Relational matching for Stereopsis

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Abstract

This paper presents the design and implementation of relational matching for solving the correspondence problem. Application such as large scale urban areas or close range scenes with large depth range relative to the base/height ratio often pose unsurmountable problems to existing matching methods. Relational matching can easier cope with geometrical distortions and it is less sensitive to the presence of occlusions, foreshortening and breaklines. Relational matching is performed by, first, representing epipolar scan lines as trees, and then searching for the minimum distance between the two structures. To demonstrate the flexibility of the matching scheme two different input signals were used. The first input is an gray levels epipolar scan line, used for matching gray level images, and the second input involves convolution values, generated by the *LoG* operator, used for matching, indirectly, zero-crossings. The results show that the matching scheme copes successfully with large geometric distortions without introducing special constraints or tuning the algorithm.

1 INTRODUCTION

Most photogrammetric processes involve two or more photographs. One of the most fundamental tasks in photogrammetry is to identify and to measure a feature of the object space in all overlapping photographs. In photogrammetry, the process of finding conjugate features in two or more images is commonly referred to as the image matching problem. The image matching problem can be described as comparing a specific feature with a set of other features and selecting the 'best' candidate based on criteria such as shape, intensity values, etc. In traditional photogrammetry this problem is solved by an operator who identifies conjugate points by fusing the overlapping photographs to form a stereo model. The human visual ability to solve the correspondence problem is unsurpassed and performed in real-time, without conscious effort. Not only does the human visual system form a stereo model but it interprets the 3-D model and stores a highly symbolic description which is more useful than the original light intensities to draw conclusions and to properly act to what one is looking at.

How the human visual system accomplishes this feat is largely unknown. This is particularly true for the higher visual processes such as image understanding and object recognition. The correspondence problem is considered an early visual process. That is, fusing two images to a 3-D model (stereopsis) is presumably being performed without *a priori* knowledge about the scene.

The most prominent image matching problems are relief distortions, occlusions, discontinuities in the surface (breaklines) and non-linear radiometric differences. Applications such as large scale urban areas or close range scenes with a large depth range relative to the base/height ratio often pose unsurmountable problems to existing matching methods.

Relational matching is new in photogrammetry. In computer vision it is the preferred method in late vision for matching features with a model base (object recognition) [4]. Relational matching can cope with geometrical distortions between the features to be compared much easier. It is less sensitive to the problems mentioned earlier. Hence it should be a more robust method for solving the correspondence problem. This paper focuses on relational matching, explores its potential in digital photogrammetry and demonstrates the usefulness in the surface reconstruction problem.

2 MATCHING TECHNIQUES

Detailed reviews of image matching techniques in computer vision can be found in Barnard and Fischler [5] covering the period from mid-70's until 1981. Dhond and Aggarwal [10] review the topic of 'structure from stereo' from 1981 to 1989. Li [25], Hannah [16], and Doorn *et.al.* [11] review image matching in digital photogrammetry.

In general, three criteria characterize matching techniques :

(1) The selection of features and relationships to be matced. Features can be in the form of patches extracted

from the image, including the 1-D case of scan lines, (segmented) edges, or specific geometric objects.

(2) The control strategy that specifies how to find a potential match.

(3) The criteria for determining (selecting) the best match from several candidates. The matching criteria are measures of similarity between different features.

2.1 Area-Based Matching

In area-based matching (ABM) a rectangular area (templet) of one image is compared with an area of the same size in the other image. Fischler [13] shows that if images differ only due to horizontal and vertical displacement then 'unnormalized' cross-correlation is the optimal matching method. Since ABM techniques use image patches they are sensitive to perspective distortion (relief distortion), to changes in illumination and contrast, and to occlusions and shadows. Of all the positions compared, the one that renders the best similarity measure between the templet and the search window is chosen as the match position. The similarity criterion can be checked by either searching for the maximum cross-correlation coefficient, or by minimizing the gray level differences using least-squares adjustment (LSM).

