Propagation strategies for stereo image matching based on the dynamic triangle constraint

Qing Zhu [a], Bo Wu [a,b,*], Yixiang Tian [a,c]

[a] *State Key Laboratory of Information Engineering in Surveying Mapping and Remote Sensing, Wuhan University, P.O. Box C310, 129 LuoYu Road, Wuhan, Hubei, 430079, PR China*
[b] *Mapping and GIS Laboratory, Department of Civil and Environmental Engineering and Geodetic Science, The Ohio State University, 470 Hitchcock Hall, 2070 Neil Avenue, Columbus, OH 43210, USA*
[c] *Department of Earth Observation Science, International Institute for Geo-Information Science and Earth Observation- ITC, Hengelosestraat 99, P.O. Box 6, 7500 AA Enschede, The Netherlands*

Abstract

For the purpose of reliable stereo image matching, this paper discusses a novel propagation strategy of image matching under the dynamic triangle constraint. Firstly, the construction and the dynamic updating method for the corresponding triangulations on the stereo pairs are introduced, which are used as both constraints and carriers during the matching propagation. Then, three propagation strategies: the stochastic propagation, the adjacent propagation based on the topological relationship of triangles, and the self-adaptive propagation, which considers the texture features are proposed. The detailed algorithms of these three propagation strategies are also presented. To compare these strategies, a stereo pair with typic texture features is employed to describe the different propagation manners of these three strategies, and an experimental analysis is illustrated with different aerial stereo pairs. From test results, the following has been found: (1) stochastic propagation gives the worst matching results; (2) self-adaptive propagation performs better than the adjacent propagation by making use of the global "best first" strategy. From these conclusions, the self-adaptive propagation strategy is recommended for reliable stereo image matching under the dynamic triangle constraint.
© 2007 International Society for Photogrammetry and Remote Sensing, Inc. (ISPRS). Published by Elsevier B.V. All rights reserved.

Keywords: Matching propagation; Dynamic triangle constraint; Stochastic propagation; Adjacent propagation; Self-adaptive propagation

1. Introduction

Reliable stereo image matching has received great attention since they came into use. Stereo image matching remains the essential and difficult task in digital photogrammetry, and it is also one of the most important and challenging subjects in computer vision and image understanding. The existing image matching methods work well in open areas with relatively smooth terrain. However, they still meet many problems in the case of larger scale images of nature, especially in the dense city centers, forestry areas and the textureless regions such as water bodies (Heipke, 2001). The reliability of image matching is still a big issue in these cases. For example, the

* Corresponding author. Mapping and GIS Laboratory, Department of Civil and Environmental Engineering and Geodetic Science, The Ohio State University, 470 Hitchcock Hall, 2070 Neil Avenue, Columbus, OH 43210, USA. Tel.: +1 614 292 4303; fax: +1 614 292 2957.
E-mail address: wu.573@osu.edu (B. Wu).

corners of buildings and some object boundary points sometimes cannot be matched successfully, and there are many blunders in the automatically derived digital surface models that need to be manually removed, which leads to the decrease of the automatization in digital photogrammetry.

For the purpose of reliable stereo image matching, Zhu et al. (2005) presented a novel image matching method based on the triangle constraint. They firstly triangulate a few seed points on the edge of irregular image areas to form a coarse corresponding Delaunay triangulation pair; then detect certain amount of interest points within a pair of triangles by making use of the improved Harris detector (Harris and Stephens, 1988; Schmid et al., 2000; Mikolajczyk and Schmid, 2004; Zhu et al., 2007), match these interest points under the triangle constraint, and obtain a pair of corresponding points with maximum reliability; after that, insert the new matched corresponding points into the triangulations, and update the triangulations dynamically, then handle the next pair of triangles, and repeat the same process until the termination conditions (the triangles are small enough or cannot match successfully for at least one pair of points) of the matching propagation are met. Because the most distinctive point is always successfully matched first, the dynamic updating of triangulations is just the process of self-adaptive matching propagation. The dynamic updating triangles not only divide the images into many local continuous areas, but also propagate the geometry constraint information from the best regions with favorable textures to the poorest regions, such as the textureless regions and the geometrically or radiometrically distorted regions. This local geometry constraint of triangles can adapt to the changes in image texture automatically, and will finally produce more reliable matching results.

Due to the crucial effects of the local geometrical constraint from the dynamically updated triangles with respect to the final matching results, which is related to the propagation strategy, So this paper investigates further into the propagation strategies of image matching under the dynamic triangle constraint. The remaining of this paper is organized as follows: Section 2 briefly reviews the state-of-the-art image matching propagation methods. Section 3 introduces the construction and the dynamic updating method of the corresponding triangulations on the stereo pairs, which are used as both constraints and carriers during the matching propagation. Section 4 presents the detailed algorithms of three propagation strategies: the stochastic propagation, the adjacent propagation and the self-adaptive propagation. The experimental results with different actual stereo pairs are then presented and analyzed in Section 5. Finally, some concluding remarks are given in Section 6.

2. Related work

The propagation of image matching is the process of matching new points using a prior knowledge related to the preceding matched corresponding points. Many dense matching methods using region growing considered the matching propagation in detail (Tang et al., 2002a; Lhuillier, 1998; Kanade and Okutomi, 1994). The main strategies of these methods are: 1) a few highly distinctive features like points are firstly extracted and matched; 2) these initial matches are then used in a correlation-based region growing step, which merges the neighboring points into larger regions based on some similarity comparison criteria. From the consecutive region growing, the image matching is then propagated to the rest regions of the images. Compared with the traditional pixel based methods, the region growing methods significantly improve the efficiency of dense matching. However, this method can only be applied to good texture images, with the propagation failing in poor texture images.

Many methods have been reported up to now to improve the reliability of image matching propagation. They may be divided into the following three groups:

1. The first group contains the methods that reduce the search area for matching propagation. One of the approaches to reduce the search area is to segment the images using geometrical figures before image matching. Tang et al. (2002b) tried to reduce the search area of matching by making use of a Voronoi diagram. Their method is based on the propagation from N seed points. The whole image is first divided into N cells by means of the Voronoi diagram of the seed points; each cell contains a feature point, which is taken as the seed for propagation inside this region, and the eight corresponding neighboring points of each seed are found using the disparity of this centered point under the continuity constraint. In this way, corresponding relations propagate from the seeds towards the boundaries of the Voronoi diagram. The basic idea to reduce the search area of is also consistent with the matching method based on Delaunay Triangulation (Shen et al., 1998), which restricts the search area by many small triangles. These methods can improve the matching reliability in a certain extent, but the actual results depend on the rationality of image segmentation. Another generally used method to reduce the searching

range is the epipolar constraint (Heuchel, 2005), it takes the searching range from 2D to 1D along the epipolar line, and the matching propagation proceeds from one pixel to another neighboring pixel along the epipolar line. The epipolar constraint can improve the matching reliability and efficiency, but the results depend on the accuracy of the epipolar parameters, and the mismatches may still occur along the epipolar line.

