IMAGE MATCHING USING RELATIONAL GRAPH REPRESENTATION

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- Keywords: Image Matching, Structural Description, Graph Matching, Relational Graph, Association Graph, and Maximal Clique.
- Abstract: A stereo matching strategy that involves the usage of structural description from the image is proposed. This structural matching strategy is to address the problem of image features that undergo occlusion and also the missing feature situation. The description of the image scene is done by the construction of a relational graph that described the relationship among image primitives. Consequently, the matching between these relational graphs is determined by comparing these structures using graph theory. The best available match between these relational graphs can be determined by finding the best maximal clique in an association graph.

1 INTRODUCTION

Image matching is the process of identifying and establishing the matching between corresponding positions in the image data, which are cast by the same physical point in the real scene. It is an integral part of numerous tasks in computer vision, such as recovering 3D structure from stereo images (Ohta, et. al. 1985, Trapp, et. al. 1988, Zhang, et. al. 2001), or from image sequences of moving scene (Liu, et. al. 1992, Polefeys, 1999). Those applications may involve different approaches, but virtually all these works, shared the same basic aim of image matching. In this paper, we would like to present an approach that intends to solve the stereo matching problem, which is to match corresponding points in the images of the scene to establish a local triangulation.

Numerous image-matching algorithms have been proposed, which can roughly be classified into two categories: the area-based (template) matching and feature matching. Area-based matching correlates grey level template as the matching primitives. In the feature-based approach, salient image primitives like points or edges are extracted. Its corresponding features in the other image are searched by enforcing some constraints and then finally verified using some similarity scheme. Most of these feature based matching methods narrow down the number of possible matches for each feature by enforcing certain constraints on feasible matches. Viewing geometry parameters such as epipolar constraint or analytical constraint control the searching of matching candidates. These methods are fast because only a small subset of the image pixels are used, but may fail if the image primitives cannot be reliably detected in the images. Sometimes, feature based method cannot address well in the problem of occlusion, missing features, feature extraction, or other similar problem domain.

The approach we propose in this paper aims at exploiting a structural (graph) matching to particularly handling the dissimilarity between image features due to occlusion or missing features. We first represent the image data as relational graph and later match using graph matching between these relational graphs. The best available match between relational graphs can be determined by finding the best maximal clique in the association graph.

2 RELATED WORK

In this section, we review some efforts related to the feature-based matching, focusing on some commonly used matching constraints. Epipolar constraint is commonly applied to reduce the search space for potential matching candidates from two

400 Chui Yen L., Daman D. and Shafry Mohd Rahim M. (2006). IMAGE MATCHING USING RELATIONAL GRAPH REPRESENTATION. In *Proceedings of the First International Conference on Computer Graphics Theory and Applications*, pages 400-406 DOI: 10.5220/0001351704000406 Copyright © SciTePress dimensional to one dimensional (Horaud, et. al. 1989). This epipolar constraint is vital in reducing ambiguity problems and computation cost. Other commonly used constraint is similarity constraint, in which the matching features must have similar or highly correlated attributes values. Uniqueness or exclusion constraint is also used as it imposes restrictions to a given feature in one image; where it can only be matched with a single feature from the other image (i.e. one-to-one mapping) (Pla, et. al. 1997). In some cases, after an initial matching, some procedures are used to remove ambiguous matches and later propagate other correct match candidates to its nearby features (Zhang, et. al. 2001, Pla, F., et. al. 1997, Zhang, et. al. 1992). The feature-based matching may be integrated with hierarchical or global matching technique, such as "coarse to fine" multi-resolution matching strategies (Pla et. al. 1997) and relaxation matching (Strickland, et. al. 1992).

3 RESEARCH METHODOLOGY

3.1 Feature Extraction and Feature Grouping

Feature extraction is a key step to derive the structural descriptions of each image to be match. It is basically comprised of edge detection, edge thinning and edge linking to form a straight-line segment. Edge elements are extracted from each image and later linked or grouped together to form a line segment. The result of feature extraction gives the basis to obtain structural descriptions of the images, which later used to construct relational graph.

3.2 Construction of the Relational Graph

There will be a total of two relational graphs that each constructed from the two stereo images to be matched. In each relational graph, the feature extraction image is cast into structural description in terms of line features (line segments), feature attributes, and relationships between nearby features. In relational graph, the set of line features that resulted from feature extraction may be represented by a set of nodes and a network of pointers, where each node represents a line with its attributes and each pointer represents a relation between two nearby lines. There can be a variety of relations to represent with the pointers in relational graph (Figure 2).