Area-based matching (ABM) schemes offer these advantages:

- Flexible mathematical model: LSM is the method of choice in photogrammetry, because it provides a general approach to area correlation by offering a tractable mathematical model (least square adjustments). It is easy to use multiple images whereby all image patches are matched simultaneously. It enables photogrammetrists to apply familiar mathematical and statistical principles [19]

- Simple matching algorithm: Both, cross-correlation and LSM are considered simple algorithms with well-known procedures for fast implementations.

- Small storage resources: Only the templet and the search window need be kept in memory resulting in very small memory requirements.

- High accuracy: The accuracy of matched points is high. Ackermann reports in [1] accuracies of points (geometric targets, fiducial marks) with a standard deviation of 3.7 μm.

Area-based matching methods suffer from the following problems:

- Break lines: It is assumed that the template and the search window cover a smooth surface area. If this assumption does not hold, for example when a breakline crosses the surface patch, then the matching results may be wrong. Breaklines possess rich information about the surface. Unfortunately, ABM performs poorly on these interesting areas.

- Matching 'meaningless' points: ABM methods match pixels on the basis of gray levels differences. Pixels have no explicit information about interesting areas of the object space. Therefore, the matching results (3-D position of points in object space) are on the same low level of abstraction as the original image and have no meaning associated. It may be that totally uninteresting areas are matched with a very high accuracy.

- Photometric differences: ABM methods have difficulties with images of different radiometric properties. The radiometric differences between images may result from using different cameras, images from different epochs, or from different reflections of bright objects such as water bodies, etc.. Rosenholm concludes in [32] that the radiometric quality of the images is critical for gray level matching with the LSM method.

- Geometric differences: One of the basic assumptions of image matching techniques is that the two windows (templet and reference window) cover the same area in the object space. This is only the case if the surface is parallel to the camera base. In real situations the two windows cover different areas, hence different gray levels, which affects the matching results (see Horn [22] for more details).

- Problematic texture: In areas such as grass, or in areas with repetitive patterns, there is a problem to determine the position of the best match (e.g flat correlation surface).

2.2 Feature-Based Matching

In feature-based matching (FBM) selected features of each image are first determined on the basis of distinctive image values. The features so determined may include points (*feature points*), corners (intersection of feature lines), and edges. After the location of features is determined a relationship between conjugate features is established (matching). This process is usually performed on the basis of similarity of the feature attributes, for example shape, orientation, gradient, etc..

Some of the advantages of feature-based matching (FBM) are summarized below:

- High reliability: Generally, FBM produces more reliable results than ABM because of the distinctive properties of features. Also, features (particularly edges) are derived over a large spatial extent and thus add to the robustness.

- Captures important information: Feature possess more explicit information about the object space than the raw gray levels. Matching zero-crossings, for example, renders the 3-D location of potential object boundaries. This stems from the relationship between discontinuities in the surface and gray level discontinuities (edges). Matched edges are an essential step toward image understanding and object recognition.

- Compact output: Features can be represented as graphs, a more compact representation than raster.

Feature-based matching schemes have the following problems:

- Localization vs. Detection: Being a high-pass filter, edge operators enhance not only edges but also noise. In order to reduce noise effects, a smoothing operation is applied, such as filtering with a Gaussian. This process causes the edge to be dislocated. The choice of the variance σ^2 of the Gaussian influences the degree of noise suppression as well as the positional accuracy of the edge. This phenomenon is known as the localization-detection trade-off.

- Complex algorithms: From an implementation point of view dealing with features requires more complex data structures and algorithms. Matching by searching trees or graphs is less straightforward than cross-correlation.

- Goodness of match: Unlike LSM no well known statistical methods exist to analyze the matching results.

3 RELATIONAL MATCHING

Relational matching plays an important role in computer vision and so far it has not been used by researchers in photogrammetry. A thorough introduction to relational matching techniques is given in Ballard [4].

The relational matching can be thought of as an extension to feature-based matching. It is particularly important in image understanding, where it can be described as a model fitting. The method is attractive because it can be used in all levels of the computer vision paradigm. A very important conceptual difference exists between area-based approach, and relational matching approach. The area-based method is based on statistical decision theory, while the relational matching is formulated as a problem of combinatorial optimization. In order to perform relational matching, features need to be represented in a symbolic way, usually by using a graph theoretic approach. The solution is then found by performing some kind of graph searching.

