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관계영상정합을 이용한 초기근사값 결정

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RELATIONAL MATCHING FOR SOLVING INITIAL APPROXIMATION

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Abstract

The objective of this research is to investigate the potential of relational matching in one of the fundamental photogrammetric processes, that is initial approximation problem. The automatic relative orientation procedures of aerial stereopairs have been investigated. The fact that the existing methods suffer from approximations, distortions (geometric and radiometric), occlusions, and breaklines is the motivation to investigate relational matching which appears to be a much more general solution.

An elegant way of solving the initial approximation problem by using distinct(special) relationship from relational description is suggested and experimented. As for evaluation function, the cost function was implemented.

The detection of erroneous matching is incorporated as a part of proposed relational matching scheme. Experiments with real urban area images where large numbers of repetitive patterns, breaklines, and occluded areas are present prove the feasibility of implementation of the proposed relational matching scheme.

The investigation of relational matching in the domain of image matching problem provides advantages and disadvantages over the existing image matching methods and shows the future

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area of development and implementation of relational matching in the field of digital photogrammetry.

요 약

이 연구는 수치사진측량의 기본과정 중의 하나인 입체영상 표정에서 관계영상정합(relational matching)을 이용한 초기 근사값 결정에 관한 연구를 목적으로 한다. 수치입체영상에 대한 상호표정(relative orientation)을 자동화하기 위한 연구가 수치사진측량(Digital Photogrammetry) 및 컴퓨터 비젼(Computer Vision) 분야에서 많이 이루어져 왔다. 그러나 현재까지의 자동화된 상호표정에 있어서는 초기 근사값 산정에 의한 문제가 제약조건이 되어 왔으므로, 보다 일반적인 적용을 목적으로 관계영상정합이 제안되고 이에 대해 연구가 시작되었다.

이 연구에서는 특수한 관계설정(relational description)을 사용하여, 초기 근사값을 결정하는 보다 유연한 방법이 제시되고 적용되었으며, Cost 함수를 평가함수(evaluation function)로 적용하였다.

본 연구에서 제시된 관계정합방법에 일부로서 매칭오류(mismatch) 탐색과정을 부가하였다. 또한, 반복적인 형태, 파단선, 사각지역 등이 다수 포함되어 있는 도심지의 영상에 대해 적용하므로서 본 연구에서 제시된 관계영상정합이 실제 적용가능하다는 것을 입증하였다.

영상정합의 분야에서의 관계영상정합에 대한 이 연구는 기존의 영상정합법에 대한 장단점을 도출하였으며, 수치사진측량 분야에서의 관계영상정합의 응용과 개발에 대한 향후의 연구방향을 제시하였다.

Key Words : Orientation, Relational Matching , Initial Approximation, Evaluation Function, Inexact Matching, Mismatch Detection, Automation

1. INTRODUCTION

One of most fundamental tasks in photogrammetry is to find conjugate features in two or more images, which is commonly referred to as the matching problem. In conventional photogrammetry, the matching problem is solved by a human operator who identifies conjugate features in two or more images without conscious effort, in real time. The human visual system is easily able to form a stereo model and to describe the scene content in a highly symbolic fashion. In digital photogrammetry, the matching problem, which is called image matching problem in this study, is yet far from being solved fully automatically. The most persistent problems are occlusions, foreshortenings (relief distortions), breaklines (discontinuities in surface) and nonlinear radiometric differences among the images (Doorn et al., 1990; Zilberstein, 1992).

The image matching problem can be described as comparing a specific feature in one image with a set of other features in the other image and selecting the best candidate, based on the similarity measure between feature descriptions. The feature description can be described at different levels of abstraction. Depending on the level of feature description, the image matching methods are usually divided into the three groups: area-based matching, feature-based matching, and relational matching. For a detailed description of the area-based and feature-based matchings, the reader is referred to the papers (Schenk, 1992; Haralick and Shapiro, 1992).