The construction of relational graph from the extracted image line features is best showed with the example in Figure 1 and Figure 2 (Horaud, R, et. al. 1989). Figure 1(a) shows a set of six left image lines $(l_1 - l_6)$ and Figure 1(b) shows a set of nine right image lines $(r_a - r_i)$. Whilst, Figure 2(a) and 2(b) shows the left and right relational graph of the left and right line structures (Figure 1(a) and (b)), respectively. Obviously, the left and right line structures to be matched are not identical (isomorphic). Part of the left structure, as shown in Figure 1(a), is occluded. Besides, some lines are broken into pieces in one image, but not in the other image. Here, the stereo matching problem between image features is cast into a double sub-graph isomorphism problem, where the matching between two relational graphs that are not identical can be solved in an association graph (Section 3.3).



Figure 1: Two images to be matched; (a) left structure, and (b) right structure.



Figure 2(a): left relational graph to be matched; the represented interline relations are: left of (1), right of (2), same junction as (3), and collinear with (4).



Figure 2(b): right relational graph to be matched; the represented interline relations are: left of (1), right of (2), same junction as (3), and collinear with (4).

3.3 Construction of the Association Graph

To perform the graph matching between the two relational graphs, an association (correspondence) graph needs to be constructing from two relational graphs. The association graph cast the matching process into a mapping function between the left set of elements and right set of elements, while preserves the compatibilities of relations between features. We take an instance from Figure 1 and Figure 2, l_1 and l_4 are the two left features, r_c and r_e are two corresponding right features; while R_{14} represents the relation between l_1 and l_4 (i.e. left-of) and R_{ce} represents the relation between r_c and r_e (*i.e.* left of). The matching is carried out as a mapping function of left element l_l to right element $r_c (l_l \rightarrow r_c)$ and of left element l_4 to right element r_e $(l_4 \rightarrow r_e)$, and must satisfy some conditions:

- (1) The relation R_{14} between l_1 and l_4 must be compatible with relation R_{ce} between r_c and r_e ,
- (2) The mapping is one-to-one, i.e. each feature in the left image is assigned to a single feature in the right image.

To satisfy the first condition, we apply an association graph to search the best available mapping between the set of left and right elements while preserves the compatibilities of relations between features. For second condition, some geometric constraints such as epipolar constraint to find a list of potential corresponding features in the right image for each feature in the left image. These potential pairs of left-to-right matching, i.e. the matching between l_1 and r_c $(l_1 \rightarrow r_c)$ and the matching between l_4 and r_e $(l_4 \rightarrow r_e)$, are then represented by set of nodes in a association graph (Figure 3) (Horaud, et. al. 1989). Take an instance from the example, the matching pair $(l_1 \rightarrow r_c)$ is represented by node (m_{1c}) , and the matching pair $(l_4 \rightarrow r_e)$ is represented by node (m_{4e}) in the association graph. As we can see from the association graph (Figure 3), when the relation R_{14} between l_1 and l_4 is compatible with relation R_{ce} between r_c and r_e , which both the relations are the same "left of" relations, an arc is linked between node (m_{1c}) and node (m_{4e}) . We called these mutually linked or connected nodes in the association graph as a maximal clique.

Therefore, in the end of association graph building process, there will be a number of maximal cliques which constitute of different combination of mutually connected nodes, which own compatible relations among each other (Figure 3). The largest maximal clique with the largest set of mutually connected nodes in the association graph will provide the largest number of feature matching pairs with compatibility of relations. Hence, the largest maximal clique can be regarded as the best available solution of the matching between two stereo images. In other word, stereo matching becomes equivalent searching for the largest set of mutually to compatible nodes or largest maximal clique in this association graph.

Of course, in practice, a compatible relation is not necessary in order to indicate the 'exactly' same relations. Relations between two nodes can be regarded as compatible when it satisfies some predefined evaluation criteria or rules. Also, in practice, the largest set of mutually compatible nodes (largest maximal clique) is not necessary to give the best solution. Commonly, a cost function is assigned to each maximal clique and the best maximal clique is selected based on cost function, in order to determine the best available match.