2. The second group includes the methods that employ other matching constraints. Lhuillier and Quan (2000a) utilized local and global geometric constraints for robust matching propagation. This starts by constructing a matching map using a growing propagation schema from a list of seed matches, which may contain the bad matches; then the matching is regularized using the local geometric constraints encoded by planar affine applications. After local regularization, the global geometric constraint encoded by the fundamental matrix is recovered and used to constrain the final propagation. Zhang and Shan (2000) introduced a progressive scheme for stereo matching. It starts from robustly matched seed points, and then densifies the matching by using a growing principle. It considers simultaneously multiple current matches and propagates in a larger area instead of one seed match in a small-predefined area. These methods can also improve the reliability of the matching propagation in a certain extent, but mismatches are still frequent around textureless and occluding areas.

3. The last group optimizes the matching propagation by making use of some propagation strategies. A familiar strategy to optimize the matching propagation is the pyramid image matching based on the "from coarse to fine" strategy (Marapane and Trivedi, 1994; Hung et al., 1998). Pyramid images is the image set with resolution from low to high decomposed from the same original image, and the matching result in the layer with low resolution can be think of the initial value when matching in the layer of higher resolution, the final results are more precise and reliable. Lhuillier and Quan (2000b) presented a quasi-dense matching algorithm based on the "best-first" matching propagation strategy. The algorithm starts from a set of sparse seed matches. The set is implemented with a heap data structure for both fast selection of the ZNCC (Zero-mean Normalized Cross-Correlation)-best match and incremental additions of seeds. Then the matching is propagated to the neighboring pixels around the ZNCC-best points. The risk of bad propagation in this method is significantly diminished, because the bad seed points

have no chance of being developed if they are not ranked on top of the sorted heap, and, the propagation by bad seed points is stopped very quickly due to lack of consistency in its neighborhood even if the bad seed points might occasionally ranked high in the heap. This method is also reliable in textureless and occlude areas mainly due to the enforcement of the global "best-first" strategy.

In all of the matching propagation methods mentioned above, matching begins from some seed points, and then extends to the other regions along their neighboring ways. The propagation of these methods is a "pixel-to-pixel" strategy, and the complexity of matching propagation is directly related to the size (the number of pixels) of the image. When applying "pixel-to-pixel" strategy to large-scale images and images with complicated textures as found in high resolution aerial or satellite images, the matching propagation becomes very difficult due to the complexity of the images. Otto and Chau (1989) designed a "Gotcha" (Gruen–Otto–Chau) ALSC—Adaptative Least Square Correlation algorithm to match two SPOT images, of which deformable windows and "patch-to-patch" propagation are used instead of the disparity constraints and "pixel-to-pixel" propagation strategy. The main advantage of this approach is that the matching can reach sub-pixel accuracy from ALSC patch optimization. However, this patch-based optimization and propagation cannot deal with fine texture details unless the patches are enough small, and the large window size is unavoidable for stable adaptive least squares.

Differing with the "pixel-to-pixel" and "patch-to-patch" propagation strategies, this paper presents a novel "triangle-to-triangle" propagation strategy. This strategy is based on the initial corresponding triangulations on the stereo pairs constructed from a few seed points (Zhu et al., 2006), and the basic object being considered during propagation is the triangle, the matching is propagated only between the local regions constrained by the triangles. The triangles herein not only serve as the constraints in image matching, but also as the propagation carrier. This strategy takes into account the local texture features to constrain as well as lead the propagation of image matching, and along with the dynamic updating of triangulations during the matching propagation, the geometric shape of the dynamic changed triangles automatically adapt to the changes in image texture. This method is more appropriate for high resolution aerial or satellite images covering large areas.

To set out the matching propagation under the dynamic triangle constraint, the following section introduces the

construction and the dynamic updating method of the corresponding triangulations on the stereo pairs.

3. The corresponding triangulations

During the triangle constrained matching propagation, two corresponding triangulations are constructed on the stereo pairs from a few seed points at first. Along with the matching propagation, newly matched corresponding points are inserted into the initial corresponding triangulations, and the correspondences between the nodes and the triangles must be maintained in the updated triangulations all through the matching propagation process. To ensure the correspondences between the nodes and the triangles during the matching propagation, a triangulation is constructed on a master image (e.g. the left image) according to the Delaunay criterion (Lawson, 1977) strictly, while on the slave image, the points are jointed directly to form a triangulation according the corresponding relationship between these points and the points in the master image. An example for a pair of corresponding triangulations can be seen in Fig. 1.

3.1. Construction of corresponding triangulations

As mentioned above, the newly matched points will be inserted into the corresponding triangulations dynamically during the entire matching propagation process, so, the "point insert algorithm" (Li et al., 2004) is selected to construct the triangulations. The "point insert algorithm" is based on the iteration-based principles, which begin with an initial triangle covered the whole data set, then insert all the points in the data set into the existed triangulation iteratively. When a new point is ready for insertion, the three vertices of the triangle containing this point are connected to this point, respectively, which resulting three new triangles. The new generated triangles and their adjacent triangles form some quadrangles with co-edges. Within each quadrangle, the diagonals will be exchanged if the Delaunay criterion is not fulfilled in this quadrangle (Local Optimization Procedure, LOP). The "point insert algorithm" guarantees that the dynamic insertion of the new points will only modify the triangulation locally.

Derived from the surface structure presented by MaCullagh and Ross (1980), this paper designs a conjugate surface structure to organize the geometry and topological data of the corresponding triangulations. Fig. 2 shows the conjugate surface structure of the corresponding triangulations in Fig. 1, which includes:

a) the 2D coordinate lists of the vertices (cf. Fig. 2a and b), which record the 2D pixel coordinate of the point P_i in the left image and its corresponding point P'_i in the right image, respectively;

b) the triangle list (cf. Fig. 2c), in which each triangle is indicated by the indexes of its three vertices;

c) the adjacent triangle list (cf. Fig. 2d), in which the indexes of the three adjacent triangles of each triangle are recorded.

In the conjugate surface structure, each of the two corresponding triangulations has its own coordinate list, but they share the same triangle list and adjacent triangle list. Because the topological relationships between the triangles are recorded in the conjugate surface structure, so it is highly efficient in the local structure analysis.