Critical step in applying relational matching is the proper representation of the features and their relations. Shapiro in [37, 38] presents example of useful feature representations. Shapiro and Haralick [35] formulate structural description as a relational representation of a 2-D or 3-D entity consisting of a set of primitives each having its own attributes and named relations. Relational matching is then to compare two relations whereas structural matching establishes a correspondence between the primitives of the structural descriptions.

3.1 Examples of Relational Matching Implementation

Linear segment matching combined with graph search is used by Medioni and Navatia [30], Ayach and Faverjon [3]. Lim and Binford [26] performed junction matching. Here the matching begins in the highest level of a hierarchical representation. The results are propagated to each successive lower level in order to guide the matching at that level. Features include objects, surface boundaries, junctions and edgles. Herman and Kende [20] extend this approach by incorporating geometric knowledge. Boyer in [6, 7] shows that structural descriptions of the scene may be used in solving the correspondence problem. The process starts by computing zero-crossings contours of the two images. The zero-crossing contours are then used to construct an attributed structural graph, from which the structural descriptions are built. Now matching is implemented as a tree search on the basis of a consistent labeling problem [17, 18]. Horaud and Skordas [21] propose a method for matching straight lines, and the relation between them. In order to find a map between the structural descriptions, a correspondence graph is being constructed, and the best match is the largest maximal clique.

4 SIGNAL MATCHING

Representation of signals[1] or linear patterns, such as speech signals, electrocardiograms or seismograms by strings, is well known. Enrich and Foith [12] extend this representation by introducing the concept of relational trees. Such models are very useful in pattern recognition. However, the use of complex structures raises the question of how to compare different structures. Various methods have been developed to answer these questions, some depend on the idea of measuring a distance [27, 13, 28] between graphs or trees. Other approaches define a tree grammar which then can be used in syntactic and inference analysis. Detailed information on structural methods in pattern recognition is given in [31] and applications of syntactic pattern recognition is described in [14].

4.1 Examples of Signal Matching Implementation

Witkin, Terzopoulos and Kass [43] formulate the problem of signal matching as a minimization of an energy measure that combines the smoothness term and similarity term as constraints. Anderson's Dynamic Wave Matching [2] is a generalization of cross correlation that is useful in waveform classification, and feature extraction problems. It matches signals by shifting and warping the signals relatively one to the other until a correspondence features are properly aligned. The 'best match', which is in this case translated to the optimum degree of shift and warp, determined by dynamic programming. Dan and Dubuisson [9] propose to match zero-crossings using string matching. The method is based on global and local matching. In the first step (global matching) vertical columns are matched to form a constraint window. Now the local matching takes place by matching the zero-crossing of two epipolar lines. The string

[1] In this paper signal, wave, waveform, and scan lines are used interchangeably

is a collection of zero-crossings and the codes (locations and orientations of zero-crossings) are the alphabet. The matching is performed by using Wagner and Fisher algorithm [41] which determines the matching cost between two strings. The string that has the minimum cost is selected as the 'best match'. Zuxun [45] proposes a method for matching epipolar lines using feature points. Each feature consists of three points: the zero-crossing and two deflection points. The epipolar line is segmented according to the detected features which are then used as matching entities. The matching process consists of geometric correction (resampling) and similarity assessment (correlation). The method of multi-point least-squares matching, modified to handle irregular distributed points, is then applied to refine the matching accuracy.

5 TREE MATCHING

Representing data as trees allows the construction of structural information either explicitly using geometrical properties or abstractly in the form of hierarchical relations between primitive elements. Such models are very useful in pattern recognition, however, the use of complex structures raises the question on how structures can be compared. Various methods have been developed, some depending on the idea of measuring a distance between trees [27, 13, 28], others by defining a tree grammar which then can be used in syntactic inference analysis [15, 24]. Detailed information on structural methods in pattern recognition is given in [31], and applications of syntactic pattern recognition are presented in [14].

6 THE IMAGE MATCHING SCHEME

Figure 1 shows an overview of the implementation of the matching scheme which include the following steps:

(1) Design a data structure that represents the signal (see section 6.2. The data structure incorporates the following information:

- amplitude using the quantization level.
- duration as a real interval.
- peak detection and peak tree representation.