In computer vision, relational matching has been used for problems like object recognition and location, scene analysis, and navigation. Recently, relational matching began to gain attention in digital photogrammetry (Vosselman, 1992; Zilberstein, 1992; Shahin, 1994; Tsingas, 1994). As the name suggests, relational matching seeks to find the best mapping between two relational descriptions. Relational description consists of not only features but also geometrical and topological relationships among the features. In order to find the best mapping, relational matching has to employ the measure of similarity while mapping one relational description into the other relational description. The measure of similarity between two relational descriptions can be achieved by an evaluation function which is usually defined as a cost function or benefit (merit) function. The cost function is to be minimized and is zero if two relational descriptions are identical. Unlike a cost function, the benefit function is to be maximized; and it achieves a maximum when two relational descriptions are best matched.

The motivation for proposing a relational matching scheme for initial approximation problem stems from the fact that the method is much less sensitive to many factors which are limiting the existing image matching methods. Consequently, relational matching appears to be a much more general solution.

2. FEATURE EXTRACTION

Point features provide the most stable geometry for image matching problem. The extraction of distinct points such as corner points is a basic procedure in digital photogrammetry and computer vision. There has been much research in the field of distinct point detection (Moravec, 1977; Förstner, 1994; Tang and Heipke, 1994). These previous works show that the Moravec operator and the Förstner interest operator perform best for real images. The Förstner interest operator was chosen because of its salient features such as rotation invariant and subpixel accuracy. For a more detailed description of the Förstner interest operator the reader is referred to Förstner and Gülch [1987].

In addition, linear feature extraction (edge detection) plays a crucial part in digital photogrammetry and computer vision. Boundaries of objects tend to show up as intensity discontinuities in an image (edges). An edge operator algorithm is designed to detect local edges within small spatial extents. The computer vision and image processing literature is abound with edge operators, see, e.g. (Ballard et al., 1982; Haralick and Shapiro, 1992).

To obtain the straight lines with corner points as their end points, the straight line extraction algorithm must be well behaved around the corner points and should produce as long and straight lines as possible. In addition, the algorithm must have good geometric precision (localization). After investigating existing linear feature extraction algorithms, a simple algorithm which fulfills to some extent all the necessities described above is developed.

The proposed straight line extraction algorithm is based on two properties:

1. good geometric precision (localization).
2. lines are as straight and long as possible.

The first property can be achieved by applying the 2×2 Robert gradient operator which is optimal among 2×2 operators (Haralick and Shapiro, 1992). The computed gradient magnitude is thresholded by a free parameter which is estimated from the whole image content. This weight threshold step prevents generating weak and less meaningful straight lines. The second property, long and straight line, can be obtained by the analysis of the chain of edge pixels which results from edge following. The edge following can be implemented in two different ways:

- gradient magnitude based approach,
- gradient orientation based approach.

The paper (Burns et al., 1986) shows that the gradient orientation varies relatively less over the intensity surface than the gradient magnitude. Thus, the gradient orientation based approach of edge following is selected. Next, the chain of edge pixels is analyzed to extract a long and straight line from the chain. The algorithm for extracting a long and straight line from the chain of edge pixels is mainly based on an algorithm of Douglas and Peuker (Ballard and Brown, 1982). With the Douglas and Peuker algorithm, the straightness of line can be achieved by a small threshold for norm distance.

The suggested algorithm is simple, computing efficient and does not require any postprocessing such as thinning. Since the 2×2 Robert gradient operator is implemented, it interacts well with the physical boundaries. However, because the operator window size is small, it may suffer from the noise in an image. It must be noted that the success of matching depends heavily on good feature descriptions. However, the primary concern of this work is not feature extraction but relational matching and its related procedures.

2.1 Feature Postprocessing

The interest point operator fails to detect corner points of feature lines that intersect outside of the threshold angle. The gradient disturbance around corner points also causes the failure of detecting corner points. Some of those missing corner points can be recovered by using extracted straight lines. When two or more straight lines extracted by the suggested algorithm meet at a point which is not detected as a corner point by the interest point operator, the point is considered as a corner point. However, if the angle between straight lines is less than 30 degrees, the point is not considered as a corner point and also two straight lines are not taken as one long straight line.