Figure 3: The association graph are formed from relational graph.

4 RESULT OF EXPERIMENT

The structural-based technique proposed in this paper applied to match some stereo images. The experiment has been done using fourteen(14) pairs of stereo images, where each pair consists of left image and right image. The brief of the data used in the experiments are summarized in Table 1.

Syntactic stereo images of a house use PNG format from VASC. The data is a pair of syntactic grey scale image depicted a scene of a house with image dimension 250 x 250 (Figure 4 (a) and (b)). In the edge detection process, there are six edges detected from the left image and six edges detected from the right image. In the edge-tracing process, no edges are eliminated and therefore the edge-tracing image (Figure 4 (e) and (f)) appears the same with edge detection image (Figure 4 (c) and (d)). After undergoing the step of line segment extraction, there are 23 line segments derived from the left image and 23 line segments derived from the right image (see Figure 4 (g) and (h)). The structural information interpreted from the left and right line segment image is represented by the left and right relational graph respectively (see Figure 4 (i) and (j)).

Ex	Size	Туре	Descriptions
р			
1	250 x	PNG	Syntactic stereo
	250	(VASC)	images of a house
2	250 x	PNG	Syntactic stereo
	250	(VASC)	images of a house
3	288 x	GIF(©	Syntactic stereo
	384	INRIA)	images of a block
4	288 x	GIF(©	Syntactic stereo
	384	INRIA)	images of note
5	256 x	PNG	Syntactic stereo
	206	(VASC)	images of some
			rectangles
6	250 x	PNG	Stereo images of a
	250	(VASC)	book
7	300 x	PGM	Stereo images of a
	300	(VGG)	piece of gear
8	347 x	PGM	Stereo images of a
	496	(VGG)	piece of gear
9	134 x	PNG(VA	Stereo images of a
	212	SC)	Rubik cube and a
		00	wooden block
10	512 x	PNG(VA	Stereo images of
	512	SC)	arch of blocks
11	256 x	PNG(VA	Stereo images of a
[]	256	SC)	telephone and a
	0		cup
12	512 x	PNG(VA	Stereo images of a
~	512	SC)	tennis ball, an ice
		·	chest and two
			cylinders
13	250 x	PNG(VA	Stereo images of
	250	SC)	an indoor room
14	250 x	PNG(VA	Stereo images of
	250	SC)	an indoor room

Table 1: The image data used in experiments.

Association graph is constructed from both the left and right relational graph. The resulted association graph has 68 nodes and 257 arcs, as shown in Figure 4.(o). Then, the maximal clique search is performed. The largest maximal clique is a clique of size 19, which comprised of 19 mutually, connected nodes. With 23 lines in the left image and 23 lines in the right image, the matching algorithm found 19 left-to-right correct matching pairs, with no false matched (mismatched) lines. There are four unmatched lines. 83 % of the left lines are matched correctly. Figures 4 (k) and 4(l) show the left-to-right matching lines found by the largest maximal clique. The unmatched lines are shown in Figures 4 (m) and 4(n).





Ambiguity in image matching might happen. (Can be observed from the left and right image of the house where two similar structures are formed by the house windows). For instance, line labeled 20 of the first window in the left image might match falsely to line labeled 15 of the second window in the right image due to the similarity between these two window structures, and line labeled 21 in the left image might match falsely to line labeled 16 in the right image, and so forth. However, the matching result shows that mismatch case is not occurred at all. This observation shows that the structural information is plausible to reduce the ambiguity in image matching.

For structural-based image matching, again 14 samples of image are used. The structural-based matching technique is set of rules and procedures to accomplish image matching by taking into account the structural descriptions of image. Here, structural information of an image is described in terms of the line features and its properties and inter-line The derivation of structural relationships. descriptions is a consequence of edge detection and line segment fitting, line labelling and the derivation of relationship between two neighbouring lines and relational graph representation. Some information about the relational graphs that represent the structural descriptions, derived from the left and right feature images is given in Table 2.

The density of adjacency matrix of a relational graph ρ is the number of non-zero elements *nnz* divided by the total number of matrix elements *nElnt*.

$$\rho = \frac{nnz}{nElement} \tag{1}$$

The density act as a rough indicator of the richness of structural descriptions derived from the left and right feature image and is represented by the relational graph. The matrices with low density indicate that the inter-line relationship that successfully derived by the structural description module is relatively in low quantity.