3.2. Dynamic updating of corresponding triangulations

When a pair of corresponding points are successfully matched during the matching propagation, the point on the master image is inserted into its surrounding triangulation immediately using the "point insert algorithm", and its corresponding point is also inserted into the triangulation on the slave image according the corresponding geometric relationships. Figs. 3 and 4 illustrate the process of inserting a pair of corresponding points (P_7, P'_7) into the corresponding triangulations shown in Fig. 1.

After the points (P_7, P'_7) are inserted into the corresponding triangulations, the conjugate surface structure is updated as Fig. 5 shows, in which the pixel coordinates of new inserted points are inserted into the bottom of the corresponding coordinate list, respectively. The current triangle is updated by one of the new generated triangles, and the rest new triangles are inserted into the bottom of the triangle list, then the topological relationship of triangles is also updated in the adjacent triangle list.

From the above description of inserting the corresponding points into the corresponding triangulations by means of the "point insert algorithm", only few triangles are employed, and the inserting process is restricted in a small area. Therefore, this method performs desired efficiency during the actual matching propagation.

4. The "triangle-to-triangle" propagation strategies

The critical issues for this "triangle-to-triangle" propagation are (1) the choice of the first pair of triangles for matching, and (2) the propagation strategy. This paper presents three strategies: stochastic propagation, adjacent propagation and self-adaptive propagation.
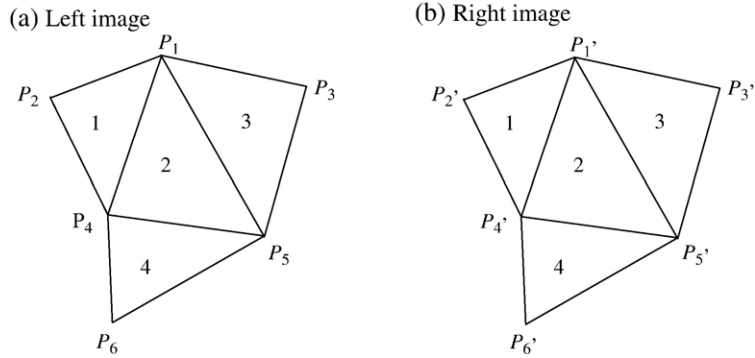
(a) Left image   (b) Right image

Fig. 1. The corresponding triangulations.

To implement the "triangle-to-triangle" propagation, a triangle data structure, which is corresponding with the conjugate surface structure, is designed as:

```
struct TriList
{
    int nID;
    int v1,v2,v3;
    int v12,v23,v31;
}
```

Where,

nID records the sequence number of the triangles recorded in the triangle list;
v1, v2 and v3 are the sequence number of the triangle's three vertices recorded in the coordinate list;
v12, v23 and v31 are the sequence number of the triangle's three adjacent triangles recorded in adjacent triangle list.

In the data structure TriList, only the common information of the two corresponding triangulations are recorded, while the pixel coordinates of the corresponding points in the two triangulations can be indexed quickly through the items v1, v2 and v3 in the corresponding coordinate list.

4.1. Stochastic propagation

Stochastic propagation is the strategy of matching propagation according to the natural sequence of the triangles recorded in the TriList structure.

Derived from the TriList structure, a data structure used for stochastic propagation is designed as:

```
struct TriPropagation1
{
    TriList tTriList;
    BOOL bTriStatus;
}
```

Where,

tTriList overloading the structure TriList;
bTriStatus describes the process status of the triangles during the matching propagation. If the

(a) Coordinate list of left image				(b) Coordinate list of right image				(c) Triangle list			(d) Adjacent triangle list	
No.	Point	X	Y	No.	Point	X	Y	No.	V_1 V_2 V_3		No.	T_1 T_2 T_3
1	P_1	…	…	1	P_1'	…	…	1	1 2 4		1	2 - -
2	P_2	…	…	2	P_2'	…	…	2	1 4 5		2	1 3 4
3	P_3	…	…	3	P_3'	…	…	3	1 3 5		3	2 - -
4	P_4	…	…	4	P_4'	…	…	4	4 5 6		4	2 - -
5	P_5	…	…	5	P_5'	…	…	…	… … …		…	… … …
6	P_6	…	…	6	P_6'	…	…	…	… … …		…	… … …
…	…	…	…	…	…	…	…	…	… … …		…	… … …

Fig. 2. The conjugate surface structure.
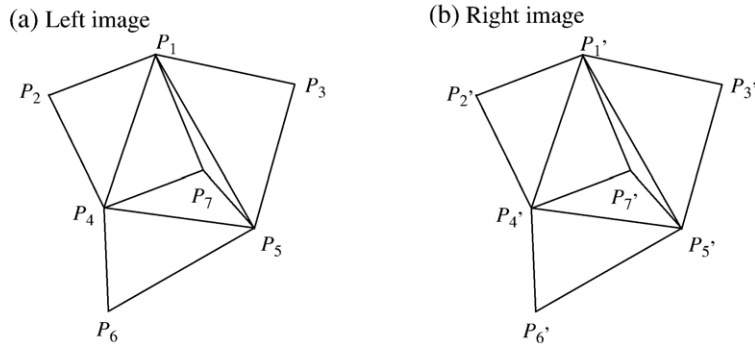
(a) Left image   (b) Right image

Fig. 3. Inserting a pair of corresponding points P_7, P_7'.

current triangle has not been processed, that is to say, the triangle is new generated or updated, and then its bTriStatus is set as FALSE. If the current triangle does not need to be processed, that is to say, the triangle is small enough or cannot match successfully for at least one pair of points, and then its bTriStatus is set as TRUE, which simply means no successful match occurs inside this triangle. When the matching propagation begins, the bTriStatus value of all the initial triangles are set as FALSE.

The algorithm of stochastic propagation is described as follows:

1) To handle the first triangle from the top of TriPropagation1 list;
2) To do the matching under triangle constraint. If the matching is successful, then to insert the new matched point into the triangulations, set the bTriStatus of all the new triangles (including the current triangle, the new generated triangles, as well as the updated triangles) as FALSE, and go to step 3;

or else set the current triangle's bTriStatus as TRUE, go to step 4;
3) To search for the triangle, whose bTriStatus is equal to FALSE, from the top of TriPropagation1 list. If such triangle exist, then to select this triangle as current triangle, go to step 2; or else go to step 4;
4) To handle the next triangle in the TriPropagation1 list. If the bTriStatus of this triangle is equal to FALSE, then to select this triangle as current triangle, go to step 2; or else if the bTriStatus of this triangle is equal to TRUE, then continue to handle the next triangle;
5) If the bTriStatus of all the triangles in the TriPropagation1 list are equal to TRUE, then the propagation terminates.