Due to noise, low resolution of the image, and shadow cast by a building, the line following does not reach the corner points detected by the interest point operator or passes over the corner points. To solve this problem, a corner point is searched inside a rectangular area around both end points of the straight lines, which is created by width w and distance d. The search for a corner point is based on the following two rules:

1. Proximity.
2. Forward primary.

Based on the proximity rule, the search starts from the end point of a straight line by checking its 8 neighborhood. The forward primary rule means that the search follows primarily the extending line direction. If a corner point is not found after the search moves one pixel forward along the line, it moves one pixel backward along the line. This procedure repeats until a corner point is found or to the end of search area. When the search finds more than one corner point, the corner point that is closest to the line and is in the forward direction is selected based on the two rules.

3. PROPOSED RELATIONAL MATCHING SCHEME

The proposed scheme of relational matching utilizes straight line primitives and their special relations. Because the two special relational descriptions do not match precisely (noise, occlusion, etc.), inexact matching and nil mapping is used. The evaluation functions have been widely used to guide the heuristic search to find the solution. To match two relation sets, the proposed relational matching scheme with cost function was implemented. The cost function was selected because it tends to match as many as possible due to the controlled usage of nil mapping. The mismatch detection was then performed on those matched node points of the straight line primitives. The heuristic tree search method A* with heuristics (unit ordering and modified forward checking) is implemented to find the mapping between two relational descriptions.

3.1 Description of Primitives and Special (Node) Relations

The special (node) relational description consists of primitives and relational tuples among the primitives. Three primitives are used in this study: (1) Open straight line, (2) Half-open straight line and (3) Closed straight line. Each straight line may have none, one or two corner points at its ends. An open straight line has no corner points, the half-open straight line has one corner point, and the closed straight line has two corner points. Each line primitive has three attributes: Length, Orientation and Contrast. The units of length and orientation are in pixels and degrees, respectively.

The half-open and closed line primitives have one and two corner points at the ends, respectively. These two line primitives may share the same corner points as their end points. In that case, the identical corner point is called node point. Now, the binary relations between two line primitives which share the same corner point at the end are called node relations in this study. Since the node relations are distinct from the other binary relations, the node relations are particularly suited to be matched in order to determine initial approximations.

Each node relation has three attributes:

1. Angles between two line primitives (α, β).
2. Orientation between two node points (Φ).
3. Distance between two node points (d).

Figure 1 illustrates the node relations and their attributes. Whereas the angles (α, β) and distance (d) are orientation-invariant quantities, orientation (Φ) is orientation-variant. Thus, the node relation cannot be used for matching a stereopair with a large kappa angle.

All pairs of line primitives with node points are extracted and all combinations of node relations are created. Relational matching is performed by A* search with forward checking. For the matched node points, the mismatch detection process is then performed, which is discussed in next section. Using the matched node points, the initial approximation between two relational descriptions can be estimated. The initial approximation is represented by the base vector (shift) $b = (b_{row}, b_{col})^T$ between two relational descriptions. The base vector with matched m node relations is computed as

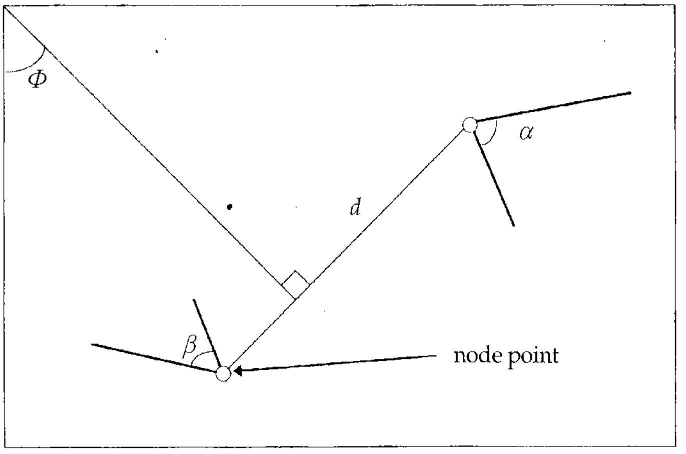

Figure 1: The node relation with its attributes.

$$b_{row} = \frac{\sum_{k=1}^{m} (r_{row_k} - l_{row_k})}{m}, \quad b_{col} = \frac{\sum_{k=1}^{m} (r_{col_k} - l_{col_k})}{m}. \qquad (1)$$

where r and l stand for right and left image, respectively. The base vector as an initial approximation serves the mapping function to find the corresponding line primitives for image matching problem.