Here, the incorporation of inter-line relationship, ordering (to the left of-to the right of or to the top of-to the bottom of), intersection and co-linearity is to impose some spatial constraints to the feature matching process. The relationship is useful in assisting the feature-matching algorithm to prune away false matching candidates as well as to reduce matching ambiguities whenever in the foregoing problematic circumstances.

Our experiments have verified that the incorporation of structural information is applicable and reasonable to reduce the dependence on the quality of the image, the performance of feature extraction and the quality of extracted feature. The experimental results have demonstrated that the proposed technique is not constrained much by the foregoing problems, and work reasonably with two descriptions that are not likely to have a strict oneto-one correspondence at the feature extraction level, as can observed from the edge detection and edge tracing images. The results also demonstrate that the structural information compensate for the bad effect that may cause by the foregoing problems, at least to certain extent. As we can observe from the matching result, false match case is not occurring and the number of false matched lines is relatively in a very small quantity compared to the number of matched lines.

Exp	Left			Right		
	nnz	nElnt	ρ	nnz	nElnt	ρ
1	95	529	0.18	91	529	0.17
2	96	576	0.17	97	625	0.16
3	65	361	0.18	66	324	0.20
4	56	169	0.33	20	36	0.56
5	284	5776	0.05	301	6400	0.05
6	108	729	0.15	130	1024	0.13
7	157	1156	0.14	382	8100	0.05
8	476	11025	0.04	571	15376	0.04
9	394	9409	0.04	391	7744	0.05
10	275	5329	0.05	279	5476	0.05
11	927	49284	0.02	959	51529	0.02
12	351	8281	0.04	345	8281	0.04
13	658	25600	0.03	770	31329	0.02
14	748	29929	0.02	713	30276	0.02

Table 2: The resulted relational graph.

Table 3: The matching results.

Exp	left	right	match	Un-match	false	Match
					match	(%)
1	23	23	19	4	0	83%
2	24	25	20	4	0	83%
3	19	18	16	3	0	84%
4	13	6	4	9	1	31%
5	76	80	41	29	6	62%
6	27	32	4	19	4	30%
7	34	90	9	25	0	26%
8	105	124	0	99	6	6%
9	97	88	78	18	1	81%
10	73	74	22	50	1	32%
11	222	227	4	218	0	2%
12	91	91	7	83	1	9%
13	160	177	6	154	0	4%
14	173	174	6	167	0	3%

5 CONCLUSIONS

In this paper, a structural-based image matching technique is presented. The procedures consist of the interpretation of the structural descriptions of an image, then representing the derived structural descriptions in relational graph and finally perform relational graph matching in an association graph, to accomplish image matching.

The study on structural descriptions of a feature image has contributed to the specifications of structural descriptions of an image in order to facilitate the relational graph representation and graph matching. The structural information is described in terms of feature, feature's properties and relationship between features. With respect to this, we have developed set of rules and procedures to detect line features and inter-line relation exists in an image. The inter-line relations focused in this study are ordering, co-linearity, and intersection. Structural descriptions derived from an image are represented by a relational graph. The structural descriptions are representing as network of nodes and arcs in the relational graph. In the resulted relational graph, each node represents a line feature of the image, with its attached properties and arc (if exist) is inserted between any two nodes to represent the relationship between lines.

The study on deriving structural descriptions of an image to represent in relational graph and incorporating structural information into image matching has contributed to the structural-based image matching technique. Between two relational graphs, image matching is carried out to search for the best sub-graph isomorphism. The process involves the derivation of an association graph from both the relational graphs and the searching for the largest maximal clique in the association graph to represent the best correspondence between images.

6 FUTURE WORK

The next challenge is related to extend the incorporation of other possible spatial relationships between line segments features, such as disjoint, contains, inside, overlap and others. To improve the robustness of the method described in this paper, more varieties of relationship are needed to describe the structural information of an image. Further investigations are needed on the usage of other alternate matching primitive. The possible alternative matching primitive is using region.

Region as matching primitives can reduce the size and complexity of the relational and association graph because the number of regions to be matched is always less than the number of line segments for any given image. The method is worthwhile to extend to other kind of features with their specific relationships. Further extension to incorporate with other feature properties such as orientation, texture and contrast is needed to increase the robustness of similarity measure.

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