can be generated by re-arranging of the original IKONOS image pair. However, the computation of the unknown parameters of the epipolar geometry needs a certain number of well-distributed conjugate points. These conjugate points are extracted by the 2D matching.

2.10 Fast Image Correlation

The most time-consuming step in image matching is calculation normalized cross-correlation, but the calculation has a lot of redundant computation. To relieve this redundancy, the necessary storage space is retained for the calculated intermediate results. These stored results can be used directly. Effectiveness will increase four to ten times according to the size of the match window.

2.11 Matching Procedure

The match processing is an iterative procedure, and can be formulated as follows:

- 2D matching procedure results in several hundreds of conjugate points; these points can be used to recover the epipolar geometry and interpolate the approximate values for the following point matching procedure.
- Quasi-Epipolar Image Generation
- The match points are selected and distributed in the form of a regular grid in the left image or interest points which extracted by SUSAN. Given a point in the left image, a search window in the right quasi-epipolar image can be determined by the 2D matched points. The correct match of this point should lie in this search window. However, due to repetitive texture or poor texture information, there could be several candidate matches appearing in the search window. These candidate matches are located along the epipolar curve. They can be derived by normalized cross-correlation technique, and the candidate matches are selected if their correlation coefficient lies above a certain user-defined threshold. We use the fast image correlation in this step.
- Achievement subpixel accuracy of all candidate by correlation interpolation
- Compute the matching strength for each candidate match
- Update the matches by modified greedy algorithm
- Check the false match by the local reliability constrain
- Interpolate the null match point by finite element

The parallax map of the IKONOS images by our image matching is the figure 6.

3. TEST DATA

IKONOS images over Dutch were used for the experiments. The left and right pair was acquired on the same day of. The size of each image was 6560by 7556pixels. The images cover approximately 8kms by 8kms on the ground. Figure 1 shows the IKONOS image (left). The image contains dense population of residential houses, apartments and industrial buildings as well as rivers and hills. Automated matching such images is a challenge to any stereo matching algorithms.

4. CONCLUSION

We have proposed in this paper a new approach to match two images by both epipolar constraint and local reliability constraint with modified greedy algorithm and new support of a match. The method has been experimented on some real

Remote Sensing Imagery, from the formerly descript experiments and other experiments not presented here, some conclusions can be drawn. The image matching becomes much harder on pushbroom images. The new algorithm can select a unique point from several candidates point with both global constraint and local constraint.

There still exist a number of ways to improve our algorithm:
For example the precision of the final estimation of the epipolar geometric depends tightly on those of the 2D matched points. To have a better estimation of the epipolar geometric, we should increase the accuracy of the matched points and make the good distribution of the 2D matched points. For example, extracting certain SUSAN points in every block in the left image and deselecting some matched point where many points in one block are good method.

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Figure 1. The origin left image of IKONOS