3.2 Evaluation Function and Heuristics

The evaluation function guides the search algorithm to a solution, based on the similarity measure between two relational descriptions. There are two ways of estimating the similarity measure using the cost function: distance measure approach and conditional probability approach. The distance measure approach that utilizes the absolute differences between geometric attributes of conjugate primitives (relational tuples) is implemented in this research. Details of the conditional probability approach can be found in (Boyer and Kak, 1988).

It is assumed that all attributes of all primitives and relational tuples are independent of one another so that total measure of cost between two relational descriptions can be computed simply by summing up each cost measure among primitives and relational tuples.

Scale, different viewing directions, surface orientation, topography undulation and relative heights of objects cause the geometric attribute values and the geometric relations to be different. Thus, it is necessary for the matching to know these variations. In this study, the variation of two relational descriptions is estimated by an analytical function with a few critical parameters. The result of this analytical function approach is used to compute a cost measure as well as a benefit measure using the conditional probability function. For the analytical function, the collinearity equation is chosen because of easy manipulation of parameters of interest. For the lack of space, the implementation details of the analytical function approach are skipped. For a more detailed description of the analytical function approach and evaluation function, the reader is referred to Cho[1995].

To speed up the searching process in a tree, two well known heuristics are implemented: unit ordering and forward checking. The search space in the image matching problem is rather large. One way of reducing it is by ordering unit primitives. Tree search suffers from many backtrackings and explores fruitless paths when unit primitives at higher levels of a tree have many possible candidates. Therefore one is interested in ordering the tree in such a fashion that unit primitives with fewer label primitives are ordered at higher levels of the tree.

Forward checking examines the consistency of current unit-label pair with future unit-label pairs below the current level in a tree. The forward checking procedure is modified to be suitable for the initial approximation problem in this study. While examining future with current unit-label pairs, the modified forward checking counts and stores the number of valid future pairs at the current level. This number is stored in a 2-D table: row for unit primitives and column for label primitives. At the current level of a tree, the modified forward checking sums up the number of previous and future unit-label pairs. The total number obtained by the modified forward checking is utilized while the search tree tries to find a solution.

3.3 Matching Scheme and Mismatch Detection

Since the descriptions of the two images of a stereopair differ (due to noise, different viewing angles, difficulties in feature extraction and occlusion, etc.), inexact relational matching must be employed. The extent of nil mapping must be controlled, especially when the evaluation function is a cost function. If the tree search maps all unit primitives to nils, the total cost measure is zero and this mapping provides a trivial solution.

The proposed relational matching scheme utilizes the A* search with heuristics such as unit ordering and the modified forward checking. Since the image matching problem reaches the solution at the bottom of the tree, A* search is selected in this study.

The proposed matching scheme matches two node relational descriptions. Even though some matched pairs satisfy the interrelationships with other matched pairs, there could be mismatches due to a large search window, segmentation error, and missing corresponding features. These mismatches can be detected by two steps: a geometric approach and a radiometric approach.

The geometric approach employs the affine transformation between two matched line primitive pairs. It is assumed that rotation between two relational descriptions is small or estimated from the matched line primitives. The detailed procedure is the following.

1. Compute the affine transformation between two sets of matched end points.
2. Estimate the residuals in y coordinates between the original points and the transformed points and compute the standard deviation of residuals in y coordinates.
3. Eliminate the points whose residuals in y coordinates exceed three times the standard deviation.

In this approach, the y coordinates of the matched points are only considered because the x coordinates correspond to the object height of the points.

While the geometric approach is designed to detect the blunder-like mismatches, the radiometric approach is to detect mismatches more rigorously. The radiometric approach employs the correlation technique using the normalized correlation coefficients for the matched end point pairs. Any matched point pairs satisfying the condition $\rho \leq \rho_{threshold}$ are eliminated from the set of conjugate point pairs. The correlation coefficient threshold $\rho_{threshold}$ is set to 0.6 in this study.