(2) Design features, as part of the node description, to be used in the matching process (see section 6.3.2.

(3) Reduce the search space by

- setting the matching tables dynamically.
- incorporating a hierarchical approach for partitioning scan lines.

(4) Produce node-to-node matching to support the feature-points matching phase

(5) Produce feature-points matching to support the pixel-to-pixel matching phase (see section 6.3.2.

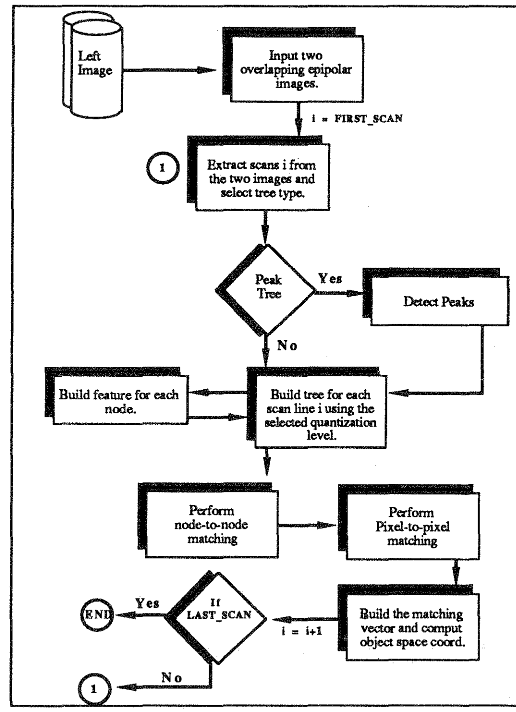

Figure 1: The general matching scheme

(6) Densify the results (pixel-to-pixel matching) by using string matching scheme (see section 6.4.

The following sections comment on the main components of the matching scheme (see Figure 1).

6.1 Assumptions

The matching scheme is based on the following assumptions:

(1) **Epipolar geometry**: The stereopair must be registered in epipolar geometry. A detailed description of how to generate epipolar images is given in Schenk [33].

(2) **Correlated features**: The signals (gray levels or convolution values) of the two corresponding scan lines must be correlated. The matching method fails in case of random images (so does LSM, but not cross-correlation methods).

6.2 Representation of Signals by Trees

Representation of linear patterns, such as speech signals, electrocardiograms or seismograms, by strings has been widely used. An extension to more sophisticated representation has been first introduced by Enrich and Foith [12]. The authors have introduced the concept of relational trees which is a two dimensional representation of a function that describes the wave as a unique ordered sequence of nested peaks. Its application to waveforms provides not only a linear description of a succession of peaks and valleys on a waveform, but also a description of the self-embedding structure of a waveform.

Cheng and Lu [8] introduce two new tree structures for the representation of waveforms, the skeletal and the complete trees. The skeletal tree captures amplitude information and the complete tree also includes duration information.

6.2.1 Skeletal Trees

In order to construct a skeletal tree, the wave is first quantized. A node is an interval created by the intersection of the wave and the quantization level. The tree is generated in a recursive fashion starting from the first quantization level, which represent the entire wave, and ending with the highest quantization level. The depth of the tree is equal to the number of quantization levels, and the leaves of the tree are a linear description of the peaks in the wave (see figure 2.A).

6.2.2 Complete Trees

After generating a skeletal tree, which basically depicts amplitude information, one can add more information to the representation by sampling the wave in the duration direction. The intersections between sampling intervals and the wave generate nodes which are inserted to the tree in the proper position (see figure 2.B).

6.2.3 Peak Trees

The skeletal and the complete tree cannot capture peaks which are smaller than the quantization interval. One solution is to select smaller quantization and sampling intervals, however this might unduly increase the size of the tree. The author suggests to detect the peaks in a pre-process and to assign a node for each peak. The peak detection is done by representing the wave in a syntactic form. The string can be parsed by a deterministic finite state automaton [23] (see figure 2.C).