This algorithm is simplified and shown as the flow chart in Fig. 6.

Because the initial triangulation is generated from irregular points using the "point insert algorithm", and the order of triangles recorded in the TriPropagation1 list is just according to the insertion sequence, this propagation is therefore stochastic.
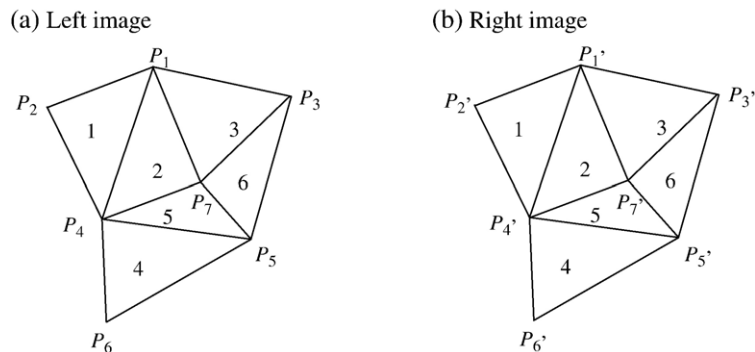
(a) Left image   (b) Right image

Fig. 4. The corresponding triangulations after LOP.

4.2. Adjacent propagation

Adjacent propagation is the strategy of matching propagation according to the topological relationships recorded in the adjacent triangle list, the matching starts from a triangle with minimal area, and extends to the rest of the image along the adjacent regions.

Derived from the TriList structure, a data structure used for adjacent propagation is designed as:

```
struct TriPropagation2
{
    TriList tTriList;
    BOOL bTriStatus;
    int nTriRank;
}
```

Where,

tTriList overloading the structure TriList;
bTriStatus denotes the same meaning with the bTriStatus in the structure TriPropagation1;
nTriRank records the propagation rank of a triangle. The propagation rank denotes the propagation priority of the triangle in the whole propagation, which varies dynamically during the propagation. The higher the value, the more priority-ranked triangles need to be processed. When the matching propagation begins, all the initial triangles' nTriRank are set as 0, and the propagation is terminated when all the triangles' are equal to NULL.

The algorithm of the adjacent propagation is described as follows:

1) To select a triangle with minimal area from the TriPropagation2 list;

2) To do the matching under the triangle constraint. If the matching is successful, then to insert the new matched point into the triangulation, set the bTriStatus of all the new triangles as FALSE, and set these triangles' nTriRank=nTriRank+1, go to step 3; or else set the current triangle's bTriStatus=TRUE and nTriRank=NULL, go to step 4;

3) To search for the triangles whose bTriStatus is equal to FALSE, and select the one with maximal nTriRank. If there are more than one such triangles with the same maximal nTriRank exist, then choose the triangle with minimal area, go to step 2;

4) To search for the adjacent triangles of the current triangle according to their topological relationships whose bTriStatus≠TRUE and nTriRank≠NULL. If such triangle exist, then to select the one with minimal area as current triangle, go to step 2; or else go to step 3;

5) If the nTriRank of all the triangles in the TriPropagation2 list are equal to NULL, and their bTriStatus are equal to TRUE, then the propagation terminates.

This algorithm is simplified and shown as the flow chart in Fig. 7.

The adjacent propagation considers the local continuity among the adjacent ranges in the image. The criterion of starting matching from the triangle with minimal area used in adjacent propagation is helpful to improve the matching reliability for the following two reasons. First, the poor textures such as the intensity-depth discontinuities around the edge of the buildings often occur in large triangles rather than small triangles, which may leads to mismatches, and second, small triangles indicate small matching search areas, and the matching reliability will certainly be improved. It should be noted that the large triangles will be divided up by the new generated triangles gradually along with the consecutive matching propagation.

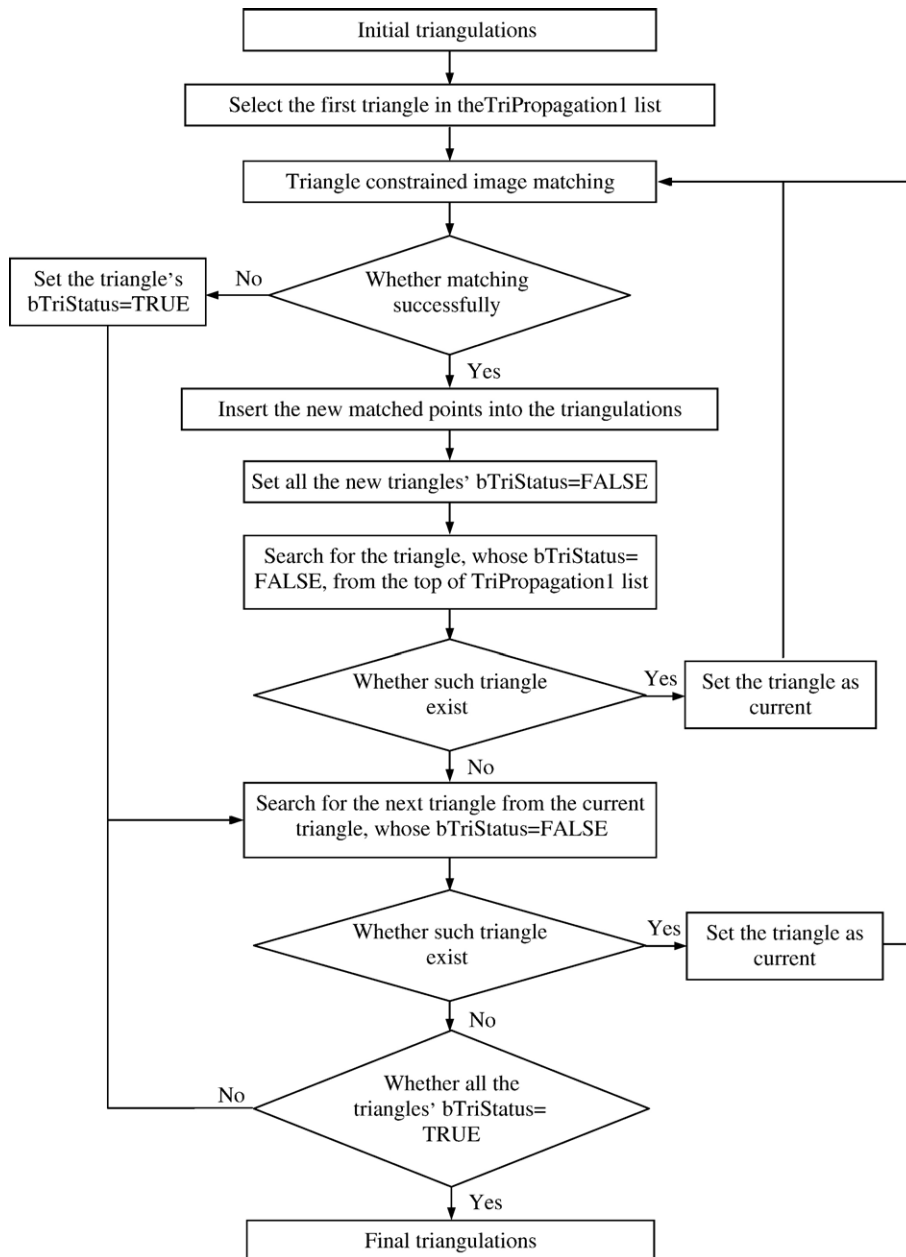| (a) Coordinate list of left image				(b) Coordinate list of right image				(c) Triangle list				(d) Adjacent triangle list		
No.	Point	X	Y	No.	Point	X	Y	No.	V_1 V_2 V_3			No.	T_1 T_2 T_3		
1	P_1	…	…	1	P_1'	…	…	1	1	2	4	1	2	-	-
2	P_2	…	…	2	P_2'	…	…	2	1	4	7	2	1	3	5
3	P_3	…	…	3	P_3'	…	…	3	1	3	7	3	2	-	6
4	P_4	…	…	4	P_4'	…	…	4	4	5	6	4	5	-	-
5	P_5	…	…	5	P_5'	…	…	5	4	5	7	5	2	6	4
6	P_6	…	…	6	P_6'	…	…	6	3	5	7	6	5	3	-
7	P_7	…	…	7	P_7'	…	…	…	… … …			…	… … …		