4. EXPERIMENTS AND RESULTS

To assess the feasibility of the proposed relational matching scheme, a software prototype was developed and experiments with two stereomodels have been performed. Because of a limited space, the author describes one of data sets used, and reports and analyzes the major results. All computations, such as generating image pyramids, image subsampling, feature extraction, and relational matching were performed on an Intergraph workstation InterPro 6000.

The stereopair consists of two digitized images depicting the campus of The Ohio State University at a scale 1: 4000. The diapositives were scanned by the Intergraph Photoscan with a resolution of 30μm. An image pyramid was generated using a Gaussian kernel. Images with a resolution of 512×512 pixels were used to extract corner points and straight lines. Figure 2 and 3 show the stereopair superimposed with corner points.

Figure 2: OSU left image superimposed with interest corner points: 97% confidence using 7×7 operator window size, 7×7 non-maxima window size, $q = 0.75$, and $f = 1.5$.

4.1 Feature Extraction

Corner points and straight lines were extracted from the images. For the Förstner interest operator, $f = 1.5$, $q = 0.75$, 97% confidence level and 7×7 window size, also for nonmaxima suppression. It is important to use an orientation-invariant gradient operator, because the

Figure 3: OSU right image superimposed with interest corner points: 97% confidence using 7×7 operator window size, 7×7 non-maxima window size, $q = 0.75$, and $f = 1.5$.

Förstner interest operator is also orientation-invariant. Several gradient operators were tested and was found that the 2×2 Robert operator performs best with the Förstner interest operator. Most corner points are detected well by the interest operator. However, a closer examination of the OSU campus model reveals that some corner points remained undetected where the gradient distribution around the point is not symmetrical.

Table 1: Number of straight lines of three different types after postprocessing.

Line Type	Left Image	Right Image
Closed line	56	68
Half-open line	141	148
Open line	139	127