6.3 Description of The Matching process

6.3.1 Node-to-Node Matching

The matching process begins with representing the scan lines as two quantized trees (see figure 3. Starting on the coarse level, the only available information comes from the orientation procedure. The system can use the parallax approximation, or perform a peak-tree matching with no constraint. In this phase the node-to-node matching table is generated where each node represents a subsection of the wave bounded by the quantization interval.

6.3.2 Feature Point Matching

From the node-to-node table, a vector of sparse pixel-to-pixel matching results can be constructed. Because of quantization and noise, the matching table cannot be directly

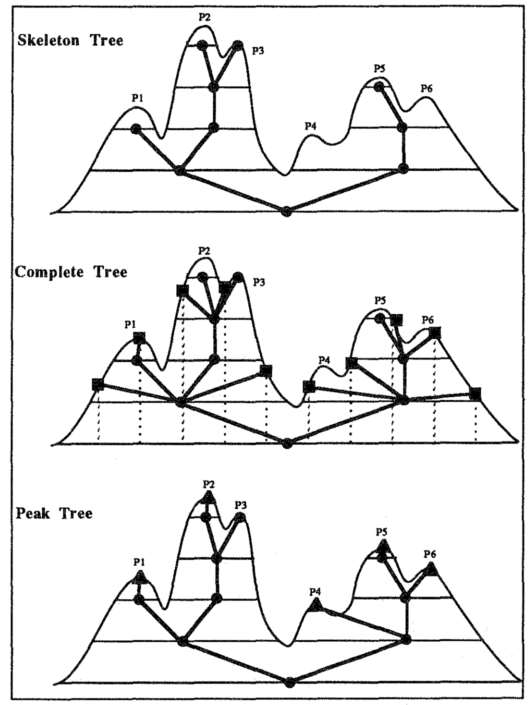

Figure 2: Skeletal, complete, and peak trees

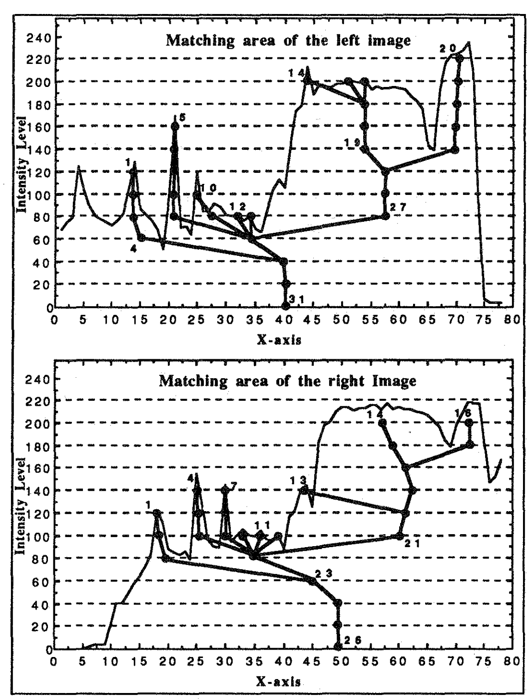

Figure 3: The scan lines and their tree structure

used to identify conjugate pixels. For example, a single pixel node can be matched against a node which represents a ramp. In order to improve this situation, a feature point matching procedure is introduced. Matched points are classified according to their position with respect to the feature definition. Class 1 are points which represent maxima in the feature interval, class 2 are points which represent feature boundaries and class 3 are the node boundaries (see Figure 4).

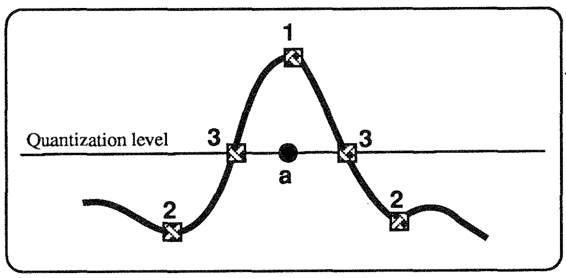

Figure 4: Description of feature points classes 1,2,3

The feature point matching begins with a consistency check followed by matching points according to their class. The type of consistency check depends on the type of the input signal. The following explains the consistency check for gray levels and zero-crossing matching.