Fig. 5. The updated conjugate surface structure.

Fig. 6. Flowchart of the stochastic propagation algorithm.

4.3. Self-adaptive propagation

The self-adaptive propagation is the strategy of matching propagation considering the texture features, which starts the matching from the triangles with good textures and desired matching reliability, and then propagates the matching to the other triangles with poor textures.

The texture condition of a triangle coverage can be approximately described by the distinctiveness and matching reliability of the three triangle vertices. In good texture areas, the vertices are the most distinctive well-matched points, while in the poor texture areas, the vertices behave less distinctiveness and lower matching reliability (Zhu et al., 2007). Additionally, the less area of the triangle coverage, the more accuracy to describe the texture condition in this triangle by making use of the distinctiveness and matching reliability of the three triangle vertices. The distinctiveness of points can be defined using the Harris interest strength calculated
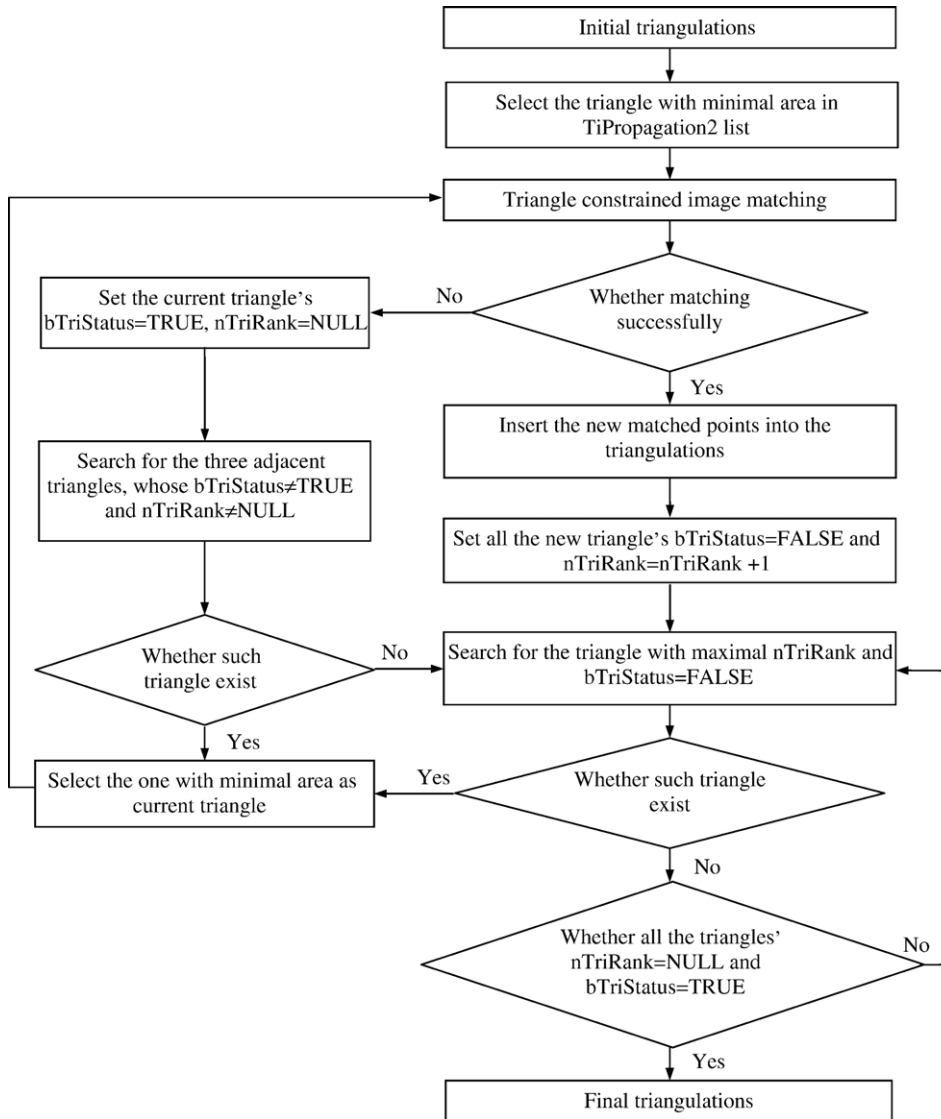
Fig. 7. Flowchart of the adjacent propagation algorithm.

through the response formulation given in Harris and Stephens (1988), and the matching reliability can be calculated when carrying out the image matching under the triangle constraint (Zhu et al., 2005). For convenience, a feature descriptor I_t for each triangle is designed as:

$$I_t = \frac{\frac{1}{3}\sum_{i=1}^{3} H_i \times \psi_i}{S_t} \qquad (1)$$

Where H_i is the Harris interest strength and ψ_i is the matching reliability of the corresponding vertices numbered i. The matching reliability can be calculated by incorporating the gray value correlation coefficient and the epipolar allowed difference of the corresponding vertices (Zhu et al.,

2005). S_t is the area of the triangle numbered t. H_i is generally larger than 0, and varies with the gray value of the image. ψ_i ranges from 0 to 1, and the matching reliability is best when $\psi_i = 1$. The matching reliability of the vertices in the initial triangulations can be considered as 1.