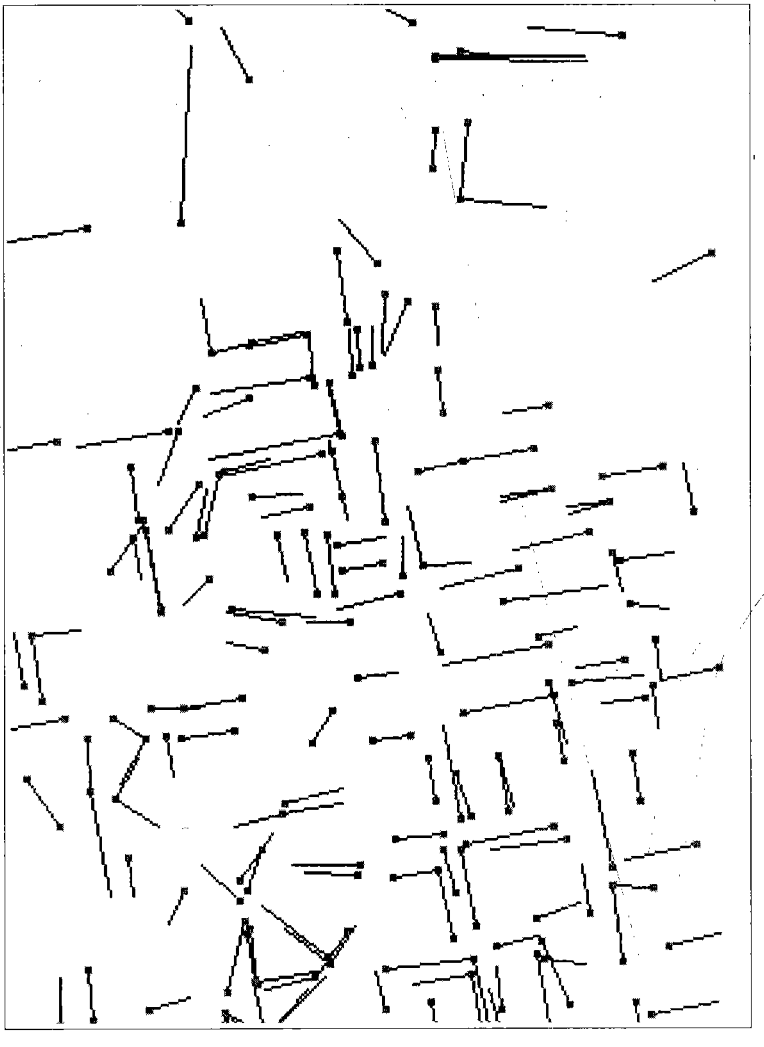

Figure 4: Extracted corner points and straight lines after feature postprocessing (OSU, left image).

The linear straight lines were obtained by the straight line extraction algorithm developed. There are four free parameters required in this algorithm: minimum line distance, norm distance, and gradient orientation and magnitude threshold. In this experiment, the minimum distance, norm distance, and orientation and magnitude threshold are 15 pixels, 1.5 pixels, 45°, mean gradient magnitude, respectively.

After the feature postprocessing, each straight line was named (closed, half-open, and open)

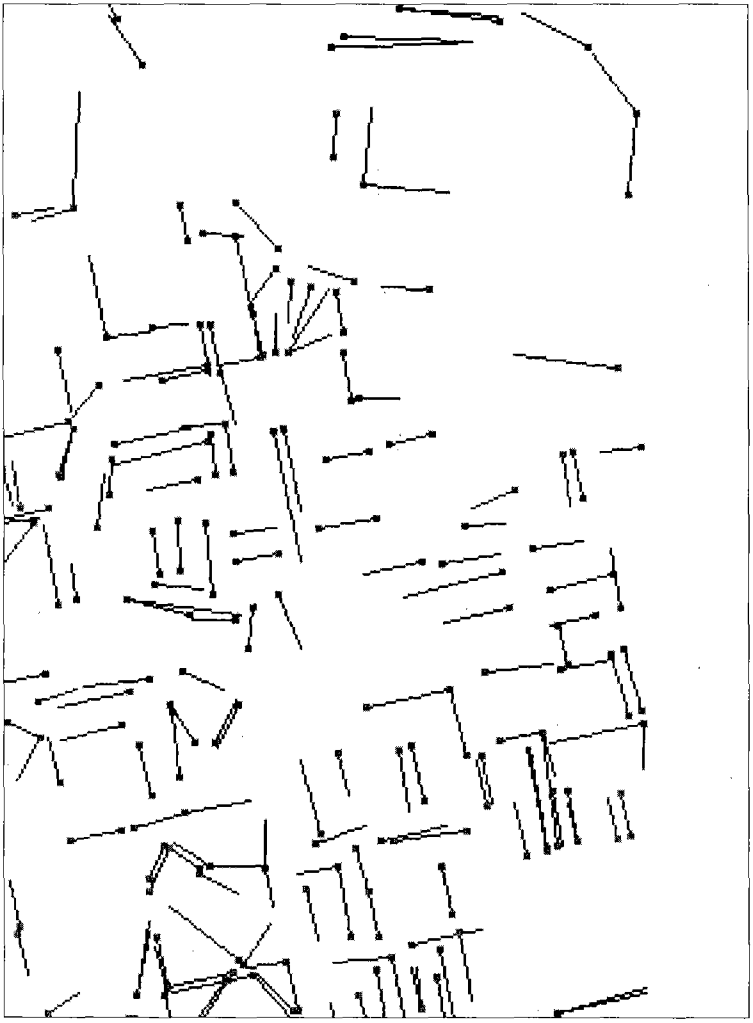

Figure 5: Extracted corner points and straight lines after feature postprocessing (OSU, right image).

based on the number of corner points connected to the line. The number of straight lines of the three different types after the feature postprocessing is listed in Table 1. Figure 4 and 5 depict the results of this postprocessing.

4.2 Node Relation Matching Results

For the OSU stereopair, the left primitive set (left image) has 22 node relations and the right primitive set has 26 node relations. Figure 6 shows two extracted node relations. To match two node relation sets, the proposed relational matching scheme with cost function was implemented. The cost function was selected because it tends to match as many as possible due to the controlled usage of nil mapping. The mismatch detection was then performed on those matched node points.