Matching Gray Levels When matching gray levels of scan lines, the consistency check includes testing shape and parallax. The shape test is applied in order to avoid matching small regions against large regions, a problem which may occur because of quantization. The length of the regions covered by the node and by its fathers are compared with the length of the matched region. The selected match is the node which generates the minimum difference in length. In the parallax test, the parallax between two points from classes 2 or 3 is computed. If it is within a tolerance then the match is accepted. General feature point (class 1 and 2) are less sensitive then class 3.

Matching Zero-Crossings In case of matching convolution values generated by the *LoG* operator, the translation from the node-to-node table to the sparse pixel-to-pixel vector is only performed on nodes with quantization index 0. The matching is accepted only in the case that the matched region represents quantization level 0. However, due to signal deformation the matched region can be positive or negative. There are three possible cases:

(1) Matching to a positive region

(2) Matching to a negative region

(3) Matching to a zero region

In the first case, the matcher searches for the first node with index 0 in the direction of the root (positive to negative direction). In the second case the matcher searches towards the terminals (negative to positive direction). The last case is straightforward (zero index matches zero index).

6.4 Densification of the Matching Results

After performing the feature matching, the system uses the output information as the input for densifying the matching results. This step can be viewed as local matching in contrast to the global node-to-node matching. It is independently performed on each feature section. The goal is to find a match between individual pixels within a pair of matched features. There are different solutions to this problem. The method of matching character subsequences is described in Wang and Pavilidis [42] which define an Optimal Character Subsequences (OCS) which can be viewed as a problem of string matching whereby amplitudes of the signal, for example the gray levels of a scan lines, form the alphabet.

7 EXPERIMENTS AND RESULTS

The following sections describe the following experiments (For a detailed discussion of the experiments the reader is referred to [46]). The first experiment demonstrates scale-space matching of scan lines from the 'Campus' model starting at resolution 128×128 pixels down to 2048×2048 pixels resolution. In this case the input signal consists of gray levels. The second experiment deals with matching a sub-image from the 'Campus' model. Again, a scale-space approach is used starting at a resolution of 512×512 pixels down to 4096×4096 pixels. In the finest resolution, the sub-image covers the Ohio State University main library; it includes large amounts of occlusions, foreshortening and abrupt surface changes. The input signal is a scan line with convolution values generated by the *LoG* operator. This experiment addresses the interesting problem of matching zero-crossings in an indirect way.

7.1 The Image Pair Used for Testing

The stereopair used in the second and third experiment consists of two aerial photographs (193,195) taken over the campus of the Ohio State University (as part of an ongoing mapping project). The photo scale is approximately 1:4000. The diapositives were scanned at a resolution of 30μm pixel size by the Intergraph Corporation using the PhotoScan system. In the image pyramid the finst resolution was only 60μm, however, yielding a 4096×4096 pixel image. The relative orientation, the resampling to the epipolar geometry, and the image pyramid was computed on the Intergraph Workstation 3050 according to the procedures described in Schenk *et. al.* [34]; Stefanidis *et. al.* [39]; Zong *et. al.* [44].

7.2 Image Matching Using Intensity Values

This section discusses the application of relational matching to gray levels of the original images using a hierarchical approach. The scan lines of level k of the image pyramid are partitioned into sections which are then individually matched. The partitioning is based on the matching results obtained in the previous level $k-1$. For example, the first scan line of the top level of the image pyramid (resolution 128×128 pixels) is row 88. This corresponds to row 172 of the second level (256×256 pixel resolution). Partitioning odd numbered rows (which do not exist on level $k-1$) is done by using the partitions from the two neighboring even numbered scan lines.

7.3 Matching Zero-Crossings

In this application the input signal is a scan line with convolution values as the amplitudes. The input signal is a profile along the scan line through the convolution surface obtained by convolving an image with the *LoG* operator. Zero-crossings are defined as the transition from positive to negative values or vice versa. Therefore, zero-crossings are found between a peak of a positive convolution value and a valley with negative values.

7.4 Analysis of the Matching Results

In relational matching the quality of the matching results cannot be statistically described. The matching cost which reflects the distance between the two trees cannot be translated into a quality measure such as the variance-covariance matrix in LSM.