Derived from the TriList structure, a data structure used for self-adaptive propagation is designed as:

```
struct TriPropagation3
{
    TriList tTriList;
    BOOL bTriStatus;
    double dTriFeatureDescriptor;
}
```
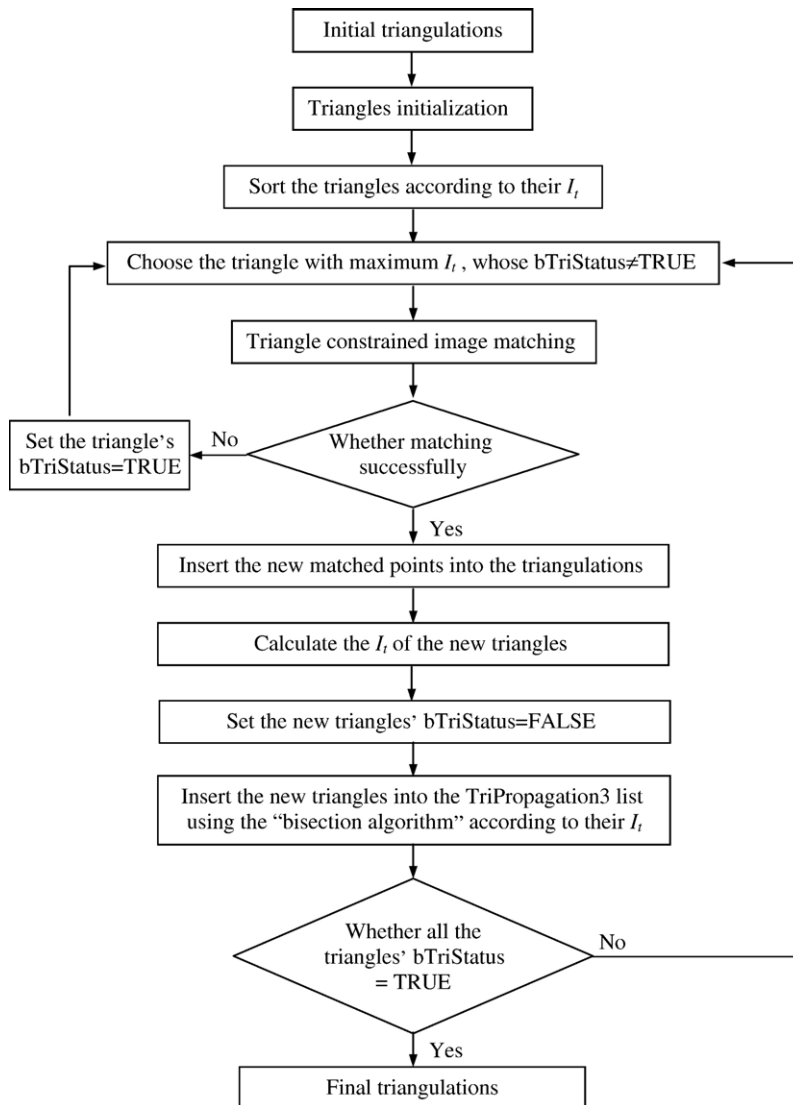
Fig. 8. Flowchart of the self-adaptive propagation algorithm.

Where,

tTriList overloading the structure TriList;
bTriStatus denotes the same meaning with the bTriStatus in the structure TriPropagation1;
dTriFeatureDescriptor records the feature descriptor I_t of each triangle.

The algorithm of the self-adaptive propagation is described as follows:

1) To do the initialization: to calculate the feature descriptor I_t of all the triangles in the TriPropagation3 list using Eq. (1), and record the value of I_t to the item dTriFeatureDescriptor of each triangle;

2) To rank the triangles in the TriPropagation3 list according to their dTriFeatureDescriptor;
3) To select the triangle with maximal dTriFeatureDescriptor, whose bTriStatus is not equal to TRUE;
4) To do the matching under the triangle constraint. If the match is successful, then insert the new matched point into the triangulation, calculate the I_t of all the new triangles using Eq. (1), and record the value of I_t to the item dTriFeatureDescriptor of these new triangles, and set these new triangles' bTriStatus as FALSE, go to step 5; or else set the current triangle's bTriStatus as TRUE, go to step 3;
5) To insert the new triangles into the TriPropagation3 list according to their dTriFeatureDescriptor using the "bisection algorithm", then go to step 3;
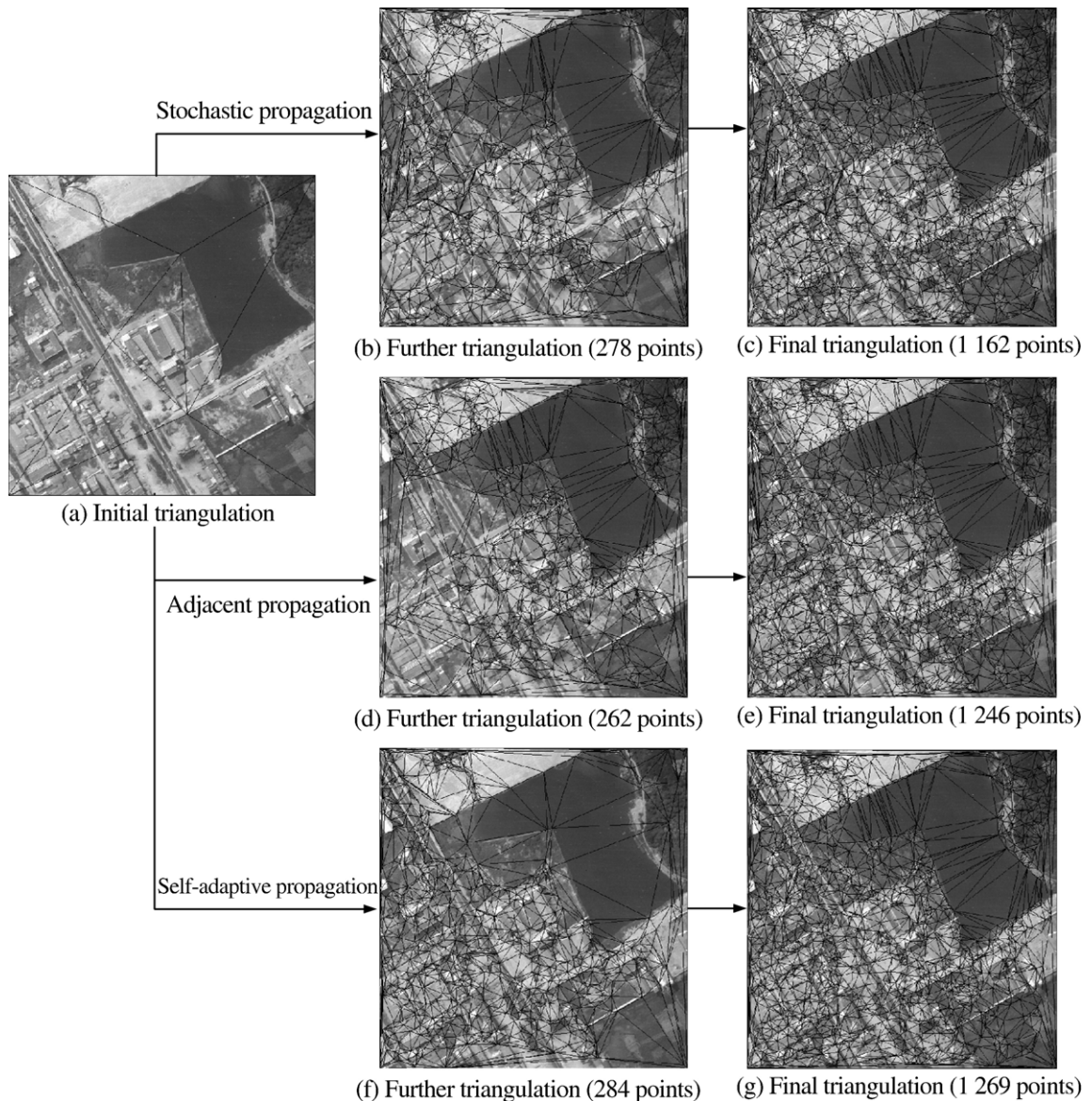
Fig. 9. The propagating process of image matching.