Figure 2. Origin image

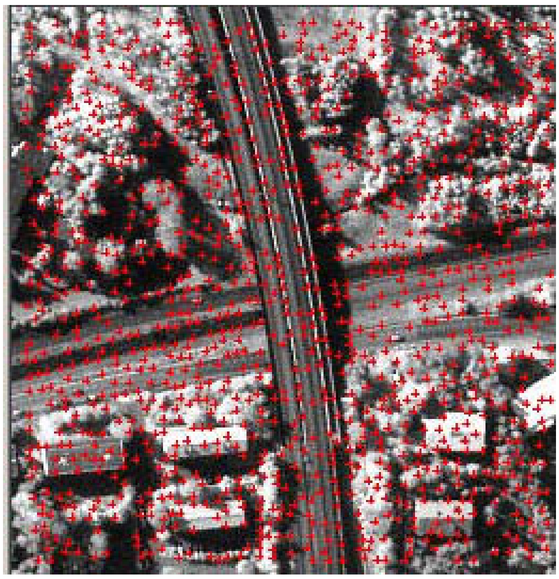

Figure 3. SUSAN points

Figure 4. Pyramid of the image

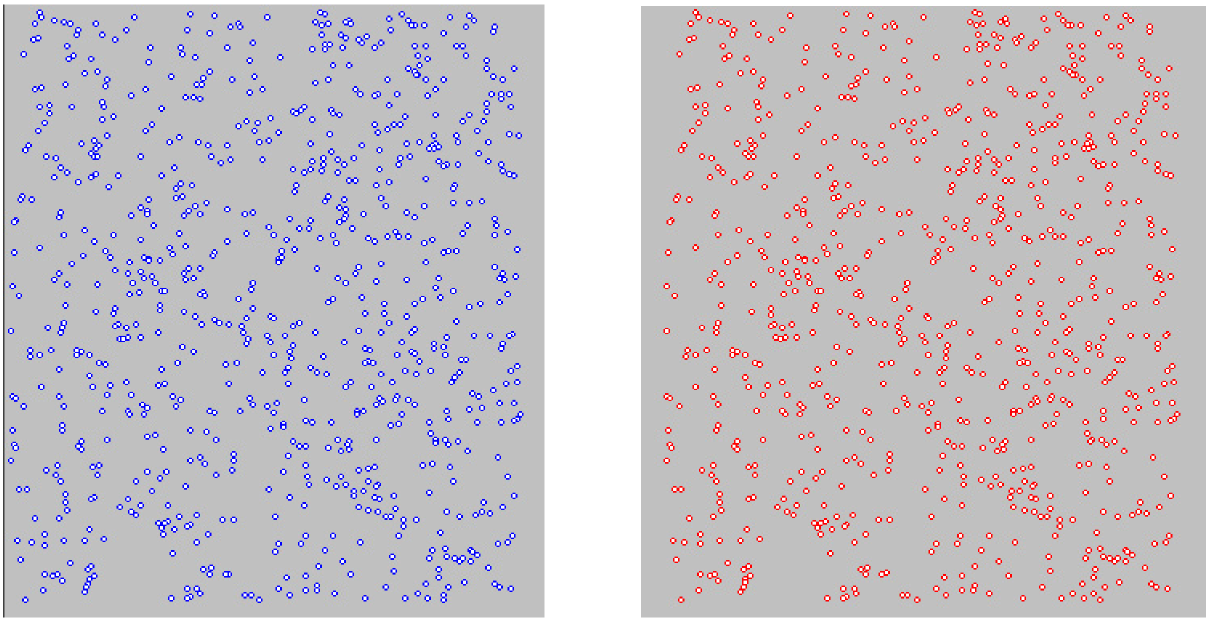

Figure 5. Distribution of the 2D matching points

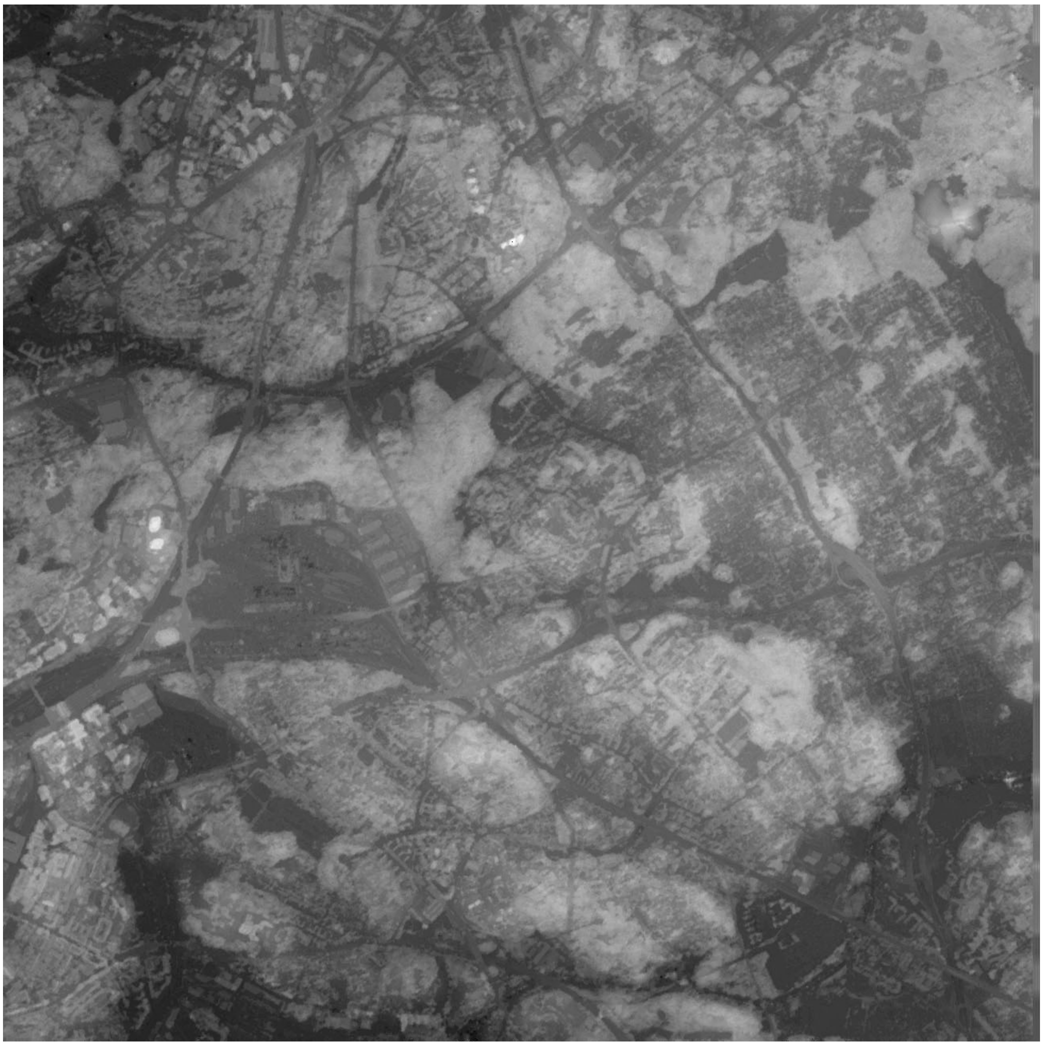

Figure 6. The parallax map of the IKONOS images

Feature Space	**Search Strategy**	**Similarity Measure**	**Achievement subpixel accuracy**
Raw Intensity	Hierarchical	Normalized cross-correlation	Intensity interpolation
Matching Against Model	Genetic Algorithm	Correlation coefficient	Correlation interpolation
Higher Level	Simulated Annealing	Statistical correlation and matched filters	Single point Least Squares matching
Statistical	Hopfield networks	Phase-correlation	
Salient/corner	Relaxation	Sum of absolute differences	
Surface	Tree and graph match	Masked correlation	
Contour	Linear Programming		
Edges	Least squares matching		
	Winner take all		

Table 1. Numerous techniques for image matching