The discussion presents problems, explanations and possible solutions. In order to assess the accuracy of the results, the matched points were transformed to the object space and plotted as depth profiles against the 'true' profile. The true profile was obtained by measuring the same points manually on a high resolution display screen.

The following general comments can be made:

- Matching gray levels with the relational matching scheme produces a large number of correctly matched points (note that model 'Library' is a difficult model).
- Occlusions are better dealt with by matching zero-crossings rather than matching gray levels.
- Combining the results from matching zero-crossings with those from gray levels offers the possibility to detect errors. Also it increases the confidence of matched points.
- Apart from matched points the matching scheme renders additional attribute information suitable for performing consistency checks.
- The method is robust in that it copes with extreme distortions, and if it fails then it does it locally.

Figure 5 shows matching results of scan line 256 superimposed on the gray-level image. Figure 5.A shows the effect of the border problem while in Figure 5.B this effect is removed by increasing the length of the scan lines. For a detailed discussion of the border effect the reader is referred to [46].

Note the error caused by matching part of the occluded left side of the building (the sixth match from left) and on the right side (the eighth match from right). This error is only local, the system recovered immediately and matched the rest of the scan line correctly; a clear demonstration of the power of global matching.

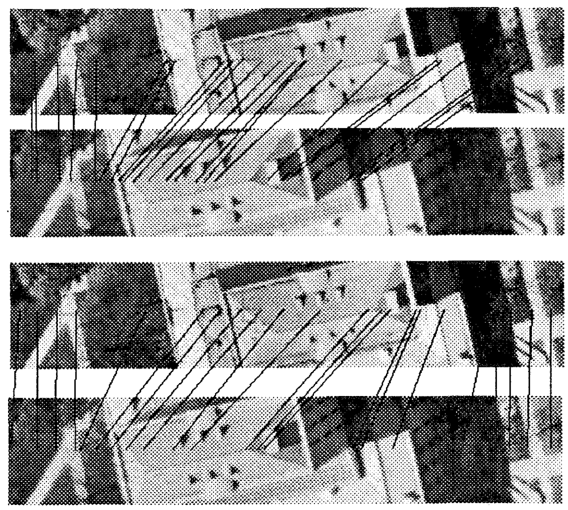

Figure 5: Matching results of 256 superimposed on the intensity images

7.5 Comparison of Matching Results with 'True' Matches

The accuracy and reliability of the relational matching scheme is evaluated with results that were obtained manually, and thus are considered 'true'.

The accuracy of the manually established matched points is ± 1 pixel (mean square error) corresponding to ± 3 feet in object space. In Figure 6 the matching results of scan line 256 are superimposed on the true profile. The discrepancy on the left side as well as the mismatch on the right side are caused by occlusions. All other points are within the excepted tolerances.

8 CONCLUSIONS

In this research, relational matching in the form of tree matching was used to solve the image matching problem for surface reconstruction. As shown, relational matching is a flexible scheme capable of handling different types of input signals. Two different input signals were used in the experiments. In the first case a scan line of a gray level image is the signal. The other type is a scan line of the convolution surface obtained by convolving the image with

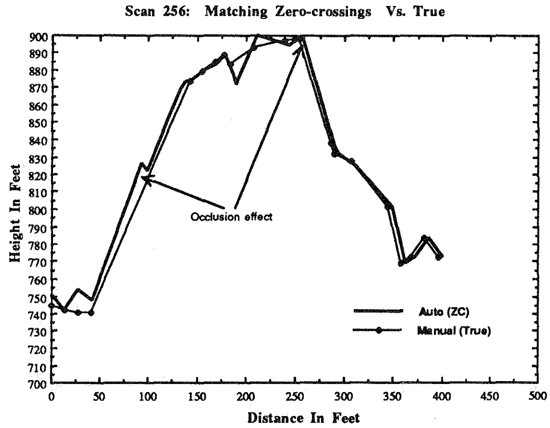

Figure 6: Scan line 256 ('library'): zero-crossing vs. 'true' matching

the *LoG* operator. Special attention was given to matching scan lines corrupted by foreshortening and occluded sections. The results confirm the theoretical expectations that relational matching successfully copes with large geometric distortions without introducing special constraints or tuning the algorithm. This means a more robust solution.

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