In Figure 7, the matched node relations after the mismatch detection are shown. Since the node relations are distinct from one another, there were no wrong matches for the OSU stereopair. Using equation (1), the base vector b = (-0.25, -186.375) was computed. The processing time for node relation matching is 9.5 seconds for the OSU stereopair.

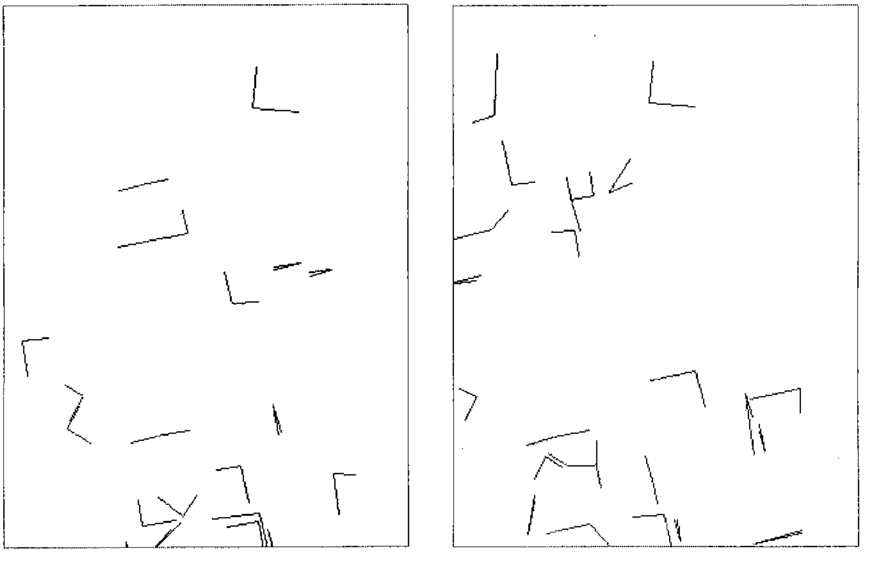

Figure 6: Extracted node relations from both images.

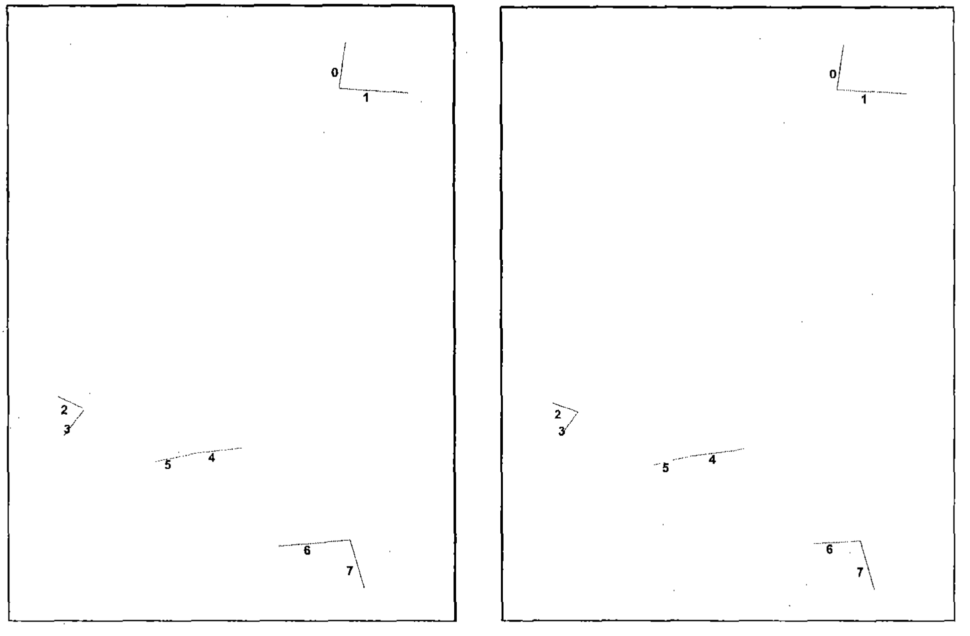

Figure 7: The matched node relations after mismatch detection.