6) If the bTriStatus of all the triangles in the TriPropagation3 list are equal to TRUE, then the propagation terminates.

This algorithm is simplified and shown as the flow chart in Fig. 8.

The self-adaptive propagation is a global "best first" strategy, the triangles with larger dTriFeatureDescriptor have more matching priority in the propagation, and the image matching is always propagated from the triangles with good textures to poor textures. The risk of bad matching propagation is significantly diminished for two reasons: (1) the triangles with less dTriFeature-

Descriptor would be ranked at the bottom of TriPropagation3 list, these triangles therefore would not be processed firstly; and (2) for those triangles of poor texture areas, even their dTriFeatureDescriptor might occasionally ranked higher in the TriPropagation3 list, because no successful matching in these triangles the matching propagation would not be continued.

5. Experimental analysis

Zhu et al. (2005) gave a systemic comparison between the dynamic triangle constrained image-matching method and the traditional matching method

(a) Left image   (b) Right image

Fig. 10. Stereo pair 1.

based on the gray value correlation, in which the stochastic propagation strategy was employed, and the conclusions proved that the dynamic triangle con-strained matching method performs better than the traditional matching methods. In this paper, the comparison of the proposed three propagation strategies is illustrated. Fig. 9 shows the reference image of a typical stereo pair, which covers the better building areas and the textureless water area. Fig. 9(a) shows the same initial triangulation for the different propagation strategies, which constructed from 7 seed points including 4 boundary points. The numbers of matched points in the different stage of different matching

propagation strategies are shown in Fig. 9. Fig. 9(a)–(b)–(c) demonstrates the stochastic propagating process. Because of the random distribution of the new matched points, the triangulation shape is then not very good, and some important feature points have not been matched successfully. In the mean time, there are many malformed triangles in the triangulation, and this may results from some mismatches. Fig. 9(a)–(d)–(e) is the process of adjacent propagation, which extends the matching among the adjacent regions of the image. The mismatches are reduced and more feature points are matched out as can be seen from Fig. 9(d) and (e). The self-adaptive propagation results are shown in Fig. 9(a)–

(a) Left image   (b) Right image
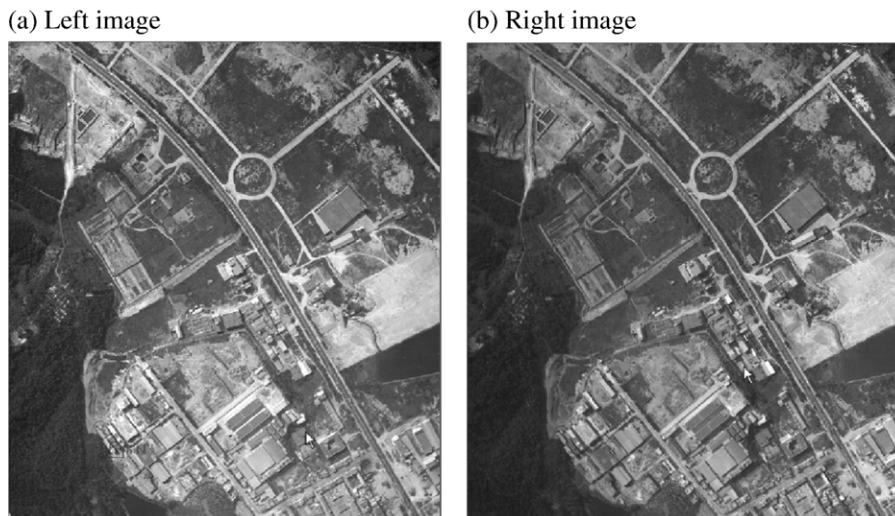

Fig. 11. Stereo pair 2.

(f)–(g), this matching takes account of texture feature over the whole image, extends the matching from the most distinctive and reliable building area to the textureless water area according to the global "best first" strategy. In the further triangulation as Fig. 9(f) shows, the distribution of triangles is more adaptive with the texture features of the image. As to the final triangulation shown in Fig. 9(g), the size and shape of the triangles are even, and there are less malformed triangles exist.

To compare the image matching results of the three propagation strategies, other two aerial stereo pairs with different textures (cf. Table 1, Figs. 10, 11) were also tested. The stereo pair 1 was downloaded from the ISPRS official website (http://www.isprs.org/data/avenches), The stereo pair 2 was collected from Gaungdong province, China.