5. CONCLUSIONS

In this study, relational matching with cost function as evaluation function was implemented to solve initial approximation problem. As shown, the proposed relational matching scheme provided reliable results of initial approximation for stereoimages containing breaklines, occlusions, and repetitive pattern by using special (node) relationships between two straight line primitives. Implementing heuristics such as unit ordering and the modified forward checking also helped the relational matching reach a solution without expanding unnecessary subtrees.

One way of obtaining an initial approximation between two images with little rotation was developed and implemented. It showed that the distinct and prominent relations such as node relations were a good way of solving the initial approximation problem. Despite the limited experiments in this study, the results confirm that relational matching successfully deals with many problems in urban area images.

From the experiments in this study, the following issues are identified for future research.

- A feature extraction algorithm which detects and interacts well with the physical boundaries must be explored.

- The higher the abstraction of feature description, the better and faster the relational matching reaches a solution. A way of acquiring a high level of abstraction of feature description prior to relational matching must be explored.
- Some attributes in the primitives and relations are orientation variant. In order for the proposed relational matching scheme to be implemented for more general cases, those attributes should be replaced with orientation invariant ones.
- The computation complexity of relational matching in the form of a tree must be reduced by investigating other existing search methods such as relaxation technique, maximal clique and simulated annealing.

REFERENCES

Ballard, Dana H. and Brown, Christopher M. 1982. *Computer Vision.* Prentice-Hall, Inc.

Boyer, K. L., Kak, A. C. 1988. Structural Stereopsis for 3-D Vision. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 10, No. 2, March, 144-166.

Burns, J. B., Hanson, A. R., and Riseman, E. M. 1986. Extracting Straight Lines. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* Vol. 8, No. 4, July, 425- 455.

Cho, Woosug 1995. Relational Matching for Automatic Orientation. Ph.D Dissertation, The Ohio State University, Columbus, Ohio.

Doorn, B., Agouris, P., Al-Tahir, R., Stefanidis, A. and Zilberstein, O. 1990. Digital Stereo Matching: In Perspective. Technical Notes in Photogrammetry No. 10, Department of Geodetic Science and Surveying, The Ohio State University, Columbus, Ohio.

Föstner, Wolfgang and Güch, E. 1987. A Fast Operator for Detection and Precise Location of Distinct Points, Corners and Centers of Circular Features. *ISPRS Intercommissiom Workshop,* Interlaken, June, 281-305.

Haralick, Robert M. and Shapiro, Linda G. 1992. Computer and Robot Vision. Addison-Wesley Publishing Company, Inc.

Moravec, H.P. 1977. Toward Automatic Visual Obstacle Avoidance, *Proceedings of the 5th Joint Conference on Artificial Intelligence,* Cambridge, 584.

Schenk, T. 1992. Algorithms and Software Concepts for Digital Photogrammetric Workstations. Report No. 418, Department of Geodetic Science and Surveying, The Ohio State University, Columbus, Ohio.

Shahin, Fayez. 1994. An Automatic Correspondence for Digital Images Using Linear Features. Ph D Dissertation, Department of Geodetic Science and Surveying, The Ohio State University, Columbus, Ohio.

Tang, L. and Heipke, C. 1994. An Automatic Procedure for the Relative Orientation of Aerial Images. Proceedings on Integration, Automation, and Intelligence in Photogrammetry, Remote Sensing and GIS. 3rd Liesmars Colloquium, Wuhan, October, 49-58.

Tsingas, Vassilios 1994. A Graph-Theoretical Approach for Multiple Feature Matching and Its Application on Digital Point Transfer. Munich Commission III, Institute for Photogrammetry, University of Stuttgart, 865-871, Stuttgart, FRG.

Vosselman, George 1992. Relational Matching. Lecture Notes in Computer Science 628, Springer-Verlag, Berlin Heidelberg.

Zilberstein, Ofer 1992. Relational Matching for Stereopsis. *International Archives of Photogrammetry and Remote Sensing*, Commission III, Washington D.C., 711-719.