At first, 29 and 13 seed points were selected on the stereo pair 1 and stereo pair 2, respectively, then, the Harris detector with a 5 * 5 filtering window was used to detect interest points, after that, the triangle constrained image-matching methods with three different propagation strategies were carried out, and the threshold of matching reliability was set to 0.8 to ensure good matching results, and finally, the triangulated DSMs (Digital Surface Models) were obtained, respectively. After eliminating the gross errors, the derived DSM of stereo pair 1 was compared to a reference DSM downloaded from the ISPRS official website, and the derived DSM of stereo pair 2 was compared to a reference DSM collected interactively from VirtuoZo digital photogrammetric workstation. By interpolating the elevation values of all the matched points from the reference DSM, the RMSE (root mean square error) were computed. The experimental results are shown in Table 2.

Considering the RMSE of the two test stereo pairs from the experimental results, stochastic propagation gives the worst results, and self-adaptive propagation performs better than the adjacent propagation. The number of the successfully matched points for the stereo pairs under different propagation strategies denotes the same tendency. More extensive experi-

Table 1
Description of the test stereo pairs

Stereo pair	Size (pixels)	Camera focal length (mm)	Scale	Image overlap (%)	Pixel size (μm/pixel)
1	1800 * 1800	152.850	1:5000	60	15
2	1504 * 1607	153.645	1:10,000	65	25

Table 2
The experimental results for different propagation strategies

Stereo pair	Propagation strategies	Matched points	RMSE (m)
1	Stochastic	2921	1.661
	Adjacent	3203	1.213
	Self-adaptive	3687	0.817
2	Stochastic	2641	0.645
	Adjacent	3219	0.462
	Self-adaptive	3242	0.308

ments making use of different stereo pairs also prove the similar results (Wu, 2006).

6. Conclusions

The following conclusions is summarized:

1) This paper proposed three propagation strategies for image matching based on the dynamic triangle constraint: the stochastic propagation, the adjacent propagation, and the self-adaptive propagation. The detailed algorithms of these propagation strategies were also presented;
2) Intensive experiments proved that the self-adaptive propagation performs better than the others due to the global "best first" strategy.

Acknowledgement

References

Harris, C., Stephens, M., 1988. A combined corner and edge detector. Proceedings 4th Alvey Vision Conference, Manchester, England, 1988, pp. 147–151.

Heipke, C., 2001. Digital photogrammetric workstations — a review of the state-of-the-art for topographic applications. GIM International 15 (4), 35–37.

Heuchel, T., 2005. Experience in applying matching techniques using images from digital cameras. Photogrammetric Week, vol. 05. Wichmann, Verlag, pp. 181–188.

Hung, Y.P., Chen, C.S., Hung, K.C., Chen, Y.S., Fuh, C.S., 1998. Multipass hierarchical stereo matching for generation of digital

terrain models from aerial images. Machine Vision and Applications 10 (5/6), 280–291.

Kanade, T., Okutomi, M., 1994. A stereo matching algorithm with an adaptive window: theory and experiment. IEEE Transactions on Pattern Analysis and Machine Intelligence 16 (9), 920–932.

Lawson, C.L., 1977. Software for surface interpolation. In: Rice, J. (Ed.), Mathematical Software, vol. III. Academic Press, New York, pp. 161–194.

Lhuillier, M., 1998. Efficient dense matching for textured scenes using region growing. Proc. 9th British Machine Vision Conference, Southampton, England, 1998, pp. 700–709.

Lhuillier, M., Quan, L., 2000a. Robust dense matching using local and global geometric constraints. Proc. 16th International Conference on Pattern Recognition, Barcelona, Spain, 2000, vol. 1, pp. 968–972.

Lhuillier, M., Quan, L., 2000b. Match propagation for image-based modeling and rendering. IEEE Transactions on Pattern Analysis and Machine Intelligence 24 (8), 1140–1146.

Li, Z.L., Zhu, Q., Gold, C., 2004. Digital Terrain Modeling: Principles and Methodology. CRC Press (Taylor & Francis Group), London, pp. 65–114.

MaCullagh, M.J., Ross, C.G., 1980. Delaunay triangulation of a random data set for isarithmic mapping. The Cartographic Journal 17 (2), 93–99.

Marapane, S.B., Trivedi, M.M., 1994. Multi-primitive hierarchical (MPH) stereo analysis. IEEE Transactions on Pattern Analysis and Machine Intelligence 16 (3), 227–240.

Mikolajczyk, K., Schmid, C., 2004. Scale and affine invariant interest point detectors. International Journal of Computer Vision 60 (1), 63–86.

Otto, G.P., Chau, T.K., 1989. A region-growing algorithm for matching of terrain images. Image and Vision Computing 7 (2), 83–94.

Schmid, C., Mohr, R., Bauckhage, C., 2000. Evaluation of interest point detectors. International Journal of Computer Vision 37 (2), 151–172.

Shen, P.Y., Wang, W., Wu, C.K., 1998. Image dense matching based on Delaunay triangulation. Proceedings SPIE Conference on Mathematical Modeling and estimation Techniques in Computer Vision, vol. 3457, pp. 109–116.

Tang, L., Wu, C.K., Chen, Z.Z., 2002a. Image dense matching based on region growth with adaptive window. Pattern Recognition Letters 23 (10), 1169–1178.

Tang, L., Tsui, H.T., Wu, C.K., 2002b. Dense stereo matching based on propagation with a Voronoi diagram. Proceedings 3rd Indian Conference on Computer Vision, Graphics & Image Processing, Ahmadabad, India, December 16–18.

Wu, B., 2006. A Reliable Stereo Image Matching Method Based on the Self-adaptive Triangle Constraint. Ph.D. Dissertation, Wuhan University, 110 pp.

Zhang, Z., Shan, Y., 2000. A progressive scheme for stereo matching. Proc. 2nd Workshop Structure from Multiple Image of Large Scale Environments, ECCV Workshop, July 2000, pp. 26–31.

Zhu, Q., Zhao, J., Lin, H., Gong, J.Y., 2005. Triangulation of well-defined points as a constraint for reliable image matching. Photogrammetric Engineering & Remote Sensing 71 (9), 1063–1069.

Zhu, Q., Wu, B., Xu, Z.X., 2006. Seed point selection method for triangle constrained image matching propagation. IEEE Geoscience and Remote Sensing Letters 3 (2), 207–211.

Zhu, Q., Wu, B., Wan, N., 2007. A filtering strategy for interest point detecting to improve repeatability and information content. Photogrammetric Engineering & Remote Sensing 73 (5), 547–553.